

Human vs. AI Influencers: Comparing Audience Engagement with Identical Content on Instagram

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Abstract—Recent advances in generative AI have enabled influencers and brands to deploy AI-based creator identities at scale, yet little is known about how audiences respond when identical content is delivered by human versus AI influencers. This exploratory study provides the first exploration of this topic by comparing the engagement of audiences with identical Instagram video content delivered by the same influencer as both human and AI influencers. Eleven pairs of matched video reels addressing women’s empowerment themes were posted to an audience of approximately 500,000 followers. The results revealed that while both human and AI influencers achieved comparable engagement metrics, the human influencer generated significantly higher levels of active engagement in terms of likes and follows. Furthermore, sentiment analysis of 2,287 comments revealed that the human influencer delivered more total comments but with mixed sentiment, whereas the AI influencer delivered fewer comments but with higher proportions of positive sentiment. These findings suggest that AI influencers can capture attention, but struggle to convert exposure into sustained behavioural commitment and deeper audience relationships. The research provides exploratory insights for the strategic use of human and AI influencers in digital marketing campaigns and provides the first real-world comparison of human and AI influencers using identical content. Although the research was limited to a single influencer profile and audience, these findings are exploratory and specific to the context studied and should not be generalised beyond this setting pending replication across diverse influencer accounts, platforms, and audiences. Nevertheless, the study provides preliminary insights for the use of human and AI influencers and has implications for the development of AI influencers and their use in digital marketing campaigns.

Index Terms—AI Influencers, Generative AI, Social Media Marketing, Human-AI Comparison, Instagram, Influencer Marketing, Generative Adversarial Networks, Audience Engagement, Sentiment Analysis, Emerging Technologies.

I. INTRODUCTION

Artificial intelligence is transforming digital marketing, enabling new approaches to content creation, delivery, and personalisation [1], [2]. One notable development is the emergence of AI (Artificial Intelligence) influencers—computer-generated avatars with curated personas that interact with audiences on platforms such as Instagram [3]–[5]. Beyond marketing, the proliferation of AI-generated influencers has broader societal implications, particularly for how citizens

receive and process information in democratic contexts. The question of whether AI influencers are as effective as human influencers has not been fully determined; whether they are perceived and interacted with differently by consumers or not has not been fully determined.

Existing research has begun examining AI influencer characteristics and potential [4], [6], [7]. However, most studies consider AI influencers in isolation or compare them to humans using different content, making it difficult to determine whether observed effects stem from influencer identity or from variations in messaging and presentation [8], [9]. A direct, controlled comparison using identical content has been missing.

This exploratory study addresses this gap by comparing audience engagement with identical Instagram content presented by a single influencer in two forms: as herself (real human influencer) and as an AI-generated likeness. Using a within-subjects design, eleven pairs of matched video reels (22 videos total) were posted to the same audience with prior disclosure of the AI influencer. Engagement was assessed across seven quantitative metrics (views, reach, likes, shares, follows, comments, saves), and 2,287 audience comments were analysed through sentiment classification.

A. Scope and Limitations

This study is limited to a single Instagram account with a pre-existing audience interested in women’s empowerment, constraining generalisability to other populations, platforms, or cultural contexts. The AI influencer was designed as a likeness of the researcher, which may have influenced audience perception through familiarity. These limitations are discussed extensively in Section VI. Despite this limited scope, the study makes three contributions.

First, it provides the first controlled, real-world comparison of human versus AI influencers using identical content, overcoming confounding issues in previous research. Second, it integrates quantitative engagement metrics with qualitative sentiment analysis, offering both behavioural and attitudinal insights. Third, it connects findings with established theoretical frameworks—Source Credibility Theory [10], Parasocial Interaction Theory [11], and the Uncanny Valley Effect

[12]—to explain how authenticity and human-likeness shape engagement. Beyond theoretical contributions, the study offers preliminary practical indications on when brands should deploy human versus AI influencers depending on campaign objectives.

