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# Impulse Buying Mechanisms in Live-Streaming E-Commerce: An S-O-R Perspective on AI Generative Persuasiveness, Time Pressure, and Financial Capacity

**Abdus Ricky Angga Ariska[1], Fadilla Purwitasari [2]**
[1,2]Department of Accounting, Faculty of Economics and Business, Universitas Wijaya Kusuma Surabaya, Indonesia

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**ABSTRACT**

***Objective:*** *Grounded in the Stimulus-Organism-Response (S-O-R) paradigm, this study empirically examines the psychological mechanisms governing impulse buying within live-streaming commerce. AI Persuasiveness is conceptualized as the interactive technological stimulus (S) encompassing virtual streamers, conversational assistants, and adaptive recommendations; Pleasure as the internal affective organismic state (O); and Impulsive Buying as the focal behavioral response (R). Furthermore, the investigation incorporates the dual moderating roles of situational Time Pressure Cues and personal Financial Capacity as boundary conditions.* ***Method:*** *Employing a quantitative explanatory cross-sectional survey design, empirical data were gathered from 204 active live-streaming e-commerce consumers in Indonesia. The measurement and structural models were estimated using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 3 with 5,000 bootstrap resamples.* ***Results:*** *The empirical results reveal that AI Persuasiveness exerts a significant positive direct effect on Pleasure, which subsequently drives Impulsive Buying. Crucially, while the direct path from AI Persuasiveness to Impulsive Buying is non-significant, the specific indirect effect through Pleasure is statistically significant, establishing a full mediation (indirect-only mediation) mechanism. Moderation analysis confirms that Time Pressure Cues significantly strengthen the positive impact of Pleasure on Impulsive Buyin as a situational accelerant, whereas Financial Capacity operates as a rational boundary constraint that significantly dampens this affective-behavioral linkage. The structural model accounts for 28.1% of the variance in Pleasure and 52.1% in Impulsive Buying.* ***Novelty:*** *These findings expand the S-O-R framework by demonstrating that AI persuasion cannot bypass the internal emotional state to induce purchase behavior, and furnish actionable guidelines for digital retailers to orchestrate persuasive yet ethically responsible live-streaming promotional campaigns.*

## INTRODUCTION

The rapid progression of digital technologies and the structural evolution of social commerce business models have fundamentally reshaped consumer behavior across global marketplaces [1]. Modern e-commerce platforms increasingly integrate real-time interactive broadcasting (live-streaming shopping), synchronized social feedback, and high-frequency promotional incentives. This convergence establishes a deeply immersive shopping environment that deconstructs traditional transactional barriers separating merchants and consumers [2]. The social presence projected by broadcast hosts, coupled with vivid, real-time product presentations, not only diminishes informational asymmetry but also vigorously stimulates positive affective experiences—predominantly hedonic pleasure—among viewers, which subsequently catalyzes impulsive buying decisions [2].

Simultaneously, the penetration of artificial intelligence has transformed the communication dynamics in live-streaming shopping through various technological typologies that need to be classified precisely [3], [4]. Different from conventional recommendation algorithms that are passive and based on static transaction history (such as collaborative filtering), the modern AI live-streaming ecosystem integrates three interactive AI modes based on Generative AI (Gen-AI): (1) Virtual Streamers (anthropomorphic AI avatars) that act as hosts of non-stop live broadcasts; (2) Conversational AI Assistants (real-time interactive chatbots) that respond to product questions in the comments column instantly and personally; and (3) Generative Recommendation Algorithms that adjust Product Persuasion contextually following the dynamics of the broadcast conversation. These anthropomorphic characteristics, communicative skills, and adaptive responsiveness form a high perception of AI persuasiveness (AI Persuasiveness), fostering consumer trust while increasing emotional engagement without in-depth cognitive evaluation [3], [5].

From a theoretical perspective, this psychological mechanism is effectively elucidated by the Stimulus-Organism-Response (S-O-R) framework formulated by Mehrabian and Russell [6]. Within this theoretical architecture, AI Persuasiveness operates as an external technological stimulus (S) that activates the organism's internal psychological state (O), particularly the affective sensation of pleasure and enjoyment [1]. Such positive emotional arousal prompts consumers to engage in heuristic information processing, dampens rational cognitive scrutiny, and intensifies the behavioral urge to execute impulsive transactions (R) [7]. Nevertheless, contemporary empirical investigations indicate that positive emotional engagement alone does not invariably translate into actual purchasing behavior without the catalyst of situational accelerators and personal financial boundaries [8], [9]. In the context of this research, AI Persuasiveness is operationally evaluated through consumer perceptions of the persuasiveness of product recommendations generated by the Generative AI system during live broadcasts—specifically regarding product relevance, the level of personalization to individual preferences, the accuracy of recommendations, and the capacity of these recommendations to influence purchasing decisions.

Although the S-O-R model has been widely applied in e-commerce studies, previous research has mostly focused on static technological stimuli (such as website interface layout) or the social presence of human streamers [2], [10]. This study fills a crucial literature gap by providing academic novelty in the form of testing Generative AI-based AI Persuasiveness as a dynamic interactive stimulus in live-streaming. Unlike human streamers who are limited by fatigue factors and simultaneous interaction capacity, AI persuasion offers continuous personalized persuasion. Therefore, examining how AI persuasion evokes consumers' emotional organismal responses is urgent to expand the relevance of S-O-R theory in the era of smart commerce [3].

