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Examining the Impact of Generative AI Content on Impulse Buying Behavior in Social Commerce

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ABSTRACT

The growing adoption of generative artificial intelligence (AI) in social commerce, particularly for promotional videos and live-streaming scripts, has transformed consumer persuasion processes, yet its role in stimulating impulse buying remains insufficiently examined. This study investigates the effects of AI-generated content attributes (credibility, attractiveness, novelty, and trust) on impulse buying tendency, with perceived interactivity examined as a mediating variable. Survey data were collected from 266 Indonesian social commerce users and analyzed using multiple regression and mediation analysis via the SPSS PROCESS macro (Model 4) with 5,000 bootstrap samples. The results indicate that credibility (β = 0.341, $p < 0.001$), attractiveness (β = 0.178, p = 0.003), novelty (β = 0.141, p = 0.019), and trust (β = 0.125, p = 0.025) have significant positive effects on impulse buying tendency. Mediation analysis shows that perceived interactivity partially mediates all relationships, with the strongest indirect effect observed for trust (indirect effect = 0.203). The findings extend impulse buying theory to AI-mediated contexts and suggest that social commerce practitioners should prioritize interactive and credible AI content to enhance consumer engagement and unplanned purchasing behavior.

Keywords: Artificial Intelligence; Impulse Buying; Perceived Interactivity; Social Commerce; Trust

INTRODUCTION

The launch of ChatGPT-3.5 in 2022 marked a pivotal moment, accelerating the adoption of generative artificial intelligence (AI) and revolutionizing digital content creation and marketing tactics worldwide. This technology's ability to produce multimodal content efficiently has dramatically reduced production costs and enabled rapid content scaling (McKinsey Global Institute, 2023). In parallel, the explosive growth of social commerce across Southeast Asia has deepened the reliance on short-form videos, live streaming, and interactive features. Indonesia, with a social media user base surpassing 143 million in 2024 (Kemp, 2024), stands as a hyper-active social commerce arena where platforms like TikTok Shop and Shopee Live critically shape consumers' spontaneous purchasing decisions (Chevalier & Stephanie, 2023). Prior inquiries into AI have considered its utility in generating content alongside the wider consequences for consumer psychology, such as shifts in persuadability and adoption propensity, a specific knowledge gap persists: there is limited empirical evidence on how distinct attributes of AI-generated content, such as its visual appeal, novelty, perceived credibility, and the trust it inspires, directly catalyze impulse buying, particularly within the resource-limited, high-stakes environment typical of small and medium-sized enterprises (SMEs)-led social commerce.

Addressing this gap carries both theoretical and practical weight. Theoretically, impulse buying represents a distinct, affect-driven behavior central to the fast-paced social commerce experience, yet most marketing studies on AI concentrate on deliberate, cognition-focused outcomes. From a practical SME perspective, AI often acts not as a substitute for human creativity but as a primary tool for amplifying content output. Consequently, it remains unclear whether AI-generated material possesses the necessary stimulative qualities to spark the spontaneous psychological processes that culminate in impulse purchases, or if it merely boosts passive engagement without translating into actual sales.

This study seeks to extend theory through an empirical investigation of PT TOTAL OPTIMAL PELITA, a Bali-based SME utilizing generative AI for crafting live stream scripts and short videos on TikTok and Shopee. The firm noted increased viewer engagement (e.g., a 21.7% rise in retention) following AI adoption, yet observed only a marginal improvement in conversion rates (1.2%), with considerable fluctuation across different content formats. This real-world contrast highlights the core managerial dilemma this research tackles: Which attributes of AI content effectively convert viewer engagement into impulse buys, and what psychological mechanism underpins this process?

Based on established literature, this study examines a series of interrelated variables. These include the dependent variable, impulse buying behavior (Moghddam et al., 2024), and four key attributes of AI-generated content conceptualized as independent variables: its visual attractiveness, perceived novelty, and credibility (Huschens et al., 2023; Lim et al., 2017; Raj et al., 2023), along with the trust it inspires (Huschens et al., 2023). Mediation analysis indicates that assigned to perceived interactivity (Indriastuti et al., 2024).

Given these shortcomings, the current investigation seeks to determine how four specific qualities of AI-crafted content, its visual appeal, novelty, perceived credibility, and the trust it engenders, affect consumers' propensity for unplanned purchases, with perceived interactivity theorized as a central explanatory mechanism. The study is designed to achieve two core objectives. From a theoretical perspective, this study extends the "S–O–R" framework by empirically demonstrating how AI-driven content characteristics function as digital stimuli, while clarifying the mediating role of perceived interactivity within AI–enabled consumption contexts. Second, in terms of practical application, it aims to produce actionable, research-informed guidance for SMEs, such as PT TOTAL OPTIMAL PELITA. This guidance will focus on optimizing AI-powered content tactics to effectively drive sales conversions, thereby shifting the focus from superficial engagement metrics to tangible business outcomes.

LITERATURE REVIEW

Theoretical Foundation: The S-O-R Framework and Online Impulse Buying Model

Grounded in the "S-O-R" paradigm (Mehrabian & Russell, 1974), this research seeks to explain how digital cues prompt consumer behavior. This foundational model outlines a sequential process: External stimuli (S) shape individuals' internal psychological states (O), which subsequently give rise to observable behavioral responses (R). For online contexts, scholars have adapted this into the Online Impulse Buying Model to clarify spontaneous digital purchases (Imbayani & Gama, 2024).