II. BACKGROUND

This section reviews concepts and empirical findings relevant to understanding audience engagement in influencer marketing, with particular attention to AI influencers on Instagram. We introduce three theoretical perspectives that inform this study: Source Credibility Theory [10], [13], which explains how perceived trustworthiness and expertise shape attitudes; Parasocial Interaction Theory [11], [14], which describes one-sided emotional bonds audiences form with media figures; and the Uncanny Valley Effect [12], [15], which accounts for discomfort provoked by entities that appear nearly but not fully human.

A. AI Influencers as a Marketing Trend

AI influencers, defined as computer-generated anthropomorphic characters with curated online identities, have become increasingly prominent in digital marketing [3], [16], [17]. Their adoption on social media has generated interest in whether audiences respond to them similarly to human influencers. Previous studies highlight that content quality and relevance [4], [18], as well as technological sophistication in design and presentation [4], [7], [19]–[22], are central to their effectiveness. However, questions remain about how AI influencers perform when compared directly with humans under controlled conditions.

B. Determinants of Engagement

Perceived authenticity and transparency: Authenticity is widely recognised as the cornerstone of influencer effectiveness, shaping trust and emotional connection [4], [7], [20]. For AI influencers, authenticity is complex. Some studies suggest that consistent storytelling and transparent disclosure of their non-human nature can maintain loyalty, particularly among digitally native audiences [19]–[21]. However, others argue that AI influencers inevitably lack the lived experiences and spontaneity of humans, potentially limiting perceived credibility.

Technological sophistication. The technical realism of AI influencers influences engagement. Advanced design, including AI-driven interactivity and high-fidelity 3D modelling, can increase immersion and capture attention [20], [23]. However, greater realism can also push AI influencers into the uncanny valley, provoking discomfort rather than connection [12]. This tension underscores the need to examine how technological sophistication interacts with audience expectations.

Content quality. Beyond influencer characteristics, content quality and resonance strongly affect engagement. Research shows that originality, relevance, and visual appeal are critical drivers of user interaction [4], [18]. Content aligning with younger digital consumers' preferences has been shown

to increase engagement [4], suggesting content strategy can sometimes override concerns about influencer identity.

C. Advantages and Limitations

AI influencers offer both opportunities and challenges. Human-like AI influencers can achieve higher perceived credibility and endorsement effectiveness than anime-like counterparts [3]. They have shown capacity to foster parasocial bonds and trust with followers, mirroring patterns observed with humans [24], [25]. Their controllability and freedom from personal controversies enhance their appeal for consistent brand messaging [3].

However, limitations remain. AI influencers may lack genuine human-likeness and authenticity, hindering deep relational connections [3]. This limitation connects directly to the uncanny valley effect [12], raising questions about whether AI influencers can fully replicate the emotional resonance of humans. Most studies examine AI influencers in isolation or compare them with humans using different content, making it difficult to disentangle influencer identity from message variations [8], [9]. The present study addresses this gap through a controlled comparison with identical content.

D. Research Gap

In the existing body of literature, authenticity, transparency, technological sophistication, and content quality are identified as factors that influence audience engagement with AI-generated influencers. However, in most existing studies, either there is an evaluation of AI-generated influencers in isolation or in comparison to human influencers using different content. The above approaches create difficulties in distinguishing between the impact of the influencer type and the impact of content/message [8], [9]. To overcome this limitation, in the proposed study, there is a direct comparison between human and AI-generated influencers who use the same content to engage with the audience.

E. Societal and Democratic Implications of AI Influencers

The rise of AI influencers raises fundamental questions about authenticity, transparency, and trust in digital communication. In democratic societies, the ability of citizens to distinguish human from AI-generated voices is essential for informed political participation. AI influencers can be deployed at scale to disseminate persuasive content without the accountability constraints that apply to human communicators, potentially distorting public discourse and undermining democratic deliberation. Understanding how audiences engage with and are influenced by AI personas is therefore not merely a marketing question but a matter of democratic significance. This study contributes to that understanding by providing empirical evidence on how audiences behaviourally and emotionally respond to AI versus human influencers, with implications for digital literacy, platform governance, and policy.

