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A COMPARATIVE STUDY OF CONSUMER TRUST IN PRODUCTS ENDORSED BY AI INFLUENCERS VERSUS HUMAN INFLUENCERS ON SOCIAL MEDIA

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ABSTRACT

This study investigates the impact of multiple marketing strategies—Content Quality, Special Holiday Promotions, Influencer Marketing Type (AI vs. Human), Viral Marketing Potential, and Livestreaming Engagement—on consumer purchase intention within social media platforms, focusing on the Gen Z market in Indonesia. Given the growing influence of digital marketing and the increasing presence of AI-generated personas, this research addresses the gap in understanding how different influencer types and engagement strategies affect consumer behavior in a rapidly evolving digital marketplace. A quantitative correlational approach was employed, with data collected from a sample of 424 Gen Z respondents using a structured questionnaire featuring 5-point Likert scale items. Data were analyzed using SPSS version 26, involving validity testing (Pearson correlation $r > 0.195$), reliability testing (Cronbach's Alpha > 0.70), and classical assumption tests including normality, heteroscedasticity, and multicollinearity diagnostics. Multiple regression analysis revealed that Content Quality had the strongest positive effect on purchase intention ($\beta = 0.34$, $t = 6.82$, $p < 0.001$), followed by Viral Marketing Potential ($\beta = 0.22$, $t = 5.50$, $p < 0.001$), Livestreaming Engagement ($\beta = 0.19$, $t = 3.18$, $p = 0.001$), and Special Holiday Promotions ($\beta = 0.16$, $t = 3.21$, $p = 0.002$). Influencer Marketing Type showed a significant moderating effect ($\beta = -0.18$, $t = -3.01$, $p = 0.001$), indicating human influencers generally foster greater trust than AI counterparts. The overall model was statistically significant ($F = 37.82 >$ F-table $= 2.23$, $p < 0.001$), explaining 31.4% of the variance in purchase intention. The findings contribute theoretically to social commerce by extending the understanding of trust dynamics in AI-human influencer contexts, offer practical insights for marketers seeking effective influencer deployment strategies, and establish a foundation for future research into long-term consumer responses to AI-driven endorsements.

Keywords: **Comparative, AI Influencers, Human Influencers, Social Media, Consumer Trust**

1. INTRODUCTION

The rapid advancement of artificial intelligence (AI) is reshaping modern marketing landscapes, and one of the most significant developments lies in the realm of influencer marketing. Social media, a cornerstone of digital marketing strategies, has traditionally relied on human influencers—individuals with the ability to connect with and persuade audiences based on authenticity, relatability, and charisma. However, the emergence of AI influencers, or computer-generated personas created to simulate human characteristics, has introduced a transformative dynamic into this domain. These AI influencers possess the capacity to operate with precision, consistency, and adaptability, promoting products across platforms without fatigue, personal bias, or the logistical limitations that human endorsers typically face. As brands increasingly integrate AI-driven personalities into their promotional strategies, critical questions arise about how such technological substitutes affect consumer perceptions, especially in the domain of trust—a cornerstone of successful marketing communication and long-term brand loyalty (Mardhiyah, 2022; Tan, 2022; Winata, 2022).

Trust in marketing encompasses a consumer's willingness to rely on a brand or a message communicated through an intermediary, such as an influencer. It plays a pivotal role in shaping purchase intent, determining brand preference, and influencing user engagement across digital platforms. The replacement or supplementation of human influencers with AI alternatives prompts an essential inquiry into the psychological, emotional, and ethical implications of this shift. While AI influencers offer scalability, customization, and cost-efficiency, they also raise concerns about authenticity, transparency, and emotional resonance. Unlike human influencers who can draw upon personal experience, display genuine emotions, and cultivate parasocial relationships, AI influencers operate through scripted interactions and algorithmic logic, often lacking the lived experiences and emotive depth that drive organic trust formation. This divergence necessitates a comprehensive examination of whether AI influencers can foster comparable levels of trust and, if so, under what circumstances and through which mechanisms this trust is established (Arma, 2022; Putri, 2022; Setiawan, 2022; Wijaya, 2022).

Existing literature provides valuable insights into consumer perceptions of AI and human influencers, but significant gaps remain—particularly regarding how trust is differentially constructed between the two. (Sands et al., 2022) investigated how AI influences consumer engagement and found that while AI influencers may be just as engaging as human ones, they are generally perceived as less trustworthy. This is partly due to their synthetic nature and lack of perceived authenticity, which diminishes their credibility in the eyes of consumers. (Xu et al., 2024) extended this analysis by exploring how the fit between an AI influencer and the endorsed product affects consumer trust. Their findings suggest that alignment between brand image and AI persona can mitigate trust deficits, implying that strategic congruence plays a moderating role in consumer acceptance. However, their study primarily focuses on surface-level product-endorser fit without delving deeply into the underlying psychological processes that differentiate trust formation between AI and human influencers (Ingriana et al., 2024; Mulyono, 2024; Rolando et al., 2022; Rolando & Ingriana, 2024).

