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Virtual vs. Human Influencers: AI-Mediated Trust Transfer and Brand Attachment Among Female Consumers

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Abstract

Virtual influencers are increasingly used in influencer marketing, yet it remains unclear whether trust generated by an artificial persona can be transferred to endorsed brands in the same way as trust generated by human influencers. This study examines artificial intelligence (AI)-mediated trust transfer among female consumers by comparing virtual and human influencers across four social media platforms. Drawing on source credibility, parasocial interaction, social presence, trust transfer, and brand attachment perspectives, we propose that influencer type is associated with brand outcomes through three observable social-cue pathways: perceived authenticity, parasocial interaction, and social presence. These cues are expected to be associated with influencer trust, which is then associated with brand trust, brand attachment, purchase intention, and recommendation intention. Using 78,432 female consumer comments from Xiaohongshu, Instagram, Weibo, and Douyin, matched across 12 virtual–human-influencer pairs, we construct text-derived linguistic indicators—proxies rather than validated psychometric constructs—through keyword dictionaries, sentiment classification, and standardized composite scoring. The results show that human influencers are associated with higher perceived authenticity, parasocial interaction, and social presence than virtual influencers. The strongest association in the model is the trust-transfer path from influencer trust to brand trust, and the indirect path is associated with a substantial share of the observed covariation between influencer type and brand attachment. Product type further qualifies these patterns: the human-influencer advantage is stronger for hedonic products than for utilitarian products. These findings suggest that virtual influencers should not be understood as universal substitutes for human influencers. Instead, their effectiveness depends on whether AI-mediated personas can generate the social and authenticity cues that the literature associates with trust transfer in a given product context.



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Keywords: virtual influencer; human influencer; AI-mediated trust transfer; brand attachment; parasocial interaction; social presence; perceived authenticity; female consumer; social media; natural language processing

1. Introduction

The rapid development of artificial intelligence (AI), computer graphics, and platform-based content production has transformed influencer marketing. Virtual influencers are computer-generated or AI-mediated personas that are designed to appear, communicate,

and collaborate with brands in ways that resemble human social media creators [1,2]. Their increasing presence in social media platforms such as Instagram, Douyin, Weibo, and Xiaohongshu shows how influencer marketing has now transcended beyond human influencers. The new dilemma for brands is that of choosing whether to opt for human influencers, who have the advantage of embodiment and authenticity, or virtual influencers who provide an element of visual control and consistency along with reduced operational risks.

This problem is acquiring importance in practical terms as the field of influencer marketing develops [3–5]. From recent experiences within the industry, it seems that despite increasing budgets for influencer marketing, the problems relating to authenticity, quality, measurability, and trust continue [6]. Furthermore, the use of AI in creator processes has elevated consumer suspicion surrounding the artificial nature of creations and openness in this regard. Consistent with this concern, recent empirical work indicates that consumers respond with skepticism to AI-generated personas, and that disclosure of an influencer's virtual nature can shape brand trust [7,8]. These developments add theoretical and managerial importance to the concept of virtual influencers since they enable scalability and control but reduce social signaling.

Previous studies have examined the differences between virtual influencers and human influencers in aspects of credibility, attitude toward the brand, purchase intentions, and endorsement effectiveness [7–14]. These results are partially inconsistent. Whereas some research shows that virtual influencers can function successfully in cases where novelty, visual appeal, or information control become significant, the other literature suggests that human influencers possess advantages in authenticity, identification, and emotional engagement. The above evidence implies that evaluating the efficacy of virtual influencers in relation to their traditional counterparts is not just about determining who is superior to whom. Rather, the more insightful query is about how trustworthiness can be created for the influencer, which is AI-driven, and how this trust can translate into trust in the endorsed brand.

Trust-transfer theory provides a valuable yet under-theorized perspective on the challenge at hand. In classical influencer marketing, trust transfer between an individual consumer and an endorsed brand through associations and relationships can be achieved [15–18]. The presence of a virtual influencer complicates this matter further because the source of trust in this case is not an actual person. The virtual influencer might demonstrate both human likeness visually and through communication, but at the same time, the consumer might believe that the influencer does not have any lived experience with autonomous preference and use of the particular brand. Therefore, it is not about how the virtual influencer can help develop consumer trust, but rather about the strength of the cues from an artificial source to create such trust transferability.

Brand attachment represents one of the major downstream outcomes associated with this phenomenon. Unlike temporary attitudes and click-through behavior, brand attachment denotes a deeper cognitive and emotional bond between consumers and brands [19–23]. In influencer marketing, brand attachment is possible where endorsements are viewed as credible, relational, and consistent with individual consumers' self-image or goals. Such an approach assumes significance especially in beauty, fashion, lifestyle, and social commerce for female consumers, who tend to receive information via social comparison and affective processing [24–26]. However, the specific focus on female consumers should be understood in terms of being limited by theory but not necessarily as a basis for generalization across all contexts.