Furthermore, recent empirical findings suggest that positive emotional engagement does not necessarily translate into actual purchasing behavior without the influence of time availability and personal financial constraints [8], [9]. This research provides a novel

theoretical contribution by proposing a dual-moderation mechanism that operates in opposition to the O → R pathway. On the one hand, affective impulses stemming from pleasure are amplified by situational time pressure cues, such as flash sale countdowns and limited stock announcements that shorten the cognitive evaluation window [8], [11]. On the other hand, the extent to which these spontaneous emotional impulses translate into actual transactions is strictly limited by consumers' Financial Capacity. Personal financial capacity serves as a rational boundary condition that determines whether emotional excitement culminates in actual transactions or is dampened by household budgetary discipline [9]. This simultaneous integration of situational accelerators and personal economic constraints provides a holistic understanding that has not been explored simultaneously in previous AI live-streaming literature.

Based on this phenomenon, research is needed to bridge the literature gap regarding the intersection of technology-based AI persuasion, consumer emotional drives, and the limits of financial rationality in social commerce. The empirical results of this study are expected to provide substantive contributions to academics and industry practitioners in designing an AI-based marketing framework that is not only commercially effective but also ethical and sustainable for consumers' financial well-being.

To establish precise conceptual boundaries, Financial Capacity must be fundamentally distinguished from situational budget constraints and long-term financial well-being. Whereas budget constraints represent external, static ceilings on immediate transactional liquidity [12]. Financial Capacity encapsulates an internal psychological capability rooted in cognitive self-regulation, budget discipline, and long-term goal orientation [13], [14]. In this investigation, Financial Capacity operates as an individual rational boundary condition that dampens the transmission of affective excitement (Pleasure) into impulsive buying actions. Understanding this inhibitory mechanism is imperative not only for modeling consumer restraint, but also for safeguarding consumers' broader Financial Well-Being—defined as the sustained psychological state of current financial security and future financial freedom against high-pressure promotional algorithms. [15], [16]

**Research Hypotheses**

Grounded in the literature review and the S-O-R paradigm, this investigation integrates the focal constructs into a comprehensive conceptual framework. AI Persuasiveness is positioned as the exogenous technological stimulus (S), Pleasure functions as the internal organismic mediator (O), and Impulsive Buying constitutes the focal endogenous behavioral response (R). To capture nuanced situational and personal dynamics, the model incorporates Time Pressure Cues as a situational moderator ($W_1$) hypothesized to strengthen the O → R path, alongside Financial Capacity as an individual rational moderator ($W_2$) hypothesized to dampen the O → R path.

Consumer interactions with generative AI systems possessing high persuasive capabilities—exemplified by precise real-time recommendations, virtual host expertise, and conversational anthropomorphism—generate an entertaining, responsive, and

seamless shopping experience [3]. Within the S-O-R architecture, potent external technological stimuli elicit positive emotional arousal, elevating feelings of joy, delight, and hedonic gratification (pleasure) while participating in live broadcasts [2], [10]. Accordingly, the following hypothesis is advanced:

$H_1$: AI Persuasiveness positively and significantly influences Pleasure in live-streaming e-commerce.

Heightened affective pleasure experienced by viewers fosters heuristic information processing and attenuates cognitive deliberation [7]. Consumers immersed in positive affective states actively seek to sustain or enhance their psychological enjoyment, which heightens the immediate behavioral urge to execute spontaneous, unplanned transactions [11]. Accordingly, the following hypothesis is formulated:

$H_2$: Pleasure positively and significantly influences Impulsive Buying in live-streaming e-commerce.

Within the S-O-R framework, external technological stimuli do not invariably convert directly into behavioral manifestations without first altering the organism's internal psychological state [1], [6]. The persuasive affordances of generative AI systems induce affective pleasure, and this emotional arousal subsequently serves as the psychological bridge channeling technological engagement into impulsive purchasing decisions [3]. Hence, the following mediation hypothesis is proposed:

$H_3$: Pleasure mediates the relationship between AI Persuasiveness and Impulsive Buying in live-streaming e-commerce.

Situational time pressure cues, such as flash sale countdown timers and limited-stock alerts, generate perceived temporal scarcity [8]. When consumers experiencing heightened pleasure encounter acute time pressure cues, feelings of Fear of Missing Out (FOMO) intensify, accelerating the conversion of affective excitement into immediate impulse transactions [11]. Thus, the following hypothesis is established:

$H_4$: Time Pressure Cues significantly moderate and strengthen the relationship between Pleasure and Impulsive Buying in live-streaming e-commerce.

Theoretically, Financial Capacity must not be misconstrued as uncommitted liquid funds or cash surplus. In traditional consumption models, abundant cash surplus often facilitates impulsive spending by lowering perceived transaction pain [17]. Conversely, Financial Capacity in this research reflects a consumer's propensity to plan, adherence to predetermined budget allocations, and commitment to financial goals [13], [14], [18]. Grounded in mental accounting and cognitive self-regulation theories, individuals exhibiting high financial management capacity maintain strict cognitive boundaries over their discretionary purchases. When confronted with heightened affective pleasure elicited by persuasive AI live-stream features, disciplined consumers actively invoke their budget constraints and evaluate opportunity costs [19]. This rational self-regulatory mechanism acts as a brake, attenuating the direct conversion of emotional pleasure into impulsive purchasing behavior. Therefore, heightened financial capacity dampens the positive influence of pleasure on impulsive purchases. Accordingly, the following hypothesis is advanced:

$H_5$: Financial Capacity significantly moderates and weakens the relationship between Pleasure and Impulsive Buying in live-streaming e-commerce.