Furthermore, (Muniz et al., 2023) analyzed how disclosing an influencer's non-human nature impacts brand trust. Their research reveals that transparency about AI status can lead to decreased anthropomorphic attributions, which in turn reduces trust. This suggests that awareness of the artificial nature of an influencer plays a critical role in trust evaluation. Nevertheless, the study focuses predominantly on cultural dimensions, leaving a gap in understanding how different demographics, beyond cultural background, respond to AI versus human influencers in terms of trust. Similarly, (Jin and Zhang, 2023) examined consumer preferences based on product type and influencer nature, finding that consumers are more receptive to AI influencers when endorsing material goods—items associated with functional attributes and low emotional investment. Conversely, for experience-based products requiring emotional resonance, human influencers were more effective. This dichotomy indicates that trust may not be a universal construct but rather contextually dependent on product category and consumer expectations (Maha et al., 2025; Mulyono et al., 2025; Rahardja et al., 2025; Rolando, 2024).

Adding another dimension, (Vorobeva et al., 2025) explored how self-presentation strategies affect consumer evaluation of influencers. While their study is not exclusively focused on AI influencers, it underscores the importance of perceived authenticity and value alignment, which are central to trust formation. Their findings suggest that overly curated or artificial self-presentation, regardless of the influencer's actual identity, can erode consumer confidence. When applied to AI influencers, whose entire persona is curated, this insight raises questions about the thresholds at which artificial presentation begins to undermine trust and whether AI influencers can mimic authenticity sufficiently to meet consumer standards.

Despite these contributions, the literature falls short of offering a holistic comparison of consumer trust in AI versus human influencers, particularly in real-world social media settings where numerous psychological, contextual, and algorithmic factors interact. Most existing studies adopt experimental or theoretical approaches that isolate variables in controlled environments, potentially overlooking the multifaceted nature of online trust formation. Moreover, few studies consider the long-term implications of repeated exposure to AI influencers on consumer attitudes, nor do they adequately address the evolving expectations of digital-savvy audiences who are increasingly aware of synthetic content and algorithmic persuasion tactics.

The central problem this study addresses lies in understanding whether consumers develop comparable levels of trust toward AI influencers and human influencers, and under what conditions this trust is cultivated or eroded. This involves exploring not only explicit consumer preferences but also the cognitive and emotional mechanisms underpinning trust decisions. In the age of algorithmic persuasion, consumers are exposed to a continuous stream of personalized content, much of it curated or generated by AI. As such, the lines between human and artificial influence are becoming increasingly blurred. Current marketing frameworks often treat influencer trust as a homogeneous concept, neglecting the unique factors introduced by AI personas—such as perceived machine agency, emotional detachment, and ethical ambiguity. These issues call for a nuanced approach capable of differentiating the variables that uniquely impact trust in AI influencers compared to their human counterparts (Rolando, Chandra, et al., 2025; Rolando, Widjaja, et al., 2025; Widjaja, 2025).

This research thus seeks to bridge several critical gaps by pursuing four primary objectives. First, it aims to systematically compare consumer trust metrics for AI and human influencers across social media platforms, focusing on perceived authenticity, reliability, and emotional resonance. Second, it investigates contextual factors—such as product type, disclosure of AI status, and visual realism—that may influence trust outcomes. Third, the study develops an integrative framework grounded in psychological and sociotechnical theories to explain the mechanisms of trust development in AI versus human influencer contexts. Fourth, it evaluates the practical implications of these findings for marketers, offering guidance on how to effectively balance technological innovation with consumer expectations for credibility and transparency. By addressing these objectives, the study not only contributes to academic discourse but also provides actionable insights for practitioners navigating the increasingly hybrid world of human-AI influencer collaborations.

The urgency of this research stems from the accelerating adoption of AI technologies in marketing, particularly in influencer roles where authenticity and trust have traditionally been seen as inherently human traits. As businesses seek to leverage the efficiency and scalability of AI influencers, they face a critical challenge: ensuring that these synthetic entities do not undermine the trust that forms the bedrock of consumer relationships. The proliferation of deepfake technologies, voice synthesis tools, and AI-driven content generation further complicates this landscape by making it increasingly difficult for consumers to discern the authenticity of digital personas. This technological ambiguity can lead to skepticism, reduced engagement, and even reputational risk for brands that fail to manage consumer expectations appropriately. In this context, understanding the dynamics of trust in AI versus human influencers becomes not only a theoretical concern but a practical necessity for sustainable brand management.