Product type represents yet another important boundary condition. The hedonic category which comprises fashion, beauty, and lifestyle products is intrinsically related to emotions, self-expression, and symbol consistency. Consumers may rely more heavily

on authenticity and parasocial interaction in evaluating credibility in such categories. Utilitarian products are evaluated more on functionality, information content, and perceived performance. This suggests that virtual influencers face a smaller disadvantage in utilitarian contexts, where information control can partly offset their reduced human authenticity.

The main research questions being asked in this research include: How is influencer type associated with the AI-mediated transfer of trust from influencer trust to brand trust? Under what product conditions is this trust-transfer process more strongly or more weakly associated with brand attachment among female consumers? This problem is solved through the analysis of two trust-generating sources: virtual and human influencers. Rather than assuming virtual influencers' superiority or inferiority compared to human influencers, the position is that the success of virtual influencers hinges on the social cues that facilitate perceptions of authenticity, parasocial connection, and social presence.

This study makes three contributions. First, it offers a descriptive reframing of the trust-transfer framework for AI-mediated endorsement contexts, characterizing where human and virtual sources diverge along the trust-transfer chain rather than identifying a causal mechanism. Prior comparative studies of virtual and human influencers have largely asked which source type performs better on credibility or attitudinal outcomes [7–14]; we instead ask where in the trust-transfer chain the two source types differ. The results suggest that the influencer-to-brand transfer link operates similarly for both source types, whereas the formation of source trust through authenticity, parasocial, and social-presence cues is the stage at which virtual influencers are disadvantaged. Descriptively, this relocates the observed source-type gap from the source per se to the cue-formation stage of trust transfer, offered as a descriptive reframing rather than the identification of a causal mechanism. Second, the study identifies product type as a boundary condition of this process, indicating that the human-influencer advantage is concentrated in hedonic contexts and attenuated in utilitarian contexts. Third, it offers a transparent, large-scale text-analytic operationalization of trust-transfer constructs. We treat these text-derived indicators as linguistic traces of theoretically relevant constructs rather than as equivalents of validated psychometric scales, and we discuss the resulting construct-validity limits explicitly.

2. Literature Review

The academic interest in virtual influencers has grown rapidly as companies seek computer-generated personas, AI-supported avatars, and artificial celebrities. A key topic addressed in this research is whether virtual influencers can be considered substitutes for human influencers in endorsing brands. Evidence suggests that virtual influencers can benefit from several factors, including novelty, consistency, control, and safety [1,2,7,9,10]. In contrast, these source types could be considered to be less authentic, less personal, and therefore less effective in delivering the experience of the product [8,11–14]. This evidence indicates that comparison of human and virtual influencers cannot be viewed as a general ranking, since the fundamental issue of the theory lies in finding the mechanism behind the consumers' trust formation.

Source credibility theory argues that the success of endorsements depends on how the consumers judge the competence, trustworthiness, and attractiveness of the sources [27–30]. With respect to human endorsement, the concept of credibility is usually based on the consumer's perception of personal experience, self-revelation, similarity between the endorser and the brand and their sincere preferences for the product. Virtual influencers challenge these notions. Though created to be appealing and authoritative, their synthetic character can negate any sense of genuineness and authenticity of experience. In effect, perception of authenticity is positioned as a key cue linking source type to trust formation.

Parasocial interaction theory further explains why influencer marketing often works through relational rather than purely informational processes [31–36]. Followers may experience influencers as familiar social partners even when the relationship is one-sided. Human influencers can support this process through everyday disclosure, perceived vulnerability, and repeated interaction. Virtual influencers can exhibit comparable relational cues through controlled visual and textual communication, yet their capacity to sustain perceived relational closeness remains theoretically ambiguous because consumers may recognize the persona as scripted or brand-managed. This tension makes parasocial interaction an important dimension for comparing virtual and human influencers.

Social-presence theory is pertinent to the topic of virtual influencers since such actors are made to be social. Social presence refers to the extent to which an entity is perceived to be socially available, likable, responsive and human-like [37–40]. Although anthropomorphism helps improve social presence, the simple fact of being human-like might not result in trust from consumers if the entity is seen as artificially created. Therefore, social presence is associated with but different from the concepts of authenticity and parasocial interaction. Authenticity refers to being genuine; parasocial interaction deals with the perception of intimacy, and social presence is about the perceived accessibility of the social entity within the mediated context.

Trust-transfer theory relates source evaluation methods to effects on brand outcomes. Transfer of trust is possible when an individual recognizes a connection between two parties [15–18]. In the case of influencer marketing, trust placed in an influencer becomes the basis of the brand's trustworthiness. The present study aims to explore whether an AI-mediated endorsement can change the boundary conditions under which trust transfer occurs. It raises the issue as to whether the trust-transfer process follows the same pattern as in the case of human endorsement, given that the endorsing party is an artificial personality. For that purpose, perceived authenticity, parasocial interaction and social presence are proposed as cue-based precursors to influencer trust, which is then linked to brand trust and attachment.

Brand attachment theory highlights why trust transfer matters beyond the formation of initial purchase intentions. Brand attachment can be defined as the degree of attachment formed between consumer and brand [19–23] which relates to loyalty, advocacy, forgiveness of mistakes made by the brand and resilience towards the competing brand. In influencer marketing, brand attachment can be strengthened through the influencer's provision of authentic and emotional links to the brand. However, in the case of virtual influencers where such elements of authenticity are perceived less strongly, the path from evaluation of the influencer to brand attachment becomes attenuated.