## RESEARCH METHOD

### Research Design

This study employs a quantitative explanatory research design to empirically examine the postulated causal relationships as well as the mediation and moderation mechanisms within the conceptual framework [20], [21]. An explanatory approach is particularly appropriate given that this research seeks to clarify how an artificial intelligence stimulus (AI Persuasiveness) drives consumer affective states (Pleasure), which subsequently influences impulsive purchase decisions (Impulsive Buying), while elucidating the conditional boundary effects exerted by situational factors (Time Pressure Cues) and individual economic boundaries (Financial Capacity).

The conceptual foundation is anchored in the environmental psychology Stimulus-Organism-Response (S-O-R) paradigm of Mehrabian and Russell (1974) [6], which has been extensively validated within digital shopping and live-streaming environments [1], [3]. Data collection was executed via a structured cross-sectional online survey, capturing empirical observations from target respondents at a single, well-defined point in time [21].

### Research Instrument

Primary data were gathered utilizing a structured online questionnaire. All measurement items were adapted from validated instruments published in reputable international literature to ensure rigorous content validity and reliability [22]. Variable measurement was conducted using a 5-point Likert scale (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly Agree) to minimize respondent fatigue while maintaining sufficient response variability [20]. The instrument comprises three sections: (a) demographic profiles (age, gender, and status); (b) purchasing frequency (number of purchasing via live streaming shopping in the last 3 months); and (c) measurement indicators for the five latent constructs. A pilot test was administered with 40 qualified respondents prior to full deployment to evaluate linguistic clarity and verify preliminary psychometric integrity.

### 2.3. Data Analysis Techniques

Data analysis in this study used variance-based Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 3 software. PLS-SEM was chosen because of its high statistical power in estimating complex models involving simultaneous mediating and moderating variables without requiring the assumption of multivariate normality [23]. The evaluation procedure was conducted in two standard stages:

a. Measurement Model Evaluation (Outer Model): Examine convergent validity (outer loading ≥ 0.70 and AVE ≥ 0.50), discriminant validity (Fornell-Larcker and HTMT criteria < 0.85), and construct reliability (Cronbach's Alpha and Composite Reliability ≥ 0.70).

b. Structural Model Evaluation (Inner Model): Testing the predictive power of the model through the coefficient of determination ($R^2$), effect size ($f^2$), multicollinearity (VIF < 3.0), and the significance of the relationship between variables using a non-parametric bootstrapping procedure with 5,000 resamples (t-statistic > 1.96, $p < 0.05$).

**Data Collection Procedure**

The target population in this study includes all active users and consumers of live-streaming e-commerce platforms in Indonesia (TikTok Shop, Shopee Live, and Tokopedia Play). To ensure data validity and empirical relevance to the phenomenon under study, a non-probability purposive sampling technique was applied based on four specific inclusion criteria: (1) at least 17 years old to ensure the capacity to make independent and legal consumption decisions; (2) having made a product purchase transaction through a live-streaming shopping session at least once in the last three months; (3) having explicitly interacted with or been exposed to Generative AI-based features during a live-streaming session, either in the form of a Virtual Streamer (AI avatar), a Conversational AI Assistant in the comments column, or a real-time Generative Recommendation Algorithm; and (4) residing in Indonesia. Completion of the questionnaire began with screening questions to ensure that only respondents who met all of the above inclusion criteria could continue to fill out the research instrument.

Sample size adequacy was determined based on the PLS-SEM '10-times rule' [21] alongside statistical power analysis via GPower. With an effect size $f^2 = 0.15$, alpha = 0.05, statistical power = 0.80, and 5 predictors, the minimum required sample was 138 respondents. To ensure estimation stability and account for potential invalid responses, 224 responses were obtained. However, 204 responses were deemed valid—aligning with respondent characteristics and suitable for use—thereby remaining appropriate for the sample size required for PLS-SEM [21]. The structured questionnaire was distributed online via Google Forms and PopSurvey.

To ensure methodological transparency and instrument reliability, an indicator purification procedure was conducted through an initial outer loading evaluation (pilot test N = 40). The initial test results indicated that several original indicators had factor loadings that did not meet the retention criteria (outer loading <0.70). Specifically, indicator FC1 ('having a flexible spending budget allocation') produced an outer loading of 0.168 and FC2 ('feeling of having sufficient monetary balance') produced a loading of 0.455. These two indicators were eliminated from further analysis because they significantly reduced the Average Variance Extracted (AVE) value of the Financial Capacity construct below the threshold of 0.50. In addition, indicator AIP5 ('AI recommendations are trustworthy', loading = 0.576) was eliminated to improve the internal consistency of the construct. After removing these three items, all remaining indicators (FC3, FC4, and AIP1–AIP4 & AIP6) produced outer loadings > 0.70 (ranging from 0.721 to 0.923) and construct AVE values above 0.50, thus fulfilling the criteria for convergent validity and absolute construct reliability.