III. METHODS

This study employed a controlled within-subjects design to examine how influencer type (real human versus AI-generated) affected audience engagement on Instagram. A within-subjects design was selected because it controls for individual differences in audience composition and content preference, enabling direct attribution of any engagement differences to influencer type rather than content variation. The same creator appeared in both forms, human versus AI likeness of her, ensuring that content, script, and posting conditions remained constant in each matched pair of videos. By presenting identical content to the same audience in eleven matched video pairs (22 reels total), the design enabled direct paired comparisons of engagement metrics while controlling for individual differences in audience composition and exposure.

A. Study Context and Participants

The researcher is a motivational speaker and content creator with an established Instagram presence focusing on cultural and personal empowerment, particularly women's empowerment. At the time of data collection, the account had approximately 500,000 followers. Participants were these existing followers—individuals who had previously chosen to follow the account and were therefore familiar with the creator's identity, communication style, and content themes.

Methodological considerations. This use of pre-existing followers introduces both advantages and limitations. The advantage is ecological validity: the study captures authentic audience behaviour in a real social media environment rather than artificial laboratory conditions. The limitation is a significant familiarity and parasocial bias: followers' pre-existing parasocial relationships with the human creator are likely to amplify differences between conditions, potentially inflating the engagement advantage observed for the human influencer in active metrics such as likes and follows. This represents a fundamental constraint on internal validity that future studies should address by recruiting participants with no prior exposure to either influencer type. Additionally, because data were obtained from Instagram analytics, individual demographic information (age, gender, location) was not available. This precludes any subgroup analyses and limits the ability to determine whether engagement differences varied across demographic groups such as age or gender. Analyses were therefore based on aggregated engagement metrics. These design choices prioritise external validity and real-world applicability while acknowledging constraints on internal validity and generalisability, as discussed further in Section VI.

B. Materials and Procedure

Eleven pairs of video reels were created, each addressing themes related to women's empowerment (e.g., challenging gender stereotypes, professional credibility, personal agency). Within each pair, one video featured the researcher as herself (real human influencer condition), while the other featured an AI-generated likeness created using RenderNet AI, a deep learning-based generative platform that produces photorealistic

avatars. All script content, audio narration, posting conditions, and timing were kept identical within each pair. The only different variable was the visual representation of the presenter: real human versus AI-generated avatar.

Participant disclosure. Prior to posting any experimental content, an introductory disclosure video (duration: 30 seconds) was posted to the account three days before the first video pair. This video explicitly introduced the AI-generated likeness and explained that upcoming content would feature both the researcher and an AI version created using RenderNet AI. The disclosure emphasised that all video content—scripts, and messages would remain identical regardless of which presenter appeared, with only the visual representation differing. This approach ensured followers were aware of the AI influencer's nature while maintaining a naturalistic social media environment.

The AI-generated videos maintained high visual fidelity to the researcher's appearance while exhibiting the characteristic features of AI-generated imagery. RenderNet AI uses generative adversarial networks (GANs) to synthesise realistic human faces and movements based on input parameters. The resulting avatars closely resembled the researcher but retained subtle AI-generated qualities that may have been perceptible to some viewers.

Figure 1 illustrates the visual comparison between the real human influencer (left) and AI-generated counterpart (right) presenting identical content. While highly similar in overall appearance, the AI version exhibits characteristic features of GAN-generated imagery, including slightly smoothed skin texture and more uniform lighting, in contrast to the natural variation visible in the human influencer image.