Here, four attributes of generative AI content: attractiveness, novelty, credibility, and trust, are defined as the core stimuli (S). The construct of perceived interactivity serves as the internal organism (O), representing the user's interactive experience. The resultant behavior (R) is impulse buying. Thus, this framework provides a clear pathway for analyzing AI content's impact on purchasing.

Generative AI as a Novel Stimulus in Social Commerce

Generative AI refers to systems that leverage learned data patterns to create novel, coherent outputs, including text, imagery, audio, and video, which can match or approximate human-generated quality (Feuerriegel et al., 2024). Within retail, a prominent application involves the automated creation of personalized promotional content, a practice seen as both paradigmatic and cost-effective (McKinsey Global Institute, 2023). For social commerce, this technology streamlines operations such as drafting video captions and live-stream scripts, producing video materials, and performing language translation, which collectively reduce content creation hurdles for SMEs.

However, academic assessments of its effectiveness yield inconsistent findings. Research suggests AI-crafted content can markedly boost user involvement and buying intention (Mei et al., 2025). Conversely, other work warns that generative AI might fail to grasp intricate emotional subtleties, possibly undermining perceived authenticity and user trust (Finet et al., 2025). This inconsistency in prior research reveals an unresolved gap regarding how AI-generated content influences consumers' psychological processes, especially in impulse purchasing contexts.

Impulsive Purchasing Behavior in Social E-Commerce Contexts

Social commerce represents a hybrid business model merging social media with e-commerce, emphasizing user-to-user and user-to-merchant interaction, information sharing, and community-based trust. Commercial activities are embedded within social platforms like TikTok, Facebook, and Instagram. Unlike traditional e-commerce that relies on direct search, social commerce leverages short videos, live broadcasts, and comment interactions, which lower information acquisition costs for users and heighten the impetus for immediate purchases (Pranata et al., 2024).

Impulse buying constitutes a well-researched area within consumer behavior. Originating from Rook's (1987) conceptualization, it characterizes an abrupt, powerful, and enduring desire to buy, emerging spontaneously from emotional or contextual triggers and culminating in an immediate purchase. In social commerce environments, immersive multimedia, charismatic hosts, and instantaneous viewer engagement are documented to markedly increase the likelihood of such unplanned buying (Lee & Chen, 2021). Extending this, Gao et al. (2022) identified that a host's social presence during live streams fosters impulse purchases, both directly and via enhanced pleasure and arousal. Despite these insights, current scholarship on social commerce has concentrated on human elements, like host traits, influencer trustworthiness, and community dynamics, while paying scant attention to AI-generated content as a distinct environmental cue capable of influencing impulsive consumption.

AI-Generated Content Characteristics as External Stimuli (S)
Attractiveness
Attractiveness pertains to the aesthetic or visual appeal inherent in content created by AI. Scholarly work positions such as a pivotal precursor to unplanned buying behavior (Huang & Yodbutr, 2023). Empirical evidence further indicates that videos generated by AI can engage and maintain viewer attention by leveraging novel visuals and dense information (Hong et al., 2022). The present inquiry evaluates the function of this recognized factor in the unique setting of AI-sourced material.

Perceived Novelty
This construct reflects the user's judgment of the content's originality and distinctiveness. In the dense, interactive landscape of social commerce, novelty functions as a key external stimulus, empirically linked to increased impulse buying tendencies (Lee & Chen, 2021). The inherently innovative nature of AI output makes it an ideal subject for examining the impact of novelty as a stimulus.

Perceived Credibility
This denotes the user's cognitive assessment of the content's accuracy and reliability. Appel et al. (2020) contended that the assessed believability of content created by AI functions as a vital cognitive antecedent to trust, while remaining a separate construct conceptually. If users detect overly prominent "machine-like" traits, it may inhibit impulsive buying. Therefore, examining credibility's independent effect in an AI context is crucial.

Trust in AI-Generated Content
Here, trust is conceptualized as a psychological state reflecting a consumer's willingness to depend on AI-generated information when making purchase decisions. This is separate from credibility, which focuses on factual accuracy at the content level. Recent studies, such as Liu and Sundar (2018), found that while the novelty and speed of generative AI can enhance informational appeal, its impersonal nature may simultaneously raise doubts about authenticity. In social commerce, if AI content can be woven into the user's existing network of social trust, this trust enhances consumers' willingness to adopt AI-generated content and serves as a foundation for expedited purchasing actions. Consequently, examining the relationship between trust in such content and impulsive buying offers substantial value for theoretical advancement and practical application.

Perceived Interactivity as the Organism (O)
Perceived interactivity encapsulates the sense of responsiveness and reciprocal communication users experience during interactions with a platform, its content, and other users. In social commerce, features like comments and likes are central to this experience, significantly boosting user immersion and intent to purchase (Joo & Yang, 2023). Research demonstrates that high perceived interactivity deepens user immersion in content, fosters greater trust in and acceptance of information, and ultimately

influences purchasing behavior. In the context of AI-generated content, platforms incorporating real-time user-AI interaction features, such as personalized recommendations and automated comment replies, can effectively cultivate user identification and trust. This enhances the impact of content attractiveness on purchase intention (Ding & Najaf, 2024). Consequently, perceived interactivity serves as a key psychological mechanism through which AI content attributes influence impulse buying.