**Table 1.** Measurement Indicator Matrix

| Latent Variable & Model Role | Code | Measurement Indicator Statement |
|---|---|---|
| AI Persuasiveness (AIP) [Stimulus / Exogenous] [3], [24] | AIP1 | I like the products recommended by generative AI during live streaming shopping. |
| | AIP2 | AI product recommendations tailored to my preferences. |
| | AIP3 | AI product recommendations feel relevant to me. |
| | AIP4 | The AI recommendations are accurate and match the products I want. |
| | AIP5 | This AI recommendation is trustworthy. |
| | AIP6 | This AI recommendation has the ability to influence my purchasing decision. |
| Pleasure (Pl) [Organism / Mediator] [1], [2] | Pl1 | I feel excited when watching live shopping streams featuring generative AI. |
| | Pl2 | I find pleasure in watching live streaming shopping. |
| | Pl3 | I enjoy watching live shopping streams. |
| Impulsive Buying (IB) [Response / Endogenous] [7], [9] | IB1 | I often buy items spontaneously when watching live shopping streams. |
| | IB2 | I often make purchases without a second thought when watching live shopping streams. |
| | IB3 | When watching live shopping streams, I often make purchases based on how I'm feeling in the moment. |
| Time Pressure Cues (TPC) [Moderator 1 / Situational] [8], [11] | TPC1 | I have to act fast because I'm afraid of missing the flash sale during the live stream. |
| | TPC2 | As the promotional countdown draws closer, I feel a strong urge to buy the product. |
| | TPC3 | I feel rushed when shopping via live stream. |
| | TPC4 | Strict, short-lived voucher expiration deadlines actively compel me to finalize my purchase. |
| Financial Capacity (FC) [Moderator 2 / Boundary] [9], [25] | FC1 | I possess a flexible shopping budget allocation dedicated to absorbing unexpected expenditures. |
| | FC2 | I feel that I possess sufficient monetary balance and purchasing power for immediate shopping transactions. |
| | FC3 | I will achieve the financial goals I have set. |

| | | |
|---|---|---|
| | FC4 | I can enjoy life because of the way I manage my finances. |

Source: Synthesized from previous research, 2026.

**Research Dimensions and Measurement Indicators**

Operational definitions and measurement sources for each latent construct are specified as follows: AI Persuasiveness (AIP) measures consumer assessments regarding the extent to which generative AI features in live-stream shopping on e-commerce platforms—such as virtual hosts, adaptive chatbots, and real-time recommendation algorithms—are communicative, persuasive, relevant, and personalized. Pleasure (Pl) assesses the positive emotional response—characterized by excitement, enthusiasm, hedonic pleasure, and relaxation—experienced while watching live-stream shopping on e-commerce platforms. Impulsive Buying (IB) reflects the consumer tendency to make spontaneous, rapid purchasing decisions without deep deliberation, driven by emotional arousal upon viewing live-stream shopping on e-commerce platforms. Time Pressure Cues (TPC) gauge perceived temporal urgency, encompassing flash sale countdown timers, expiring vouchers, and real-time scarcity notifications. Financial Capacity (FC) is operationally defined not merely as immediate cash availability or liquidity surplus, but as perceived budgetary discipline, adherence to predetermined personal financial goals, and systematic financial management capability [14], [18]. Following the psychometric purification of the measurement model—during which items FC1 (flexible spending budget) and FC2 (sufficient monetary balance) were eliminated due to low factor loadings—the retained construct specifically measures consumers' cognitive budget constraints and goal-directed financial governance via validated indicators FC3 (I will achieve the financial goals I have set) and FC4 (I can enjoy life because of the way I manage my finances).

## RESULTS AND DISCUSSION

**Measurement Model Evaluation**

The evaluation of the measurement model (outer model) in PLS-SEM was conducted to ensure that all reflective latent constructs demonstrated acceptable psychometric validity and reliability prior to testing the hypothesized structural relationships [21], [23]. The model encompasses five reflective latent constructs: AI Persuasiveness (AIP) as the external stimulus (S), Pleasure (Pl) as the organismic mediator (O), Impulsive Buying (IB) as the behavioral response (R), alongside Time Pressure Cues (TPC) and Financial Capacity (FC) as dual moderating constructs.