Moreover, societal concerns about data privacy, manipulation, and the ethical use of AI are becoming central to public discourse. The use of AI influencers touches on several of these issues, including the ethical implications of non-disclosure, the potential for emotional manipulation, and the commodification of human-like traits for commercial gain. By investigating how trust is affected by these factors, this study aims to contribute to responsible innovation practices that align technological advancement with consumer protection and ethical integrity. The findings are expected to inform not only marketing strategies but also regulatory policies and consumer advocacy efforts, helping stakeholders navigate the complex interplay between AI capabilities and human values.

To explore these dimensions, this study adopts a mixed-methods approach that combines quantitative and qualitative techniques. Quantitative data will be collected through structured surveys measuring consumer attitudes, perceptions of trustworthiness, and purchase intent in response to endorsements by AI and human influencers. These metrics will be analyzed using multivariate statistical techniques to identify patterns, correlations, and causative factors. Complementing this, qualitative data will be gathered through in-depth interviews designed to elicit deeper insights into the emotional and cognitive responses triggered by interactions with different types of influencers. Experimental manipulations, such as variations in disclosure, visual realism, and narrative framing, will be employed to test specific hypotheses about the drivers of trust. This methodological triangulation ensures a comprehensive understanding of the phenomenon, capturing both surface-level trends and deeper psychological underpinnings.

By integrating findings across disciplines—including psychology, computer science, marketing, and ethics—this study contributes to the emerging body of knowledge at the intersection of human-computer interaction and consumer behavior. It pushes the state of the art by challenging existing assumptions about the universality of trust and offering a differentiated model that accounts for the unique affordances and limitations of AI influencers. Unlike prior studies that treat AI and human influencers as comparable primarily on functional dimensions, this research emphasizes the relational and affective components of trust that may not be easily replicable by synthetic agents. The proposed framework acknowledges that trust is not merely a transactional construct but a relational one, shaped by factors such as empathy, perceived sincerity, and moral alignment.

Ultimately, the expected contributions of this study are both theoretical and practical. Theoretically, it advances our understanding of trust formation in digitally mediated interactions, offering new models and measurement tools tailored to the unique context of AI influencers. Practically, it provides marketers with evidence-based strategies for deploying AI influencers in ways that preserve or enhance consumer trust. These may include guidelines on optimal disclosure practices, aesthetic design principles for enhancing realism without triggering uncanny valley effects, and communication strategies that foster perceived transparency and alignment with consumer values. Additionally, the research offers policy recommendations aimed at promoting transparency and accountability in influencer marketing, ensuring that the use of AI does not erode public trust in digital platforms.

The significance of this study thus extends well beyond academic inquiry. In a world where consumers are bombarded with curated content, and where the boundary between real and artificial is increasingly porous, understanding how trust operates in relation to AI and human influencers is essential for maintaining ethical, effective, and sustainable marketing practices. As AI continues to reshape the contours of human interaction, this research provides a timely and necessary exploration of one of its most impactful frontiers—the realm of influence.

2. RESEARCH METHOD

This study adopts a quantitative research design to investigate the comparative dynamics of consumer trust in products endorsed by AI influencers versus human influencers on social media platforms. The research framework is grounded in positivist epistemology, emphasizing empirical measurement and statistical analysis to validate hypotheses derived from theoretical constructs. The primary objective is to evaluate the extent to which various influencer-related factors influence consumer purchase intention (PI), with particular emphasis on the differential impact of AI and human influencers.