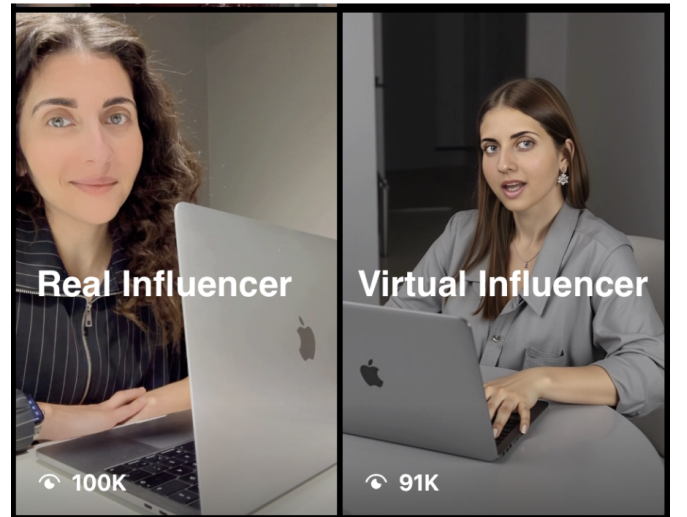


Fig. 1. Visual comparison of the real human influencer (left) and AI-generated influencer (right) presenting identical content. The AI version, created using RenderNet AI, exhibits characteristic GAN-generated features including smoothed skin texture and uniform lighting, in contrast to the natural variation visible in the human influencer image.

All 22 videos were posted to the same Instagram account during the study period. Videos within each pair were posted on same day and time. Engagement data were collected ten

days after each posting each pair to allow comparable exposure time. This window was selected to allow sufficient time for organic reach and algorithmic distribution, while remaining short enough to minimise confounding effects from differences in posting timing across pairs. Data were extracted using Meta Business Suite Insights.

C. Measures

1) *Engagement Metrics*: Seven standard Instagram engagement metrics were recorded for each video: *views* (total number of times the video was played), *reach* (number of unique accounts that viewed the video), *likes* (endorsements), *shares* (forwards to other users), *follows* (new followers gained from the video), *comments* (written responses), and *saves* (bookmarks for later viewing). These metrics capture both passive engagement (views, reach) and active engagement (likes, shares, follows, comments, saves). These seven metrics were selected as they represent the standard engagement dimensions tracked by Instagram analytics and collectively capture both passive exposure and active behavioural commitment.

2) *Sentiment Analysis*: To complement quantitative metrics, we conducted sentiment analysis of audience comments to examine whether influencer type influenced not only engagement metric but also emotional tone. The dataset comprised 2,287 comments collected from all 22 videos after removing 141 incomplete or corrupted entries from an initial 2,428 comments.

Classification procedure. A rule-based framework was developed to ensure context-aware classification aligned with video themes (gender roles, women’s empowerment, professional credibility, personal agency). Each comment was processed through structured prompts using Google Gemini API (gemma-3-4b-it model), selected for its natural language understanding capabilities and efficiency with Arabic-language content. The Gemini API was selected for its strong natural language understanding capabilities, particularly for Arabic-language content which comprised a significant portion of the comment dataset. The prompt structure followed this format:

“Read the following Instagram comment and classify its sentiment as positive, neutral, or negative from a women’s empowerment perspective. If the comment supports or encourages women or challenges gender bias, label it positive. If it is dismissive, sarcastic, or undermines women’s agency, label it negative. If it is descriptive or ambiguous, label it neutral. Explain briefly why you assigned this sentiment.”

Comments were categorised into three classes: *Positive* (supportive, empowering, affirming), *Neutral* (indifferent, factual, ambiguous, descriptive), and *Negative* (critical, dismissive, sarcastic, disempowering). Sample outputs were manually reviewed to reduce misclassifications and ensure consistency. A bilingual spreadsheet (Arabic and English) recorded raw comments, translations, and sentiment codes to support transparency and reproducibility.

D. Data Analysis

1) *Engagement Metrics*: Paired-sample t-tests were conducted to compare engagement metrics between real and

AI influencer videos across the eleven matched pairs. Paired-sample t-tests were chosen as the appropriate parametric test for matched-pair data, offering greater statistical power than between-subjects alternatives by accounting for within-pair correlation. A two-tailed test was used with significance set at $\alpha = 0.05$. This statistical approach was chosen because the within-subjects design paired each AI video with its corresponding real video, controlling for content effects. A two-tailed test was used with significance level set at $\alpha = 0.05$. Separate tests were performed for each of the seven engagement variables.

2) *Sentiment Analysis*: A chi-squared test of independence was conducted to determine whether sentiment distribution (positive, neutral, negative) differed significantly between the real and AI influencer conditions. This test was appropriate because sentiment categories are nominal and observations are independent across comments (though not across videos, a limitation discussed in Section VI).