Impulse Buying as the Response (R)

As defined, impulse buying constitutes the sudden, powerful desire to buy, followed by immediate action, absent prior planning (Khatimah et al., 2024; Utami et al., 2021). In social commerce, the factors previously noted: content richness, host appeal, and audience interactivity, are validated drivers of this tendency (Gao et al., 2022; Lee & Chen, 2021). Yet, a clear gap remains: minimal research has investigated AI-generated content as a novel environmental stimulus capable of shaping such impulsive consumer responses.

Research Gaps and Hypothesis Development

In synthesis, key research lacunae are evident. First, internationally, while preliminary work exists on generative AI and consumer trust (Kim & Priluck, 2025), most studies center on large corporations or retailers, lacking contextual investigation within SME e-commerce settings. Second, from an Indonesian perspective, related research primarily addresses general social commerce user behavior and live-stream marketing efficacy (Febrianti & Hidayat, 2022) but offers little systematic quantitative analysis on how generative AI integrates with user psychology in actual content production. Finally, existing studies often limit their variable selection, focusing narrowly on "content attractiveness" or "emotional arousal," while neglecting a more holistic examination of variables salient to social commerce, such as "trust" and "interactivity." Moreover, research samples are predominantly drawn from China and developed nations, overlooking potential cultural influences on AI content acceptance.

To address these research gaps and grounded in the Online Impulse Buying Model, this study proposes the following hypotheses to systematically uncover how AI content characteristics influence impulse buying through perceived interactivity:

H1: Content attractiveness in AI-generated materials has a positive effect on users' impulse buying tendencies.
H2: The perceived novelty of AI content significantly stimulates impulsive purchasing behavior among users.
H3: There is a positive correlation between the perceived credibility of AI-generated content and users' impulse buying behavior.
H4: Trust toward AI-generated content positively influences consumers' impulse purchase decisions.
H5: Perceived interactivity plays a mediating role in the link between AI content attributes (attractiveness, novelty, credibility, and trust) and consumers' impulse buying behavior.

Analytical Framework

The proposed research framework is illustrated in Figure 1.

Figure 1. Proposed Research Model

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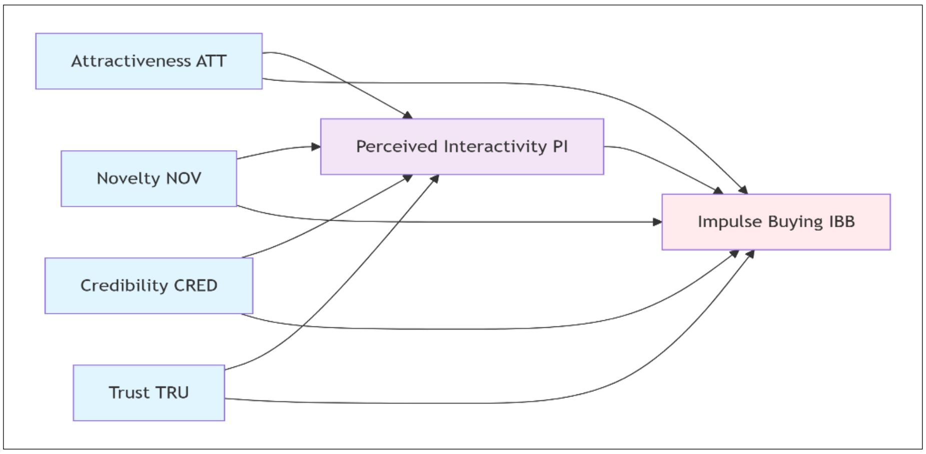

RESEARCH METHOD

Research Design

This study employs a quantitative cross-sectional survey to explore how key attributes of generative AI content, namely attractiveness, novelty, credibility, and trust, affect impulse buying behavior in social commerce. These four attributes serve as independent variables, with perceived interactivity theorized as the mediator and impulse buying tendency as the dependent variable. A conceptual distinction is maintained: credibility pertains to the perceived reliability of the AI-generated information, whereas trust reflects a broader psychological confidence in the AI-integrated shopping environment.

While the underlying model is path-oriented, the analysis does not apply full structural equation modeling (SEM). Instead, hypothesis testing is conducted specifically through mediation analysis using the SPSS PROCESS macro (Model 4). This approach is tailored to examine indirect effects, aligns with the study's aim of testing mediation among observed variables, and is methodologically suitable given the sample size and model complexity.

Sampling and Data Collection

Population and Screening Criteria

The study population consists of Indonesian consumers who use social e-commerce platforms (e.g., TikTok Shop, Shopee Live) and have previously purchased products from PT TOTAL OPTIMAL PELITA. To ensure relevance, respondents were required to: (a) have practical experience shopping in social commerce settings, and (b) have been exposed to generative AI shopping content (e.g., AI-generated scripts or short videos) at least once in the past six months. Responses failing these criteria were excluded.

Sampling Procedure and Limitations

A non-probability sampling approach was adopted. Questionnaires were distributed online via the company's customer database, brand fan communities, member groups, and social media channels (WhatsApp, Facebook), supplemented by QR code sharing and online forum invitations. While efficient and cost-effective, this method may introduce bias by over-representing highly active or digitally savvy users. Therefore, the generalizability of the findings warrants careful interpretation.

Sample Size Justification

Among the 300 questionnaires issued, 266 valid responses were retained for analysis. According to Bolin (2014), this number satisfies the recommended threshold for mediation testing using regression techniques and is well above the conventional rule of thumb regarding observations per predictor. As such, the sample size is deemed sufficient to support reliable PROCESS-based statistical analysis.