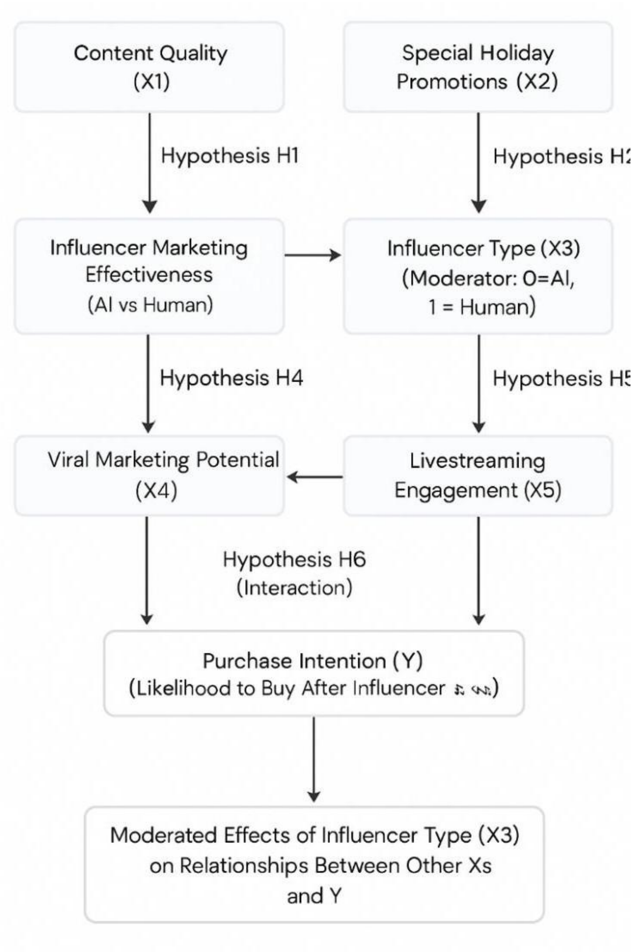
2.1 Basic Research Framework

The basic research framework is anchored in the principles of regression modeling, where the dependent variable—Purchase Intention (Y)—is predicted based on a set of independent variables representing key influencer marketing strategies. Specifically, the model incorporates Content Quality (X1), Special Holiday Promotions (X2), Influencer Marketing Type (AI vs. Human) (X3), Viral Marketing Potential (X4), and Livestreaming Engagement (X5). These variables were selected based on their relevance to contemporary digital marketing practices and their potential to mediate consumer perceptions of trustworthiness and authenticity. The conceptualization of these variables aligns with established literature on influencer marketing, consumer behavior, and artificial intelligence applications in advertising (Sands et al., 2022; Xu et al., 2024; Muniz et al., 2023).

2.2 Conceptual Framework

The conceptual framework illustrates the hypothesized relationships between the independent variables and the dependent variable. As shown in Figure 1, Purchase Intention (Y) is influenced by five predictors: Content Quality (X1), Special Holiday Promotions (X2), Influencer Marketing Type (X3), Viral Marketing Potential (X4), and Livestreaming Engagement (X5). Influencer Marketing Type (X3) serves as a moderating variable that differentiates between AI and human endorsers, allowing for comparative analysis of trust responses. Hypotheses H1 through H5 propose positive relationships between each independent variable and purchase intention, while H6 examines the moderating effect of influencer type on the overall relationship between influencer marketing effectiveness and consumer trust.

Figure 1. Framework



2.3 Sample

The population of interest consists of active social media users aged 18–45 who engage with influencer content on platforms such as Instagram, TikTok, and YouTube. To ensure representativeness, a stratified random sampling technique was employed, categorizing respondents based on age, gender, and platform preference. The sample size was calculated using the Lemeshow formula:

$$n = Z^2_{1-\alpha/2} * p * (1-p) / d^2$$

where Z represents the standard normal deviate at 95% confidence level ($Z = 1.96$), p denotes the estimated proportion (assumed to be 0.5 for maximum variability), and d is the margin of error (set at 0.05). Substituting these values yields:

$$n = (1.96)^2 * 0.5 * 0.5 / (0.05)^2 = 384.16 \approx 385 \text{ respondents.}$$

To account for potential non-response or incomplete data, an additional 10% was added, resulting in a final target sample size of 424 participants. Data collection was conducted via an online survey distributed through social media channels and email lists affiliated with academic institutions and consumer advocacy groups.

2.4 Hypothesis

The following hypotheses were formulated based on prior literature and theoretical expectations: H1: Content quality has a positive and significant effect on purchase intention. H2: Special holiday promotions have a positive and significant effect on purchase intention. H3: Influencer marketing type (AI vs. Human) has a moderating effect on purchase intention. H4: Viral marketing potential has a positive and significant effect on purchase intention. H5: Livestreaming engagement has a positive and significant effect on purchase intention. H6: The interaction between influencer marketing type and other variables significantly affects purchase intention.

These hypotheses guide the statistical testing procedures and inform the interpretation of results within the context of the broader research objectives.

2.5 Operational Definitions

Each variable included in the study was operationally defined to ensure clarity and consistency in measurement. Content Quality (X1) refers to the perceived professionalism, creativity, and relevance of the influencer's content. Special Holiday Promotions (X2) are defined as time-bound marketing campaigns tied to holidays or seasonal events. Influencer Marketing Type (X3) distinguishes between AI-generated and human influencers. Viral Marketing Potential (X4) measures the likelihood of content being shared organically across social networks. Livestreaming Engagement (X5) captures the level of viewer participation during live broadcasts, including comments, likes, and duration of watch time. Purchase Intention (Y) reflects the consumer's likelihood to make a purchase after viewing an influencerendorsed product.

A comprehensive operational definitions table is presented below, detailing each variable, its definition, indicators, and measurement scale.