IV. RESULTS

A. Engagement Metrics

Paired-sample t-tests compared engagement metrics between real and AI influencer videos across the eleven matched pairs. Results revealed statistically significant differences for two metrics: *likes*, $t(10) = 3.77$, $p = .003$, and *follows*, $t(10) = 2.50$, $p = .029$. In both cases, the real human influencer generated significantly higher engagement than the AI-generated counterpart. No significant differences emerged for *views*, *reach*, *shares*, *comments*, or *saves* (see Table I).

TABLE I
PAIRED-SAMPLE T-TEST RESULTS FOR ENGAGEMENT METRICS

Metric	Real ($M \pm SD$)	AI ($M \pm SD$)	$t(10)$	p	Sig.	Cohen’s d
Views	49574 $\pm$ 39557	53371 $\pm$ 21413	-0.41	.690	No	0.12
Reach	29467 $\pm$ 23829	31053 $\pm$ 10601	-0.28	.770	No	0.08
Likes	717 $\pm$ 452	290 $\pm$ 159	3.77	.003	Yes	1.14
Shares	9 $\pm$ 12	4 $\pm$ 3	1.67	.130	No	0.50
Follows	37 $\pm$ 45	6 $\pm$ 9	2.50	.029	Yes	0.75
Comments	207 $\pm$ 402	64 $\pm$ 96	1.50	.164	No	0.45
Saves	73 $\pm$ 76	25 $\pm$ 17	2.07	.065	No	0.62

B. Sentiment Analysis

Chi-square analysis revealed a significant association between influencer type and sentiment distribution, $\chi^2(2, N = 2287) = 36.77$, $p < .001$. Table II presents sentiment frequencies by influencer type.

TABLE II
SENTIMENT FREQUENCIES AND PROPORTIONS BY INFLUENCER TYPE

Influencer	Positive	Neutral	Negative	Total
AI	208 (36.6%)	114 (20.1%)	246 (43.3%)	568
Human	457 (26.6%)	267 (15.5%)	995 (57.9%)	1719

The human influencer generated substantially more total comments (1719 vs. 568), consistent with higher overall engagement. However, proportional analysis revealed a notable

pattern: the AI influencer received a higher percentage of positive comments (36.6% vs. 26.6%) and a lower percentage of negative comments (43.3% vs. 57.9%) compared to the human influencer. This suggests that while the human influencer stimulated broader discussion, the AI influencer attracted proportionally more favourable sentiment among those who chose to engage.

These complementary findings indicate that influencer type affects both the quantity and emotional tone of audience responses. Real influencers drive higher engagement volume but elicit more polarised reactions, whereas AI influencers generate smaller but proportionally more positive responses.

V. DISCUSSION

The results provide insight into how audiences engage with real versus AI-generated influencers when content is held constant. Across behavioural metrics, no differences emerged in initial exposure (views and reach), but the real influencer generated significantly higher levels of deeper engagement through likes and follows. Sentiment analysis revealed a complementary pattern: the human influencer prompted more overall discussion, including higher volumes of both positive and negative responses, whereas the AI influencer attracted fewer comments overall but a proportionally higher rate of positive sentiment. Together, these findings suggest that real and AI influencers elicit different engagement profiles, with human influencers driving broader behavioural commitment and emotional intensity, while AI influencers attract smaller but more curiosity-driven positive interactions.

A. Theoretical Interpretation

The Uncanny Valley Effect. The finding that views and reach did not differ significantly between influencer types indicates that the AI-generated influencer successfully captured initial audience attention. However, the lower levels of likes and follows for the AI influencer may be consistent with the uncanny valley effect [12], [26], [27]. Subtle imperfections in human-like design can evoke unease or limit perceptions of authenticity [19], [28], potentially discouraging audiences from expressing active endorsement behaviours such as liking or following. However, it is important to note that the uncanny valley was not directly measured in this study. Future research could test this explanation more explicitly by manipulating degrees of human-likeness in AI influencers or by measuring perceived discomfort directly.