Measures and Instrumentation

Measurement of Constructs

Validated measurement items from prior research were employed to capture the key constructs. Respondents evaluated each statement using a five-point agreement scale. Information on scale sources and illustrative items is summarized in Table 1.

Table 1. Measurement of Constructs

Construct		Source	No. of Items	Sample Item (Contextualized)
1	Attractiveness	Hong et al. (2022)	3	The AI-generated product displays are visually appealing.
2	Novelty	Hong et al. (2022)	3	The AI-generated content feels novel and unique.
3	Credibility	Huang & Yodbutr (2023)	3	The AI-generated video information feels believable.
4	Trust	Huang & Yodbutr (2023)	3	I believe this platform can use AI to help me shop.
5	Perceived Interactivity	Joo & Yang (2023)	5	Interacting with AI-generated content is like a two-way conversation.
6	Impulse Buying Tendency	Lee & Chen (2021)	5	After seeing recommendations based on AI-generated content, I often can't resist making some unplanned purchases.

Contextual Adaptation of Scales

Scales were contextually adapted by two researchers independently to ensure semantic equivalence and relevance to the study's generative AI and social commerce focus. Discrepancies were resolved through discussion. A pilot test with 30 target respondents confirmed item clarity and appropriateness.

Data Analysis Strategies and Ethics

Data Analysis Strategies

The study employed a stepwise analytical strategy. Data screening and preparation were conducted first, followed by evaluations of reliability and validity using factor analytic techniques. Descriptive metrics and correlation estimates for the focal constructs were then produced. Finally, the proposed hypotheses were tested using SPSS 26.0 and the PROCESS macro (Hayes, 2017). Specifically, the direct associations between the four focal predictors and impulse buying tendency were examined using multiple regression analysis. Mediation effects were tested using a resampling (bootstrapping) approach, in which indirect effects were considered significant when zero did not fall within the 95% bias-corrected confidence interval. All regression models controlled for key demographic variables, including age, gender, education, and income.

Data Collection and Ethical Considerations

The survey data were gathered over a one-month period from August 1 to September 1, 2025. Prior to participation, all respondents provided informed consent. In strict adherence to standard academic ethical guidelines, the study ensured participant anonymity and confidentiality throughout the process. Specifically, no personally identifiable information was collected at any stage.

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RESULTS

Descriptive Statistics and Correlations

Sample Descriptive Statistical Analysis

Table 2. Descriptive Statistics Example（N=266）

Survey Item		Frequency	Percentage (%)
Gender	Male	138	51.88
	Female	128	48.12
Age	18–24	31	11.65
	25–34	93	34.96
	35–44	60	22.56
	45–54	53	19.92
	55 and above	29	10.90
Education Level	High school or below	52	19.55
	Diploma/Vocational College	56	21.05
	Bachelor’s Degree	116	43.61
	Master’s Degree or above	42	15.79
Monthly Disposable Income	Less than IDR 2,000,000	20	7.52
	IDR 2,000,000–4,999,999	91	34.21
	IDR 5,000,000–9,999,999	105	39.47
	IDR 10,000,000–14,999,999	36	13.53
	IDR 15,000,000 and above	14	5.26
	Student	31	11.65
	Private company employee	64	24.06
Occupation	Government employee	51	19.17
	Freelancer/ Business owner	69	25.94
	Housewife	24	9.02
	Other	27	10.15

Table 2 presents the descriptive statistics of the respondents (N = 266). In terms of gender, the sample is relatively balanced, with 138 male respondents (51.88%) and 128 female respondents (48.12%). The age distribution indicates that most respondents are in the productive age range, with the largest proportion aged 25–34 years (34.96%), followed by those aged 35–44 years (22.56%) and 45–54 years (19.92%). Younger respondents aged 18–24 years account for 11.65% of the sample, while respondents aged 55 years and above represent the smallest proportion (10.90%).

Regarding educational attainment, the majority of respondents hold a bachelor’s degree (43.61%), followed by those with a diploma or vocational qualification (21.05%) and a high school education or below (19.55%). Respondents with a master’s degree or higher constitute 15.79% of the sample. In terms of monthly disposable income, most respondents report earnings between IDR 5,000,000 and IDR 9,999,999 (39.47%), followed by those earning IDR 2,000,000–4,999,999 (34.21%). Lower-income respondents earning less than IDR 2,000,000 account for 7.52%, while higher-income groups earning IDR 10,000,000–14,999,999 and IDR 15,000,000 and above represent 13.53% and 5.26%, respectively.

With respect to occupation, freelancers or business owners form the largest group (25.94%), followed by private company employees (24.06%) and government employees (19.17%). Students account for 11.65% of the respondents, while housewives and those in other occupations represent 9.02% and 10.15%, respectively. Overall, the descriptive statistics indicate that the sample comprises respondents with

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diverse demographic and socioeconomic backgrounds, providing a broad basis for subsequent analysis.