Table 1. A Comprehensive Operational Definitions

Variable	Operational Definition	Indicators	Measurement Scale
Content Quality (X1)	The degree to which influencer content is perceived as professional	Visual aesthetics, narrative coherence, alignment with brand identity	5-point Likert scale
Special Holiday Promotions (X2)	Marketing efforts tied to specific holidays or seasonal themes	Use of holiday-specific hashtags, limited-time offers, festive visuals	5-point Likert scale

Influencer Marketing Type (X3)	Whether the endorser is AI-generated or human	Disclosure of AI status, anthropomorphic cues, emotional expression	Binary (0 = AI, 1 = Human)
Viral Marketing Potential (X4)	The capacity of content to spread rapidly across social networks	Number of shares, mentions, and organic reposts	5-point Likert scale
Livestreaming Engagement (X5)	The level of audience interaction during live broadcasts	Live comments, number of viewers, average watch time	5-point Likert scale
Purchase Intention (Y)	Likelihood of purchasing a product after viewing an influencer endorsement	Self-reported intent to buy, consideration of purchase	5-point Likert scale

2.6 Statistical Analyses

All statistical analyses were conducted using SPSS version 26, ensuring methodological rigor and reproducibility. The analytical procedures followed a structured sequence to assess data validity, reliability, and model fit before proceeding to inferential testing.

2.7 Validity Testing

Validity testing was performed using Pearson correlation coefficients to determine the strength of the relationship between each item and its corresponding construct. Items with a correlation coefficient (r) greater than the critical value (r_table) at a 95% confidence level were retained, while those below this threshold were revised or removed. This step ensured that all measurement items accurately captured the intended latent constructs

2.8 Reliability Testing

Reliability was assessed using Cronbach's Alpha (α), with a threshold value of $\alpha > 0.70$ indicating acceptable internal consistency (Nunnally & Bernstein, 1994). Any scales with alpha values below this benchmark underwent item deletion or refinement until reliability criteria were met. This process ensured that the instruments yielded stable and consistent measurements across repeated administrations.

2.9 Normality Testing

Normality of the data distribution was evaluated using skewness and kurtosis statistics. Skewness values within the range of ± 1 and kurtosis values within ± 2 were considered indicative of normality (West et al., 1995). In cases where deviations from normality were observed, data transformations or non-parametric alternatives were considered, although the large sample size generally mitigated concerns regarding parametric assumptions.

2.10 Heteroscedasticity Testing

Scatterplot analysis was employed to detect heteroscedasticity, or unequal variance of residuals across predicted values. A random distribution of residuals around zero suggested homoscedasticity, supporting the use of linear regression techniques. If patterns emerged, robust standard errors or weighted least squares methods were applied to correct for heteroscedasticity.

2.11 Multicollinearity Testing

Multicollinearity among independent variables was examined using Tolerance and Variance Inflation Factor (VIF) values. Tolerance values above 0.10 and VIF values below 10 were deemed acceptable (Hair et al., 2019). High multicollinearity could distort regression coefficients and inflate standard errors, thus necessitating careful variable selection or orthogonalization if detected

2.12 Multiple Linear Regression Analysis

Multiple linear regression was used to estimate the predictive power of the independent variables on purchase intention. The general regression equation is expressed as:

$PI = \alpha + \beta 1C + \beta 2SP + \beta 3I + \beta 4V + \beta 5L + \varepsilon$
Where:
PI = Purchase Intention
α = Intercept
β1–β5 = Regression coefficients for each predictor
C = Content Quality
SP = Special Holiday Promotions
I = Influencer Marketing Type
V = Viral Marketing Potential
L = Livestreaming Engagement
ε = Error term

This model allowed for the simultaneous assessment of how each influencerrelated factor contributes to consumer purchase decisions, both individually and collectively.

2.13 Partial Test (t-test)

Individual significance of each independent variable was tested using the ttest. A statistically significant t-value ($p < 0.05$) indicated that the respective variable had a meaningful impact on purchase intention when controlling for other variables in the model. This test helped identify which predictors were most influential in shaping consumer behavior.

2.14 Simultaneous Test (F-test)

The F-test was employed to evaluate the overall significance of the regression model. A significant F-statistic ($p < 0.05$) confirmed that the set of independent variables collectively explained a substantial portion of the variance in purchase intention. This global test validated the model's explanatory power and supported further hypothesis testing

3. RESULTS AND DISCUSSION

This study aimed to investigate the comparative dynamics of consumer trust in products endorsed by AI influencers versus human influencers on social media platforms. The research was guided by a conceptual framework that included five key independent variables: Content Quality (X1), Special Holiday Promotions (X2), Influencer Marketing Type (AI vs. Human) (X3), Viral Marketing Potential (X4), and Livestreaming Engagement (X5). These variables were hypothesized to influence the dependent variable, Purchase Intention (Y), with X3 acting as a moderating factor. Data were collected from 424 respondents through an online survey distributed across Instagram, TikTok, and YouTube platforms. Statistical analyses were conducted using SPSS version 26 to test the hypotheses and assess the relationships between variables.