Source Credibility Theory. The higher number of likes and follows for the real influencer is consistent with Source Credibility Theory [10], [29], [30], which emphasises trustworthiness and authenticity as key drivers of persuasion and engagement. Even when content was kept constant, audiences may have been more willing to endorse and commit to a real human influencer who possesses lived experience and emotional resonance that an AI-generated likeness cannot fully replicate. This interpretation suggests that authenticity remains a crucial determinant of audience behaviour in influencer

marketing. However, credibility perceptions were not measured directly in this study. Future research could incorporate survey or experimental measures of perceived trustworthiness to validate this explanation.

Parasocial Interaction Theory. The significantly higher number of follows for the real influencer may also be understood through Parasocial Interaction Theory [11], [31], [32]. Audiences often develop one-sided emotional connections with human media figures, which can encourage sustained engagement. Such parasocial bonds may be more difficult to establish with AI influencers, particularly over a short timeframe and among audiences already familiar with the human creator. The non-significant difference in comments suggests that some interaction with the AI influencer did occur, possibly driven by curiosity or novelty. Nonetheless, the stronger audience commitment to the real influencer indicates that human presence still provides an advantage for fostering parasocial relationships. As with the other theoretical interpretations, parasocial bonds were not directly measured, limiting the strength of these inferences.

Content Value as a Moderator of Engagement. The lack of significant differences in shares and comments suggests that these forms of engagement may be influenced more by the perceived value of the content itself than by the identity of the influencer. Although the reels were designed to be identical under all conditions, it is possible that audience perceptions of originality, relevance, or visual appeal played a stronger role in motivating outward-facing behaviours, such as sharing and commenting. In this sense, content quality may have diminished the impact of influencer type for these engagement dimensions. However, because content value was not directly measured in this study, this interpretation remains speculative. Future research should explicitly examine how perceptions of content quality interact with influencer identity to shape different types of engagement [4], [18].

B. Sentiment Patterns

The polarised responses to the human influencer—including both higher positive and negative sentiment in absolute terms—are consistent with the idea that authenticity and visibility generate stronger reactions, both favourable and critical. This aligns with findings in digital marketing that real influencers often face heightened scrutiny alongside support [21].

In contrast, the AI influencer received fewer comments overall but a proportionally higher share of positive sentiment. This pattern may indicate a curiosity-driven positivity effect, where audiences who choose to engage with AI influencers view them as novel and respond with intrigue or encouragement rather than criticism. However, this interpretation remains tentative, and future research should test it explicitly through direct measurement of novelty perceptions and curiosity.

C. Practical Implications

These findings offer guidance for marketers and content creators. Human influencers appear more effective for campaigns

prioritising sustained audience relationships, brand loyalty, and deep engagement. Their ability to generate higher likes and follows suggests they are better suited for building long-term community connections, despite also attracting more critical responses.

AI influencers may be valuable for campaigns where novelty, scalability, or avoidance of personal controversy is paramount. Their ability to capture comparable initial attention (views and reach) while generating proportionally positive sentiment suggests potential applications in contexts where broad reach matters more than deep relational engagement. However, the lower conversion to active endorsement (likes, follows) indicates limitations for loyalty-building strategies.

Importantly, these recommendations are constrained by the study's scope. Results may not generalise beyond the specific audience, platform, cultural context, or content themes examined here.

D. Limitations and Future Research

Several limitations warrant consideration. First, the study was limited to a single Instagram account with a specific pre-existing audience interested in women's empowerment. This constrains generalisability to other populations, platforms, or cultural contexts. The AI influencer was designed as a likeness of the researcher, which may have influenced audience perception through familiarity. Future research should replicate this design across diverse influencer accounts and platforms to test whether these engagement patterns persist in different contexts.

Second, the use of pre-existing followers introduces familiarity bias. Participants likely possessed substantial familiarity with the human influencer's appearance, voice, and communication style, potentially amplifying differences between conditions. This limits internal validity and makes it difficult to determine whether findings reflect intrinsic distinctions between real and AI influencers or audience-specific loyalties. Future studies should recruit participants unfamiliar with either influencer type.