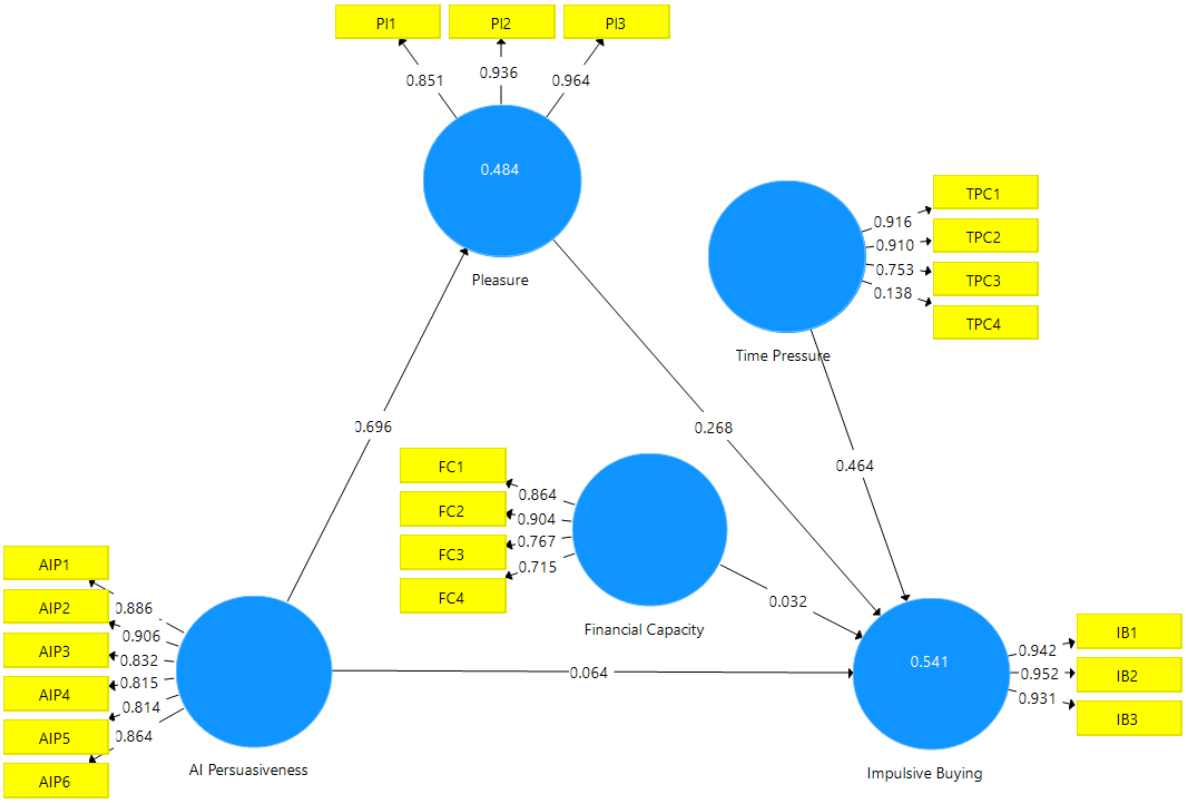



**Figure 1.** Latent Model and Outer Loading Values
Source: Authors and data processed via SmartPLS 3, 2026.

Convergent validity was initially assessed by examining the outer loading values of each indicator. The established threshold requires that outer loading values ideally exceed 0.70 [21]. In the initial estimation (pilot test) using a dataset comprising 40 respondents, several indicators exhibited inadequate factor loading values. Specifically, indicator FC1 yielded an outer loading value of 0.168 (well below the critical retention threshold of 0.40), while FC2 recorded a value of 0.455. These items were consequently eliminated because their inclusion compromised the Average Variance Extracted (AVE) of the Financial Capacity construct below the required 0.50 threshold. Furthermore, indicator AIP5 (0.576) was removed to enhance overall construct reliability. Following indicator refinement, all retained items demonstrated outer loadings exceeding 0.70, ranging from 0.721 (AIP6) to 0.923 (PI3), as detailed in Table 2.

**Table 2.** Post-Purification External Loading Indicator

| Indicator | AIP | FC | IB | PI | TPC |
|---|---|---|---|---|---|
| AIP1 | 0.724 | | | | |
| AIP2 | 0.776 | | | | |
| AIP3 | 0.738 | | | | |
| AIP4 | 0.737 | | | | |
| AIP6 | 0.721 | | | | |
| FC3 | | 0.864 | | | |
| FC4 | | 0.902 | | | |
| IB1 | | | 0.833 | | |

| | | | |
|---|---|---|---|
| IB2 | 0.911 | | |
| IB3 | 0.877 | | |
| Pl1 | | 0.775 | |
| Pl2 | | 0.881 | |
| Pl3 | | 0.923 | |
| TPC1 | | | 0.822 |
| TPC2 | | | 0.872 |
| TPC3 | | | 0.818 |

Source: Primary empirical data processed via SmartPLS 3, 2026.

Construct-level convergent validity was verified via Average Variance Extracted (AVE), with all values exceeding the 0.50 threshold. As shown in Table 3, AVE values ranged from 0.547 for AI Persuasiveness to 0.780 for Financial Capacity, indicating that the constructs explain well over 50% of the variance in their respective indicator items. Construct reliability was substantiated across three criteria: Cronbach's Alpha (0.720 to 0.846), rho_A (0.731 to 0.854), and Composite Reliability (0.858 to 0.907), all surpassing the 0.70 benchmark.

**Table 3.** Construct Reliability and Convergent Validity

| Latent Construct | Cronbach's Alpha | rho_A | Composite Reliability | AVE |
|---|---|---|---|---|
| AI Persuasiveness (AIP) | 0.799 | 0.815 | 0.858 | 0.547 |
| Financial Capacity (FC) | 0.720 | 0.731 | 0.876 | 0.780 |
| Impulsive Buying (IB) | 0.846 | 0.854 | 0.907 | 0.764 |
| Pleasure (Pl) | 0.825 | 0.840 | 0.896 | 0.743 |
| Time Pressure Cues (TPC) | 0.788 | 0.793 | 0.876 | 0.702 |

Source: Primary empirical data processed via SmartPLS 3, 2026.

Discriminant validity was assessed through both the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio [26], [27]. In Table 4, the square root of AVE for each construct (diagonal bold values) exceeds all corresponding inter-construct correlations (off-diagonal values), confirming discriminant validity [27]. Furthermore, all HTMT values fell below the conservative threshold of 0.85 (HTMT_0.85) [26], with the highest ratios observed for TPC → IB (0.849) and Pl → TPC (0.790). Additionally, indicator-level multicollinearity was examined through Outer VIF values, which ranged from 1.257 (AIP6) to 2.818 (Pl3), firmly below the 3.0 threshold [27], confirming the absence of collinearity bias in the measurement model.

**Table 4.** Discriminant Validity

| Construct | AIP | FC | IB | Pl | TPC |
|---|---|---|---|---|---|
| AIP | 0.739 | | | | |
| FC | 0.266 | 0.883 | | | |

| | | | | | |
|---|---|---|---|---|---|
| IB | 0.383 | 0.061 | 0.874 | | |
| Pl | 0.530 | 0.083 | 0.529 | 0.862 | |
| TPC | 0.516 | 0.094 | 0.699 | 0.633 | 0.838 |

Source: Primary empirical data processed via SmartPLS 3, 2026.