Variables Descriptive Statistical Analysis

Table 3. Descriptive Statistics and Correlations (N = 266)

	Variable	M	SD	1	2	3	4	5	6
1	Novelty	9.03	3.48	1					
2	Credibility	9.62	3.6	0.45**	1				
3	Trust	9.37	3.38	0.35**	0.37**	1			
4	Attractiveness	9.23	3.54	0.43**	0.42**	0.36**	1		
5	Perceived Interactivity	16.45	6.05	0.42**	0.40**	0.34**	0.48	1	
6	Impulse Buying Behavior	15.88	5.51	0.43**	0.54	0.37**	0.44**	0.42**	1

Note: M = Mean, SD = Standard Deviation. Pearson correlation coefficients are reported below the diagonal. ** p<0.01 (two-tailed)

Descriptive statistics and intercorrelations for the core variables are shown in Table 3. All variable means fell within expected theoretical ranges, with standard deviations indicating adequate dispersion. Correlation analysis revealed significant positive bivariate correlations among all research variables ($p < 0.01$). All four independent variables correlated positively with impulse buying behavior (r ranging from 0.37 to 0.54), with credibility showing the strongest association ($r = 0.54$). The mediator, perceived interactivity, also correlated significantly with all independent and dependent variables, satisfying a prerequisite for mediation testing. Notably, attractiveness shared the strongest link with perceived interactivity ($r = 0.48$). These preliminary findings align with the theoretical model.

Reliability Analysis

Table 4. Reliability Analysis Results of the Formal Scale

Total Scale	Cronbach's Alpha	Subscales	Cronbach's Alpha
Total Scale (22)	0.921	Attractiveness	0.776
		Novelty	0.858
		Content Credibility	0.807
		Content Trust	0.816
		Perceived Interactivity	0.91
		Impulse Purchase	0.884

Reliability was assessed as reported in Table 4. The overall scale exhibited strong internal consistency (Cronbach's $\alpha = 0.921$). All six subscales were also highly reliable, with α coefficients above the recommended 0.70 benchmark.

Validity Analysis

Content Validity

This was ensured by adapting items from established scales and tailoring wording to the specific context. A pilot test with 50 target respondents confirmed item clarity and applicability.

Complete Exploratory Factor Analysis (EFA) Section for Your Thesis

Exploratory factor analysis employing principal component extraction was conducted to assess the underlying factor structure of the measurement scales. Before performing the analysis, data suitability was verified.

Table 5. KMO and Bartlett's Sphericity Test Results

Indicator	Value
the KMO adequacy coefficient	0.882
Approx. Chi-Square	3279.206
df	231
Sig.	< 0.001

Results reported in Table 5 indicate a KMO value of 0.882, demonstrating excellent sampling adequacy. Furthermore, the significance of Bartlett's test of sphericity (χ^2 = 3279.206, df = 231, $p < 0.001$) confirmed that the inter-item correlations met the requirements for factor analysis.

Table 6. Total Variance Explained

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	9.399	42.722	42.722	3.966	18.028	18.028
2	2.164	9.837	52.559	3.965	18.022	36.05
3	1.645	7.479	60.037	2.381	10.821	46.871
4	1.449	6.586	66.623	2.266	10.301	57.171
5	1.162	5.28	71.903	2.193	9.968	67.139
6	1.108	5.036	76.939	2.156	9.799	76.939

Extraction Method: Principal Component Analysis

Table 6 presents the results of the total variance explained using Principal Component Analysis (PCA). Based on the eigenvalue criterion, six factors with eigenvalues greater than one were retained for further analysis. These six factors together explain 76.939% of the total variance, which indicates a high level of explanatory adequacy in line with commonly accepted methodological guidelines (Hair Jr et al., 2021). Prior to rotation, the first factor accounts for the largest proportion of variance (42.722%), followed by the second factor (9.837%), with the remaining factors contributing additional variance to the cumulative total.

After Varimax rotation, the distribution of explained variance becomes more evenly spread across the retained factors, improving the interpretability of the factor structure. The first and second rotated factors each explain approximately 18% of the total variance, while the third and fourth factors account for 10.821% and 10.301%, respectively. The fifth and sixth factors contribute 9.968% and 9.799% of the variance. The cumulative variance explained after rotation remains unchanged at 76.939%, confirming that the six-factor solution adequately represents the underlying data structure.

Table 7. Rotated Component Matrix

Item	F1	F2	F3	F4	F5	F6
V32	0.776	0.25	0.211	0.175	0.177	0.099
V33	0.798	0.271	0.173	0.136	0.15	0.085
V34	0.845	0.222	0.115	0.162	0.151	0.073
V35	0.823	0.265	0.135	0.155	0.133	0.078
V36	0.799	0.287	0.13	0.091	0.24	0.035
V27	0.227	0.803	0.149	0.144	0.178	0.099
V28	0.223	0.793	0.129	0.142	0.201	0.101
V29	0.251	0.828	0.067	0.135	0.172	0.117
V30	0.268	0.811	0.089	0.109	0.197	0.09

V31	0.288	0.804	0.126	0.12	0.131	0.133
V18	0.157	0.093	0.822	0.127	0.129	0.166
V19	0.178	0.127	0.825	0.146	0.134	0.167
V20	0.21	0.182	0.794	0.109	0.105	0.205
V21	0.091	0.115	0.107	0.817	0.184	0.123
V22	0.174	0.202	0.162	0.791	0.053	0.092
V23	0.236	0.14	0.096	0.793	0.115	0.107
V24	0.213	0.228	0.237	0.13	0.792	0.1
V25	0.223	0.252	0.083	0.14	0.74	0.199
V26	0.259	0.278	0.107	0.148	0.757	0.108
V15	0.031	0.136	0.224	0.014	0.101	0.777
V16	0.073	0.107	0.15	0.145	0.05	0.781
V17	0.121	0.102	0.101	0.144	0.169	0.811

Extraction was performed using Principal Component Analysis, with rotation conducted via the Varimax method and Kaiser Normalization.
Note: F1 through F6 denote the six extracted factors. Factor loadings exceeding 0.50 are highlighted in bold.