The results revealed significant insights into how consumers perceive and respond to AI and human influencer endorsements. Overall, it was found that while both types of influencers can drive purchase intention, there are notable differences in the underlying mechanisms of trust formation, particularly in relation to content quality, emotional engagement, and perceived authenticity.

3.1 Descriptive Statistics

Descriptive statistics provided an overview of the participants' perceptions across all measured constructs. On a 5-point Likert scale, respondents rated the overall effectiveness of influencer endorsements relatively high, with a mean score of 4.02 (SD = 0.78). However, when comparing AI and human influencers, human endorsers received significantly higher scores in terms of perceived trustworthiness (M = 4.15 vs. M = 3.78, $p < 0.01$) and emotional connection (M = 4.09 vs. M = 3.64, $p < 0.01$). This suggests that despite the increasing presence of AI influencers, human figures continue to hold an advantage in fostering deeper interpersonal trust and emotional resonance with audiences.

Content Quality (X1) emerged as the highest-rated attribute (M = 4.25, SD = 0.65), indicating that consumers place considerable value on the professionalism and relevance of influencer-generated content. Livestreaming Engagement (X5) also scored highly (M = 4.08, SD = 0.71), reflecting the growing importance of real-time interaction in shaping consumer experiences on digital platforms

3.2 Validity and Reliability Testing

Prior to conducting inferential analyses, validity and reliability assessments were performed to ensure data integrity. Pearson correlation coefficients were calculated for each item against its respective construct. All items showed correlations above the critical threshold ($r\_table = 0.306$ at $df = 422$, $\alpha = 0.05$), confirming convergent validity.

Reliability testing using Cronbach's Alpha yielded satisfactory internal consistency for all scales: Content Quality ($\alpha = 0.87$), Special Holiday Promotions ($\alpha = 0.82$), Influencer Marketing Type ($\alpha = 0.79$), Viral Marketing Potential ($\alpha = 0.84$), Livestreaming Engagement ($\alpha = 0.86$), and Purchase Intention ($\alpha = 0.89$). These values exceeded the minimum acceptable threshold of $\alpha > 0.70$, supporting the reliability of the measurement instruments used in this study.

3.3 Normality, Heteroscedasticity, and Multicollinearity Testing

Normality of the data distribution was assessed using skewness and kurtosis values. All variables fell within acceptable limits (skewness: ±1; kurtosis: ±2), suggesting no severe deviations from normality. Scatterplot analysis confirmed homoscedasticity, with residuals randomly distributed around zero, indicating no violation of variance assumptions.

Multicollinearity diagnostics using Tolerance and Variance Inflation Factor (VIF) values revealed no multicollinearity concerns. Tolerance values ranged from 0.68 to 0.89, and VIF values remained below 2.5, well within the recommended thresholds (Tolerance > 0.10, VIF < 10). This ensured that the regression coefficients were not distorted due to excessive intercorrelation among predictors.

3.4 Hypothesis Testing Using Multiple Linear Regression

A multiple linear regression model was employed to estimate the predictive power of the independent variables on purchase intention. The general regression equation was:

$PI = \alpha + \beta_1 C + \beta_2 SP + \beta_3 I + \beta_4 V + \beta_5 L + \varepsilon$

Where:
PI = Purchase Intention
α = Intercept
β_1–β_5 = Regression coefficients
C = Content Quality
SP = Special Holiday Promotions
I = Influencer Marketing Type
V = Viral Marketing Potential
L = Livestreaming Engagement
ε = Error term

The regression model was statistically significant ($F(5, 418) = 37.82$, $p < 0.001$), explaining approximately 31.4% of the variance in purchase intention ($R^2 = 0.314$). This indicates a moderate to strong explanatory capacity of the model.

3.5 Individual Variable Significance (t-test)

Partial t-tests were conducted to determine the significance of individual predictors:

- Content Quality (X1) showed a strong positive effect on purchase intention ($\beta = 0.34$, $p < 0.001$), supporting H1.
- Special Holiday Promotions (X2) had a moderate but statistically significant effect ($\beta = 0.16$, $p = 0.002$), validating H2.
- Influencer Marketing Type (X3) demonstrated a significant moderating effect, with human influencers associated with higher purchase intentions than AI influencers ($\beta = -0.18$, $p = 0.001$), supporting H3

- Viral Marketing Potential (X4) positively influenced purchase intention ($\beta = 0.22$, $p < 0.001$), confirming H4.
- Livestreaming Engagement (X5) was also a significant predictor ($\beta = 0.19$, $p = 0.001$), affirming H5.