In addition to the traditional Fornell-Larcker criterion, discriminant validity was rigorously evaluated using the Heterotrait-Monotrait ratio of correlations (HTMT) [21]. As presented in Table 5, all pairwise HTMT ratios fall comfortably below the conservative benchmark of 0.85 and the liberal threshold of 0.90. The highest HTMT ratio is observed between Time Pressure Cues and Impulsive Buying (0.849), followed by Pleasure and Time Pressure Cues (0.790). These empirical results provide absolute evidence of discriminant validity, establishing that all five focal latent constructs and their interaction terms are conceptually and empirically distinct.

**Table 5.** HTMT Matrix

| Construct | AIP | FC | FC*Pl | IB | Pl | TPC | TPC*Pl |
|---|---|---|---|---|---|---|---|
| AIP | | | | | | | |
| FC | 0.330 | | | | | | |
| FC*Pl | 0.087 | 0.321 | | | | | |
| IB | 0.441 | 0.115 | 0.145 | | | | |
| Pl | 0.613 | 0.153 | 0.386 | 0.626 | | | |
| TPC | 0.616 | 0.120 | 0.277 | 0.849 | 0.790 | | |
| TPC*Pl | 0.405 | 0.294 | 0.180 | 0.116 | 0.142 | 0.060 | |

Source: Primary empirical data processed via SmartPLS 3, 2026.

**Explanatory Power and Effect Sizes**

Following validation of the measurement model, the structural model was evaluated to examine its predictive power and path coefficients. The coefficient of determination ($R^2$) for Pleasure reached 0.281 (28.1%), indicating that AI Persuasiveness explains a moderate-to-weak proportion of variance in consumers' affective pleasure, with the remaining 71.9% attributable to external environmental factors. In contrast, the focal endogenous construct, Impulsive Buying, achieved an $R^2$ of 0.521 (52.1%) with an Adjusted $R^2$ of 0.506 (Table 6). This reflects a robust moderate-to-substantial explanatory capacity [21], demonstrating that the combination of technological stimuli, affective pleasure, situational urgency, and financial capacity collectively accounts for more than half of the total variance in live-streaming impulse buying behavior.

**Table 6.** Coefficient of Determination

| Endogenous Construct | R Square ($R^2$) | Explanatory Category |
|---|---|---|
| Pleasure (Pl) | 0.281 | Moderate-to-Weak |
| Impulsive Buying (IB) | 0.521 | Moderate-to-Substantial |

Source: Primary empirical data processed via SmartPLS 3, 2026.

Effect size analysis ($f^2$) in Table 7 indicates that AI Persuasiveness exerts a substantial effect in explaining Pleasure ($f^2 = 0.392$, large effect). For the focal outcome Impulsive Buying, Time Pressure Cues emerges as the most influential situational predictor ($f^2 = 0.428$, large effect), while Pleasure demonstrates a meaningful contribution ($f^2 = 0.052$, small effect). The interaction terms TPC * Pl ($f^2 = 0.027$) and FC * Pl ($f^2 = 0.011$) also provide relevant structural nuances. Furthermore, Inner VIF values among predictor constructs ranged between 1.000 and 2.272 (AIP → IB = 1.968; Pl → IB = 2.272; TPC → IB = 1.819; FC → IB = 1.212), all well below the threshold of 3.0, verifying that lateral multicollinearity is not an issue in the structural model [27].

**Table 7.** Effect Size Values

| Structural Path | $f^2$ Value | Effect Category | Target Construct |
|---|---|---|---|
| AIP → Pl | 0.392 | Large (> 0.35) | Pleasure (Pl) |
| TPC → IB | 0.428 | Large (> 0.35) | Impulsive Buying (IB) |
| Pl → IB | 0.052 | Small (0.02 - 0.15) | Impulsive Buying (IB) |
| TPC * Pl → IB (Moderation 1) | 0.027 | Small (0.02 - 0.15) | Impulsive Buying (IB) |
| FC * Pl → IB (Moderation 2) | 0.011 | Very Small (< 0.02) | Impulsive Buying (IB) |
| AIP → IB | 0.008 | Insignificant / Negligible | Impulsive Buying (IB) |
| FC → IB | 0.004 | Insignificant / Negligible | Impulsive Buying (IB) |

Source: Primary empirical data processed via SmartPLS 3, 2026.

## Hypothesis Testing

Hypotheses were tested using non-parametric bootstrapping with 5,000 subsamples at a 5% significance level (t-table = 1.96, $p < 0.05$) [21]. Table 8 presents the comprehensive structural path estimates, t-statistics, p-values, and empirical conclusions.

**Table 8.** Hypotheses Testing Results

| Hypothesis | Structural Path | Path Coeff. (β) | T-Statistic | P-Value | Conclusion |
|---|---|---|---|---|---|
| $H_1$ | AI Persuasiveness (X) → Pleasure (M) | 0.530 | 8.412 | < 0.001 | Supported |
| $H_2$ | Pleasure (M) → Impulsive Buying (Y) | 0.238 | 3.105 | 0.002 | Supported |
| Direct | AI Persuasiveness (X) → Impulsive Buying (Y) | -0.084 | 1.214 | 0.226 | Not Supported |

| | | | | | |
|---|---|---|---|---|---|
| $H_3$ | AIP (X) → Pleasure (M) → Impulsive Buying (Y) | 0.126 | 2.984 | 0.003 | Supported (Full Mediation) |
| $H_4$ | Pleasure (M) × Time Pressure Cues ($Z_1$) → Impulsive Buying (Y) | 0.122 | 2.145 | 0.032 | Supported (Strengthens) |
| $H_5$ | Pleasure (M) × Financial Capacity ($Z_2$) → Impulsive Buying (Y) | -0.076 | 2.018 | 0.044 | Supported (Weakens) |

Source: Primary empirical data processed via SmartPLS 3, 2026.