The factor structure resulting from the rotated factor loadings matrix presented in Table 7 indicates a clear and well-defined solution. All measurement items load strongly on their respective primary factors, with factor loadings ranging from 0.740 to 0.845, exceeding the recommended threshold of 0.50. In addition, no substantial cross-loadings were observed, as all secondary loadings remained below 0.40, suggesting a simple factor structure with satisfactory discriminant validity. Based on the thematic content and conceptual meaning of the items, six distinct factors were identified and interpreted. The first factor, comprising items V32 to V36, was labeled Impulsive Consumption, while the second factor, consisting of items V27 to V31, was interpreted as Perceived Interactivity. The third factor includes items V18 to V20 and was labeled Trust, whereas the fourth factor, represented by items V21 to V23, was identified as Perceived Trustworthiness. The fifth factor, encompassing items V24 to V26, was named Novelty, and the sixth factor, which includes items V15 to V17, was labeled Attractiveness. Overall, these results confirm that the data are highly suitable for factor analysis, and the six-factor solution demonstrates strong explanatory power and a clear, interpretable structure, providing robust evidence of the construct validity of the measurement scale.

Confirmatory Factor Analysis (CFA)

Overall Model Fit

Table 8. Model Fit Indices for Confirmatory Factor Analysis

Fit Index	Recommended Value	Model Result	Judgment
χ^2/df	< 3.0	1.813	Good
RMSEA	< 0.08	0.055	Good
GFI	> 0.85 (Acceptable)	0.894	Acceptable
CFI	> 0.90	0.95	Good
TLI	> 0.90	0.94	Good
SRMR	< 0.08	0.064	Good

As shown in Table 8, all model fit metrics met or exceeded the recommended standards:

$$\chi 2/df = 1.813 (<3), RMSEA = .055 (<.08), CFI = .950, TLI = .940 (all > .90).$$

Although GFI (.894) is slightly below the ideal value of .90, it is still acceptable given the sample size and model complexity. Overall, the measurement model fits the data well.

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Convergent Validity

Table 9. Results of Convergent Validity Assessment

Construct	Indicator	Std. Loading	Composite Reliability (CR)	Average Variance Extracted (AVE)
Attractiveness	X11	0.721	0.778	0.539
	X12	0.698		
	X13	0.781		
Novelty	X21	0.811	0.859	0.669
	X22	0.84		
	X23	0.803		
Credibility	X31	0.756	0.807	0.582
	X32	0.766		
	X33	0.767		
Trust	X41	0.838	0.819	0.603
	X42	0.716		
	X43	0.771		
Perceived Interactivity	MM1	0.823	0.91	0.67
	MM2	0.802		
	MM3	0.844		
	MM4	0.818		
	MM5	0.806		
Impulse Purchase	YY1	0.783	0.884	0.604
	YY2	0.776		
	YY3	0.792		
	YY4	0.778		
	YY5	0.755		

The adequacy of convergent validity was evaluated using factor loadings, composite reliability, and average variance extracted. Results in Table 9 demonstrate that all item loadings exceeded the recommended threshold, with values between 0.698 and 0.844. Moreover, both CR (0.778–0.910) and AVE (0.539–0.670) met established criteria, providing empirical support for the convergent validity of the constructs.

Discriminant Validity

The Fornell–Larcker criterion was applied to evaluate discriminant validity. Under this criterion, discriminant validity is established when the square root of AVE for each construct surpasses its correlations with other constructs.

Table10. Discriminant Validity Assessment: Square Roots of AVEs and Correlation Matrix

Construct	Attractiveness	Novelty	Credibility	Trust	Perceived Interactivit	Impulse Purchase
Attractiveness	0.734					
Novelty	0.45	0.818				
Credibility	0.346	0.366	0.763			
Trust	0.427	0.424	0.356	0.776		
Perceived Interactivit	0.42	0.397	0.339	0.478	0.819	
Impulse Purchase	0.428	0.536	0.372	0.438	0.42	0.777

Note: Diagonal elements in bold indicate the square roots of AVEs for each construct. Off-diagonal entries show correlation coefficients between constructs (all significant at $p < 0.001$).

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As shown in Table 10, all diagonal values (0.734–0.818) were higher than the corresponding off-diagonal correlation coefficients. For example, Factor 1 demonstrated a higher square root of AVE than its correlations with other factors, confirming satisfactory discriminant validity.

The CFA results confirm that the six-factor measurement model demonstrates good overall fit, robust convergent validity, and adequate discriminant validity, thereby establishing a reliable basis for subsequent hypothesis testing.

Common Method Bias Test

To examine potential common method bias due to self-reported data, Harman's single-factor test was applied (Podsakoff et al., 2003). All 22 measurement items were entered into an exploratory factor analysis constrained to a single factor without rotation. The extracted factor explained 42.72% of the total variance, below the 50% cutoff. This indicates that common method bias is not a major concern. Additionally, the distinct six-factor solution from the earlier EFA further supports that the variance is not primarily attributable to a single methodological source.