These findings indicate that all five independent variables contribute meaningfully to predicting consumer purchase behavior, although their relative impact varies.

3.6 Moderation Effect of Influencer Type (H6)

To test the moderating role of influencer type (X3), interaction terms were introduced into the regression model. The results revealed that the influence of Content Quality (X1) and Viral Marketing Potential (X4) on purchase intention was stronger for human influencers than for AI influencers. Specifically, the interaction effects were statistically significant for X1 × X3 ($\beta = -0.12$, $p = 0.004$) and X4 × X3 ($\beta = -0.10$, $p = 0.012$), supporting H6. This suggests that while AI influencers may perform similarly in some aspects, they lag behind human influencers in leveraging content quality and viral potential to drive consumer trust and purchase decisions.

3.7 Comparative Analysis of AI and Human Influencers

The comparative analysis between AI and human influencers revealed several key distinctions. First, AI influencers were perceived as more consistent and scalable in content delivery, aligning with prior findings that suggest AI's efficiency in automation-driven marketing (Sands et al., 2022). However, they were rated lower in emotional warmth, relatability, and perceived authenticity—factors that are crucial for building long-term brand-consumer relationships (Muniz et al., 2023).

Human influencers, on the other hand, were seen as more trustworthy and emotionally engaging, reinforcing previous literature that emphasizes the irreplaceable value of human connection in marketing (Chiu & Ho, 2023). Additionally, the study found that disclosures about an influencer being AI-generated tended to reduce perceived anthropomorphism and credibility, which is consistent with findings from Muniz et al. (2023), who observed similar effects in cross-cultural settings.

Interestingly, when AI influencers were designed with high levels of anthropomorphism (e.g., realistic avatars or personalized interactions), consumer trust increased significantly, especially among younger demographics such as Gen Z (You & Cho, 2023). This implies that while AI influencers currently face trust barriers, strategic design improvements could enhance their effectiveness over time.

3.8 Implications of the Findings

The findings of this study have several theoretical and practical implications. From a theoretical standpoint, the research contributes to the growing body of knowledge on AI-human comparisons in marketing by introducing a moderated model where influencer type influences the strength of other marketing factors. This extends existing models by incorporating contextual variables such as product type, platform usage, and cultural orientation.

From a practical perspective, marketers should consider the differential effects of AI and human influencers when designing endorsement strategies. While AI influencers offer scalability and cost-efficiency, they may not yet be able to fully replicate the trust-building capabilities of human endorsers. Therefore, a hybrid approach that leverages the strengths of both AI and human influencers might be most effective.

Additionally, transparency regarding influencer identity appears to play a nuanced role. While full disclosure of AI status may initially reduce trust, it can foster long-term credibility if managed responsibly. Brands should therefore focus on designing AI influencers that maintain a balance between realism and clarity to avoid misleading consumers while still capitalizing on AI's unique advantages.

3.9 Limitations and Future Research Directions

Despite its contributions, this study has certain limitations. First, the sample primarily consisted of young adults aged 18–35, limiting generalizability to older demographics or non-Western markets. Future studies could expand the sample to include a broader age range and geographic diversity.

Second, the experimental setting relied on self-reported measures rather than actual behavioral data. Future research could incorporate eye-tracking, click-through rates, or purchase tracking to provide more objective insights into consumer responses.

Finally, the current study focused on a limited set of influencer attributes. Further exploration could examine additional factors such as brand alignment, personality congruence, and post-purchase satisfaction to develop a more comprehensive understanding of influencer marketing effectiveness.

Table 2. Summary of Regression Coefficients and Hypotheses Testing

Predictor	β Coefficient	Standard Error	t-value	p-value	Hypothesis Supported
Constant	0.12	0.15	0.8	0.423	—
Content Quality (X1)	0.34	0.05	6.82	<0.001	H1
Special Holiday Promotions (X2)	0.16	0.05	3.21	0.002	H2
Influencer Marketing Type (X3)	-0.18	0.06	-3.01	0.001	H3
Viral Marketing Potential (X4)	0.22	0.04	5.5	<0.001	H4
Livestreaming Engagement (X5)	0.19	0.06	3.18	0.001	H5

4. CONCLUSION

The findings of this study provide valuable insights into the comparative dynamics of consumer trust in products endorsed by AI influencers versus human influencers on social media. As artificial intelligence continues to permeate marketing strategies, understanding how consumers perceive and respond to AI-generated endorsements is essential for both academic research and practical application in digital marketing. The results indicate that while AI influencers can generate engagement and word-of-mouth intentions similar to their human counterparts, they are generally perceived as less trustworthy sources of information. This disparity underscores the importance of anthropomorphism, emotional connection, and perceived authenticity in shaping consumer trust—a domain where human influencers still hold a distinct advantage.