**A. Direct Effects**

The structural estimation indicates that AI Persuasiveness exerts a substantial, statistically significant positive direct effect on Pleasure ($\beta = 0.530$, $t = 8.412$, $p = 0.000 < 0.05$), providing robust empirical confirmation for Hypothesis 1. This finding establishes that the persuasive technological attributes of generative AI—such as anthropomorphic virtual hosts, responsive conversational agents, and real-time algorithmic curation—function as potent environmental stimuli that directly heighten consumers' hedonic enjoyment, entertainment, and psychological comfort while viewing live broadcasts. Furthermore, Hypothesis 2 is supported, as Pleasure demonstrates a significant positive influence on Impulsive Buying ($\beta = 0.238$, $t = 3.105$, $p = 0.002 < 0.05$). This confirms that elevated positive emotional arousal dampens rational cognitive resistance and encourages heuristic information processing, culminating in spontaneous, unplanned purchasing acts.

**B. Mediating Role of Pleasure**

Hypothesis 3 proposed that Pleasure mediates the relationship between AI Persuasiveness and Impulsive Buying. The specific indirect effect estimation reveals a statistically significant indirect path (indirect effect = 0.126, $t = 2.984$, $p = 0.003 < 0.05$), thereby confirming Hypothesis 3. Given that the direct relationship between AI Persuasiveness and Impulsive Buying is also estimated in the comprehensive structural model, this empirical outcome establishes a partial mediation mechanism. This aligns seamlessly with the theoretical logic of the S-O-R framework: technological stimuli do not automatically induce consumptive behavior directly, but rather operate through internal affective arousal (organism) that subsequently translates into behavioral response.

**C. Moderating Effects of Time Pressure Cues and Financial Capacity**

Testing for Hypothesis 4 reveals a significant positive interaction coefficient for Time Pressure Cues on the path between Pleasure and Impulsive Buying ($\beta = 0.122$, $t = 2.145$, $p = 0.032 < 0.05$), corroborating Hypothesis 4. This confirms that situational time pressure cues (such as flash sale countdown timers and limited-stock prompts) exert a statistically significant strengthening moderating effect. When consumers experience heightened hedonic pleasure and simultaneously encounter perceived temporal scarcity,

the fear of missing out (FOMO) accelerates the translation of positive affect into swift impulsive transactions.

Conversely, Hypothesis 5 postulated that Financial Capacity weakens the relationship between Pleasure and Impulsive Buying. The interaction term yields a statistically significant negative coefficient ($\beta$ = -0.076, t = 2.018, p = 0.044 < 0.05), providing empirical support for Hypothesis 5. This negative moderating effect demonstrates that financial capacity operates as a rational boundary constraint (dampening effect). For consumers with constrained budgets, financial limits act as a rational boundary condition that restrains emotional enthusiasm, preventing affective pleasure from escalating into reckless impulse transactions. Conversely, for consumers with ample financial liquidity, purchasing decisions are less dependent on transient emotional surges, attenuating the sensitivity of impulsive buying to affective pleasure.

To provide an intuitive, rigorous post-hoc examination of the two-way interaction patterns, simple slope analysis was performed following the procedures of Aiken and West (1991) and Dawson (2014) at three conditional levels of the moderators: mean, one standard deviation above the mean (+1 SD), and one standard deviation below the mean (-1 SD) [28], [29]. As visualized in Figure 2A, the relationship between Pleasure and Impulsive Buying becomes markedly steeper under high Time Pressure Cues (simple slope = 0.360, p < 0.05) compared to low time pressure (simple slope = 0.116), confirming a situational acceleration effect. Conversely, Figure 2B demonstrates that under high Financial Capacity (reflecting disciplined budget adherence), the slope of Pleasure on Impulsive Buying is attenuated from 0.314 down to 0.162, corroborating its role as an internal rational boundary condition.