Multicollinearity Diagnostics

Table 11. Multicollinearity Diagnostics Results (Full Model)

Variable	Tolerance	Variance Inflation Factor (VIF)
Attractiveness (xx9)	0.662	1.51
Novelty (xx10)	0.646	1.547
Perceived Credibility (xx11)	0.772	1.295
Trust (xx12)	0.643	1.555
Perceived Interactivity (mm13)	0.655	1.526
Age (V10)	0.754	1.326
Gender (V11)	0.941	1.062
Education (V12)	0.966	1.035
Monthly Income (V13)	0.815	1.227
Profession (V14)	0.807	1.24

Note: The dependent variable is Impulse Buying Tendency (yy14)

Prior to hypothesis testing, multicollinearity among all predictors (including control variables) was examined by computing Variance Inflation Factors (VIFs). Table 11 displays VIF values ranging from 1.035 to 1.555, all comfortably below the conservative cutoff of 3.0 (Hair Jr et al., 2021). These results confirm that severe multicollinearity is not present, supporting the stability of the following regression estimates.

Hypothesis Testing

Statistical Analysis Results

This section employs regression analysis to assess the effects of the independent variables on the dependent variable, utilizing output derived from SPSS.

Table 12. Total Effect of Independent Variables on Impulse Purchase

Predictor	B	SE	β	t	p
Constant	5.253	2.244	—	2.341	0.02
Attractiveness	0.277	0.092	0.178	3.028	0.003
Novelty	0.223	0.094	0.141	2.364	0.019
Credibility	0.522	0.092	0.341	5.658	< .001
Trust	0.204	0.091	0.125	2.247	0.025
Age (V10)	-0.059	0.259	-0.013	-0.227	0.82

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Gender (V11)	-0.412	0.555	-0.037	-0.743	0.458
Education (V12)	-0.042	0.282	-0.007	-0.149	0.882
Monthly Income (V13)	0.226	0.308	0.04	0.735	0.463
Profession (V14)	-0.187	0.204	-0.05	-0.917	0.36

Model Evaluation Indicators: $R = 0.618$, $R^2 = 0.382$, Adjusted $R^2 = 0.360$, $F(9, 256) = 17.553$, $p < 0.001$, DW = 1.854
Note. Coefficient estimates are reported as unstandardized (B) and standardized (β) values, with SE indicating standard errors. Demographic variables were controlled for in the analysis, and all VIF statistics remained well below the commonly accepted threshold, suggesting the absence of multicollinearity.

A multiple regression analysis was performed to examine Hypotheses H1–H4, with demographic variables (age, sex, education level, income level) included as covariates. As shown in Table 12, the model was statistically significant, $F(9, 256) = 17.553$, $p < 0.001$, and had an adjusted $R^2 = 0.360$. None of the control variables significantly influenced impulsive buying ($p > 0.05$).

All four core predictors demonstrated significant positive effects: credibility ($\beta = 0.341$, $p < 0.001$), attractiveness ($\beta = 0.178$, $p = 0.003$), novelty ($\beta = 0.141$, $p = 0.019$), and trust ($\beta = 0.125$, $p = 0.025$). Collinearity diagnostics confirmed no multicollinearity issues (all VIF < 1.51). Therefore, the direct effects remained robust after controlling for demographic factors. Thus, Hypotheses H1 through H4 were fully supported.

Theoretically, this suggests that attractiveness, novelty, credibility, and trust directly and indirectly stimulate impulsive purchases by enhancing perceived interactivity. This model aligns with social e-commerce content design theory, which posits that engaging and novel content increases user interaction, while credibility and trust provide a sense of psychological security, both of which contribute to impulsive buying.

Mediation Effect Analysis
To further examine the mechanism through which perceived interactivity influences impulse buying, the PROCESS macro (Model 4; Hayes, 2017) was used to test for mediation. Given the distinct conceptual nature of the four AI-content attributes, separate analyses were conducted for each predictor to evaluate its unique indirect effect via the mediator. All analyses employed 5,000 bootstrap samples to generate bias-corrected confidence intervals (CIs).

Table 13. Results of the Mediation Analysis (PROCESS Model 4)

Model (X)	Path a (X→M)	Path b (M→Y)	R^2 (Y)	Direct Effect (c’)	Indirect Effect (a×b)	95% Boot CI	VIF (X & M)	Mediation Type
Attractiveness	0.731***	0.266***	0.253	0.484***	0.194*	[0.092, 0.328]	1.21	Partial
Novelty	0.868***	0.224***	0.338	0.672***	0.149*	[0.066, 0.254]	1.19	Partial
Credibility	0.607***	0.302***	0.236	0.424***	0.183*	[0.082, 0.314]	1.13	Partial
Trust	0.816***	0.249***	0.249	0.479***	0.203*	[0.091, 0.337]	1.3	Partial

Note: Coefficients are reported as unstandardized values. Bootstrap resampling was set to 5,000. CI = confidence interval.

The results are presented in Table 13. For all four independent variables, the indirect effects (*a*×*b*) were statistically significant, as evidenced by 95% bootstrap CIs that did not include zero. This confirms that perceived interactivity serves as a significant mediator in each relationship. Consistent with partial mediation, the direct effects (*c*′) of all predictors on impulse buying remained significant after accounting for the mediator.

An examination of the indirect effect magnitudes reveals that trust exhibited the strongest mediation through perceived interactivity (indirect effect = 0.203). Although novelty had the largest total effect on impulse buying, its indirect effect was comparatively smaller (0.149), suggesting a more substantial direct influence.

In summary, the results provide strong support for H5, indicating that perceived interactivity partially mediates the influence of all four AI-content characteristics on impulse buying tendency, with the mediating pathway being most pronounced for trust.