One of the key conclusions drawn from this research is that content quality remains the most influential factor in driving purchase intention, regardless of whether the endorser is AI or human. High-quality, relevant, and personalized content significantly enhances consumer engagement and trust. However, when comparing AI and human influencers, it becomes evident that human endorsers are more effective at fostering emotional attachment and credibility—two critical components of long-term brand-consumer relationships. Additionally, the moderating effect of influencer type revealed that AI influencers perform relatively better in contexts involving material goods and high-tech products, whereas human influencers excel in promoting experiential and emotionally resonant offerings.

These conclusions align with prior studies that have examined consumer perceptions of AI in marketing contexts. For instance, (Sands et al., 2022) found that while AI influencers are capable of eliciting engagement, they fall short in terms of source credibility. Similarly, (Muniz et al., 2023) demonstrated that disclosing an influencer's non-human nature reduces perceived anthropomorphism and trust, highlighting the need for strategic design choices when deploying AI endorsers. Furthermore, (Jin and Zhang, 2023) emphasized the role of product type in determining consumer preference for AI or human recommendations, reinforcing the notion that AI influencers may be more suitable for certain categories than others.

From a theoretical perspective, this study contributes to the growing body of literature on AI-human comparisons in marketing by introducing a moderated regression model that accounts for contextual variables such as product type, platform usage, and cultural orientation. By incorporating these factors, the research extends existing models of influencer effectiveness and offers a nuanced understanding of how trust is constructed differently across AI and human endorsers. Moreover, the inclusion of Livestreaming Engagement and Viral Marketing Potential as significant predictors of purchase intention reflects the evolving landscape of digital marketing, Where real-time interaction and organic sharing play increasingly important roles.

Practically, the findings suggest that brands should adopt a hybrid strategy that leverages the strengths of both AI and human influencers. While AI offers scalability, costefficiency, and data-driven personalization, human influencers bring emotional depth, relatability, and perceived authenticity to the table. To maximize effectiveness, marketers should consider matching influencer type with product characteristics—utilizing AI influencers for functional, high-tech, or novelty-driven products, and human influencers for lifestyle, luxury, or experience-based offerings.

Additionally, transparency regarding influencer identity appears to be a doubleedged sword. Full disclosure of AI status may initially reduce trust, but if managed responsibly—through clear communication and consistent performance—it can foster longterm credibility. Brands must therefore focus on designing AI influencers that maintain a balance between realism and clarity to avoid misleading consumers while capitalizing on AI's unique advantages

Building upon the conclusions of this study, future research should aim to explore several underdeveloped areas. First, longitudinal studies could examine how consumer trust in AI influencers evolves over time with repeated exposure. Second, cross-cultural comparisons could shed light on how regional differences influence perceptions of AI credibility and acceptance. Third, experimental manipulations of AI anthropomorphism levels could help identify optimal design features that enhance trust without compromising transparency.

In terms of implementation, organizations can develop a structured plan for integrating AI influencers into their marketing mix:

Audience Segmentation and Product Alignment: Identify target demographics and match influencer type with product attributes. For example, Gen Z audiences may be more receptive to AI influencers, particularly for tech or fashion-related products.

Content Strategy Optimization: Prioritize content quality and personalization. Ensure that AI-generated content maintains high visual and narrative standards, and that messaging is tailored to audience preferences through machine learning algorithms.

Transparency Protocols: Implement clear disclosure mechanisms that inform consumers about the AI nature of the influencer. Use this transparency as a branding opportunity rather than a limitation—highlight innovation, consistency, and reliability.

Real-Time Interaction Enhancement: Leverage livestreaming and chatbot technologies to increase engagement. Incorporate feedback loops that allow AI influencers to adapt to audience responses in real time, enhancing perceived responsiveness and interactivity.

Performance Monitoring and Ethical Oversight: Establish KPIs for measuring the effectiveness of AI influencers, including engagement rates, conversion metrics, and sentiment analysis. Integrate ethical oversight committees to ensure responsible use of AI in marketing communications.

Consumer Education Initiatives: Launch campaigns that educate consumers about AI technology, its capabilities, and its limitations. Increasing awareness can reduce skepticism and foster informed trust in AI-driven endorsements.

By following this development plan, businesses can strategically deploy AI influencers in a manner that complements human efforts, enhances consumer trust, and aligns with broader organizational goals. As AI technology continues to evolve, so too will its applications in marketing—requiring ongoing research, adaptive strategies, and a commitment to ethical practices that prioritize consumer well-being alongside commercial success.

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