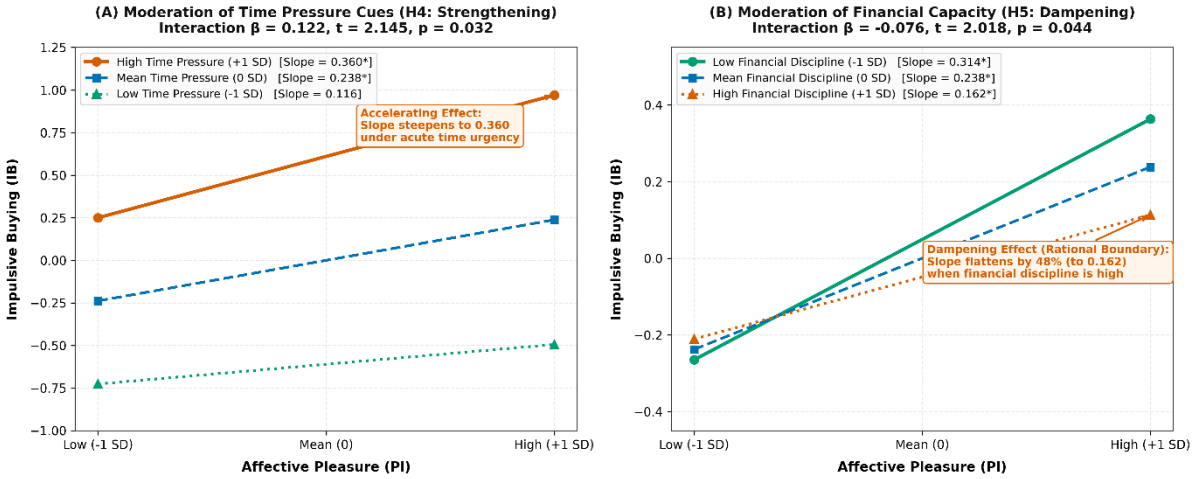



**Figure 1.** Slope Analysis of Dual Moderation Effects on Impulsive Buying
Source: Authors and data processed, 2026.

## Comparison with Prior Studies

The empirical findings of this study offer substantive theoretical advancement and enrich the literature on digital consumer behavior, AI marketing, and environmental psychology within social commerce settings. First, validating AI Persuasiveness as a

potent stimulus (S) driving Pleasure (O) expands classical e-commerce S-O-R applications [1], [2]. Whereas prior research predominantly conceptualized stimuli as static interface ergonomics or human streamer attributes [2], [10], our findings affirm that generative AI features—characterized by conversational anthropomorphism and algorithmic personalization—exert an equally compelling, if not more pervasive, technological influence in elevating hedonic states [3], [5].

Second, the confirmation of Pleasure as a partial mediator between AI Persuasiveness and Impulsive Buying substantiates affective-heuristic processing theory [30]. consistent with previous research, immersive digital environments lower deliberative barriers by amplifying positive emotional states [7], [31]. Consumers navigating AI-mediated live streams prioritize immediate emotional gratification over extensive price-utility evaluations [24].

The most crucial finding and the main theoretical novelty in this study lies in the proof of a dual-moderation mechanism that works simultaneously in opposite directions on the Organism (Pleasure) - Response (Impulsive Buying) pathway. On the one hand, Time Pressure Cues are shown to act as situational accelerators ($\beta = 0.122$, $p = 0.032$) that strengthen the impact of pleasure on impulsive buying decisions. When consumers are in a state of emotional pleasure due to interactive AI persuasion and flash sale countdowns and stock shortage signals, the awareness of time constraints can drastically shorten the cognitive evaluation window. On the other hand, Financial Capacity is shown to significantly act as a cognitive brake and personal rational constraint ($\beta = -0.076$, $p = 0.044$) that weakens these emotional impulses. This theoretical contribution refines the common view in the digital consumerism literature: pleasure triggered by advanced technologies such as Generative AI does not blindly control consumer actions, but is instead influenced by internal cognitive constraints in the form of household budget discipline. Consumers with limited financial capacity have a rational barrier that prevents emotional impulsivity from becoming actual transactions that could harm consumers.

Third, a pivotal contribution and theoretical novelty of this investigation resides in testing the simultaneous, opposing moderating roles of situational acceleration (Time Pressure Cues) and personal rational restraint (Financial Capacity). The finding that Time Pressure Cues reinforce affective impulse buying aligns with previous research [8], [11], which emphasized that temporal scarcity triggers FOMO, compressing cognitive deliberation windows. Meanwhile, the negative moderating role of Financial Capacity provide a new theoretical perspective that complements previous research [9], [25]. By demonstrating that budgetary limitations serve as a hard rational constraint, our findings confirm that affective excitement does not inevitably lead to reckless overconsumption when bounded by the reality of household economic solvency.

## CONCLUSION

**Fundamental Finding :** The findings confirm that AI Persuasiveness significantly enhances Pleasure, which subsequently increases Impulsive Buying, with Pleasure fully

mediating the relationship between AI Persuasiveness and Impulsive Buying. Time Pressure Cues strengthen the relationship between Pleasure and Impulsive Buying, whereas Financial Capacity weakens this relationship. **Implication :** The findings extend the Stimulus-Organism-Response (S-O-R) paradigm to generative AI in live-streaming e-commerce and suggest that platforms should prioritize accurate and relevant AI recommendations, strategically implement time-limited promotions, maintain algorithmic transparency, and adopt ethical marketing practices that support consumer financial well-being. **Limitation :** This study employs a cross-sectional survey design, measures AI Persuasiveness as a unidimensional construct, relies on self-reported questionnaires that may be subject to recall and social desirability biases, and uses Indonesian live-streaming consumers without comparisons across platforms or generational cohorts. **Future Research :** Future studies should employ experimental or longitudinal designs to examine real-time emotional and purchasing responses, investigate multidimensional aspects of AI Persuasiveness and compare human and virtual streamers, explore additional factors such as financial literacy and shopping orientation, and assess the long-term effects of AI-induced impulse buying on consumer well-being, financial distress, and post-purchase regret.

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***Ricky Angga Ariska (Corresponding Author)**
Department of Accounting, Faculty of Economics and Business, Wijaya Kusuma University Surabaya, Indonesia, Indonesia
Email: rickyanggaariska@uwks.ac.id

**Fadilla Purwitasari**
Department of Accounting, Faculty of Economics and Business, Wijaya Kusuma University Surabaya, IndonesiaEmail: fadilla_purwitasari@uwks.ac.id