DISCUSSION

This study proposed and tested a model examining how AI-generated content characteristics influence impulse buying in social commerce, with perceived interactivity as a key mediator. The findings largely support the proposed hypotheses, offering nuanced insights into consumer behavior in this emerging context. The following sections analyze each key finding in relation to the literature and theoretical framework.

H1: The Effect of AI-Generated Content Attractiveness on Impulse Buying

The results confirm that the attractiveness of AI-generated content significantly increases impulse buying, supporting H1. This aligns with the foundational principle of the S-O-R model, where visually appealing content acts as a potent external stimulus. In the context of AI, this attractiveness likely triggers immediate positive affect and reduces deliberative thinking, thereby facilitating impulsive decisions. This finding corroborates prior work on visual appeal in general online contexts (Asante et al., 2023; Lim et al., 2020). However, it extends this literature by demonstrating its critical role within algorithmically-generated, personalized content streams typical of social commerce, where aesthetic appeal may be hyper-optimized to capture attention. Therefore, this study specifies attractiveness as a primary design lever for AI content intended to stimulate spontaneous purchases.

H2: The Effect of AI-Generated Content Novelty on Impulse Buying

The analysis reveals that perceived novelty significantly drives impulse buying, supporting H2. Novelty functions as a curiosity-arousing stimulus within the S-O-R model, heightening psychological arousal and motivating exploratory behavior, which in turn lowers purchase barriers. This finding corroborates research on the positive impact of innovative and creative content on consumer engagement and behavioral responses (Ariasih et al., 2023; Tee & Teo, 2022). Our contribution lies in validating this effect within the rapidly evolving landscape of AI-generated marketing formats. The inherent novelty of AI scripts, virtual anchors, and personalized recommendations can break through consumer habituation, making it a critical factor for capturing attention in crowded social commerce feeds. Importantly, while novelty showed the strongest total effect, its indirect effect via interactivity was relatively smaller, suggesting its influence is also mediated by more direct, arousal-based pathways.

H3: The Effect of Perceived Credibility of AI-Generated Content on Impulse Buying

The results indicate that perceived credibility positively influences impulse buying, supporting H3. From a decision-making perspective, credible information reduces perceived risk and cognitive uncertainty, enabling faster, less deliberative purchase decisions, a core feature of impulse buying. This aligns with established literature on credibility as a cornerstone of online trust and purchase behavior (Ariasih et al., 2023). Our study extends this understanding by applying it to the unique domain of AI-originated content. In an environment where content is generated rather than human-curated, establishing credibility (e.g., through accurate information, realistic depictions) is paramount to overcoming initial skepticism and enabling the smooth, low-friction decision process that culminates in impulse purchases.

H4: The Effect of Trust in AI-Generated Content on Impulse Buying
The findings provide partial support for H4, indicating a positive but more complex relationship between trust and impulse buying. While significant, our analysis suggests this effect is deeply intertwined with platform-level trust mechanisms, such as transaction security, data privacy safeguards, and institutional reputation, rather than being solely attributable to the content itself. This distinction is crucial. Unlike credibility, which pertains to the content's believability, trust here reflects a broader psychological security in the platform ecosystem (Hajli, 2015). This finding advances the conceptualization of trust in digital commerce, highlighting its multi-layered nature where *content-specific credibility* and *platform-level institutional trust* are interrelated yet distinct constructs that jointly facilitate the risk-taking inherent in impulse buying.

H5: The Mediating Role of Perceived Interactivity
A central finding of this study is that perceived interactivity partially mediates the relationship between all four AI content characteristics and impulse buying, fully supporting H5. This confirms the “content characteristics → perceived interactivity → impulse buying” pathway, positioning interactivity as the critical organism component in the S-O-R model. It transforms passive content reception into an engaging, two-way experience, enhancing social presence and psychological immersion, which are known precursors to impulsive behavior (Ariasih et al., 2023). The partial mediation observed is theoretically meaningful: it indicates that while interactivity is a key mechanism, AI content characteristics also exert direct influence, possibly through more immediate affective or heuristic pathways. Notably, trust exhibited the strongest indirect effect through interactivity, suggesting that users who trust the platform are more likely to engage deeply with its interactive AI features, thereby increasing their impulse purchase propensity.

Summary and Theoretical Integration
Overall, the results indicate that AI-generated content influences impulse buying through both direct effects and indirect effects mediated by perceived interactivity, following the pathway of “content characteristics → perceived interactivity → impulse buying.” These findings verify the applicability of the Online Impulse Buying Model in AI-driven social commerce contexts and extend traditional S–O–R logic to emerging generative AI marketing environments.

CONCLUSION

This study investigates how generative AI-generated content in social commerce influences consumers’ impulse buying behavior through perceived interactivity, drawing on the Online Impulse Buying Model. The findings show that content attractiveness, novelty, perceived credibility, and trust all significantly and positively affect impulse buying, while perceived interactivity plays a partial mediating role in these relationships. This indicates that AI-generated content functions as an effective external stimulus, and interactive experiences further strengthen consumers’ emotional engagement and social presence, thereby amplifying impulsive purchase responses. The results extend the applicability of the Online Impulse Buying Model to AI-driven content contexts and highlight the importance of integrating high-quality AI content with interactive mechanisms in social commerce practice. Nevertheless, the study is limited by its contextual scope and reliance on self-reported data, suggesting that future research should explore diverse platforms and employ behavioral or experimental methods to enhance generalizability.

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I dedicate this writing to my student years, the most vibrant and sincere chapter of my youth.

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