Third, while followers received prior disclosure about the AI influencer, no awareness verification was conducted to confirm that individual viewers attended to this information. Future studies should include attention checks or comprehension questions to verify participant awareness of the AI versus human distinction.

Fourth, theoretical constructs such as perceived trustworthiness, parasocial bonds, and discomfort were not measured directly. While findings are consistent with Source Credibility Theory, Parasocial Interaction Theory, and the Uncanny Valley Effect, these interpretations remain tentative pending direct measurement. Future research should incorporate validated scales assessing these constructs to strengthen theoretical inferences.

Fifth, the relatively short observation window (ten days per post) may not capture long-term engagement dynamics or sentiment evolution. Longitudinal studies could assess how

perceptions of authenticity and parasocial bonds with AI influencers develop over extended periods.

Finally, the small sample of eleven paired videos limits statistical power, reducing sensitivity to detect smaller effect sizes. A post-hoc power analysis indicates the design was adequately powered to detect the large effects observed for likes and follows, but would have insufficient power to detect small-to-medium effects, meaning some differences between conditions may have gone undetected. Future research should conduct an a priori power analysis to determine the number of matched video pairs required before data collection begins. Additionally, effect sizes (Cohen's d) have been reported in Table I to allow the readers to assess the practical magnitude of observed differences independently of sample size. Future research should also conduct robustness checks such as bootstrapping or sensitivity analyses to verify the stability of findings across different analytical approaches.

Future research should also address two additional methodological priorities. First, the sentiment classification model used in this study relied on automated analysis without human-coded inter-rater reliability validation. Future studies should validate automated sentiment models against human coders to establish reliability scores and ensure classification accuracy. Second, the current design cannot fully separate novelty effects from influencer-identity effects — audiences may have responded positively to the AI influencer simply because it was new and unfamiliar. Future research should employ longitudinal designs to track whether engagement with AI influencers changes over time as novelty fades, or between-subjects designs recruiting participants unfamiliar with both influencer types to isolate identity effects from novelty responses.

Despite these limitations, this study provides the first controlled, real-world comparison of human and AI influencers using identical content, offering valuable methodological and empirical contributions to an emerging research area.

VI. CONCLUSIONS

This exploratory study compared audience engagement with identical Instagram content presented by a real human influencer and an AI-generated counterpart. Using a controlled within-subjects design with eleven matched video pairs, we found that the real influencer elicited significantly higher likes and follows, while initial exposure metrics (views and reach) did not differ. Sentiment analysis of 2,287 comments revealed that the human influencer generated more total discussion but with polarised reactions, whereas the AI influencer attracted fewer but proportionally more positive comments.

These findings make three contributions. Methodologically, the study demonstrates the value of controlled within-subjects comparisons using identical content, overcoming confounding issues in prior research that compared different influencers with different messaging. This approach provides a replicable framework for evaluating influencer effectiveness across digital platforms. Empirically, the study provides the first real-world evidence that while AI influencers can capture

comparable initial attention, they struggle to convert exposure into sustained behavioural commitment. The divergent sentiment patterns—polarised reactions to humans versus curiosity-driven positivity toward AI—reveal nuanced differences in how audiences emotionally respond to each influencer type. Theoretically, the patterns observed are broadly consistent with Source Credibility Theory, Parasocial Interaction Theory, and the Uncanny Valley Effect, though direct measurement of these constructs in future research would strengthen these interpretations. While the study’s scope is constrained by examining a single influencer profile and audience, these exploratory findings are valuable in identifying key patterns and establishing a methodological foundation that can guide and motivate more comprehensive investigations across diverse contexts, platforms, and populations.

For practitioners, the findings suggest that human influencers remain more effective for authenticity-driven campaigns and long-term relationship building, while AI influencers may suit contexts prioritising scalability, novelty, or broad reach without requiring deep audience commitment. As AI-generated content becomes increasingly sophisticated and prevalent, understanding these differential engagement patterns will be crucial not only for the strategic deployment of human versus AI influencers in digital marketing, but also for platform governance, digital literacy, and the integrity of information ecosystems that underpin democratic participation.

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