The focus on female consumers stems from the fact that such an emphasis is based on empirical reality of the influencer marketing in the domains of beauty, fashion, lifestyle, and social commerce. Indeed, according to the previous literature, female consumers tend to demonstrate higher levels of engagement with influencer content [24–26]. However, this focus should not be interpreted as implying that the mechanisms are exclusive to female consumers. Instead, female consumer comments provide a theoretically relevant context in which relational, affective, and identity-related cues are especially visible in social media discourse.

Finally, product type may explain why prior studies reach different conclusions about virtual-influencer effectiveness. Hedonic products require stronger emotional, symbolic, and identity-based cues, making human influencers more advantaged. Utilitarian products emphasize information, efficiency, and compatibility, thus limiting the potential disadvantage that is brought about by virtual influencers. The inclusion of product type in this

case helps to move away from the virtual versus human binary to explain AI-enabled trust transfer.

3. Theoretical Framework and Hypotheses

The theoretical model of this research is AI-based trust transfer. Traditional influencer marketing revolves around consumers' evaluation of human sources based on their credibility and relationship aspects, and the resulting trust would be transferred to the brand through such endorsement. Virtual influencers create an additional layer in such trust-transfer mechanisms because of their non-human nature. They can have communications that are visually controlled, standardized, and safe for their brands. However, their artificiality might affect their credibility and parasocial interactions. Thus, the key question from a theoretical perspective becomes not whether virtual influencers create trust, but rather whether the social cues linked to the AI persona are sufficient to create trust transfer.

The integration of the five theoretical perspectives follows a single organizing logic rather than an additive combination. Source credibility theory specifies what consumers evaluate (the source); trust-transfer theory specifies how source-level trust extends to the brand; and brand attachment theory specifies the downstream relational outcome of transferred trust. Perceived authenticity, parasocial interaction, and social presence are selected as the three cue mechanisms because each captures a distinct dimension on which an artificial persona may fail to reproduce a human source: authenticity concerns perceived genuineness of experience, parasocial interaction concerns perceived relational closeness, and social presence concerns perceived social availability. These three cues jointly bear on whether the first link of the trust-transfer chain (source trust) can form; the subsequent links (brand trust, attachment, intentions) follow the standard trust-transfer sequence. The hypothesized path directions therefore reflect the theoretical ordering of the trust-transfer chain, while the empirical estimates themselves remain associational given the observational design.

Figure 1 portrays the framework of theoretical integration. Influencer type is viewed as a source factor; perceived authenticity, parasocial interaction, and social presence represent cue-based factors; and influencer trust and brand trust can be seen as the elements involved in the trust-transfer process. On the other hand, brand attachment and behavioral intention constitute outcome factors. Product type is considered as a moderator variable associated with the strength of the source-cue relationship and the trust-transfer relationship.

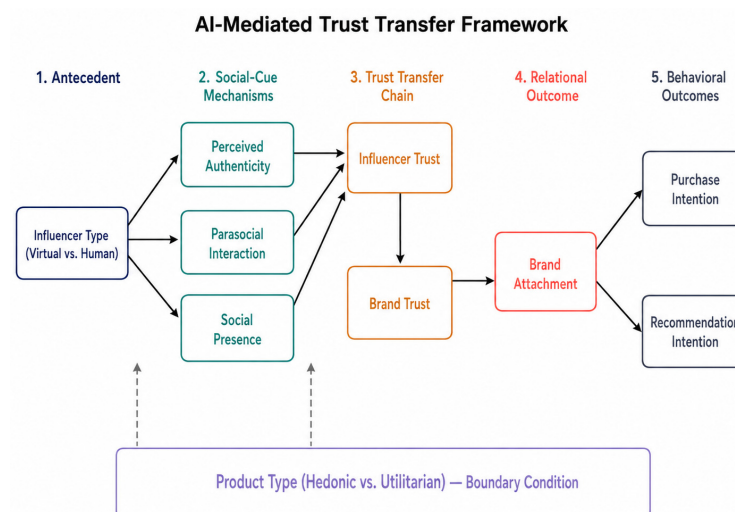


Figure 1. Integrated theoretical framework. Arrows denote the hypothesized direction of influence between constructs across the five stages of the framework, and the dashed connectors indicate product type, which is modeled as a boundary condition.

This study conceptualizes perceived authenticity, parasocial interaction, and social presence as three related but distinct mechanisms linking influencer type to influencer trust. Perceived authenticity captures whether consumers read the influencer as sincere and genuine. Parasocial interaction captures whether consumers express imagined closeness or relational involvement with the influencer. Social presence captures whether the influencer is experienced as warm, responsive, and socially present. Because human influencers possess embodied experience and perceived personal autonomy, they are expected to generate stronger authenticity, parasocial, and social-presence cues than virtual influencers. Figure 2 displays the hypothesized relationships.

Hypothesized Path Model

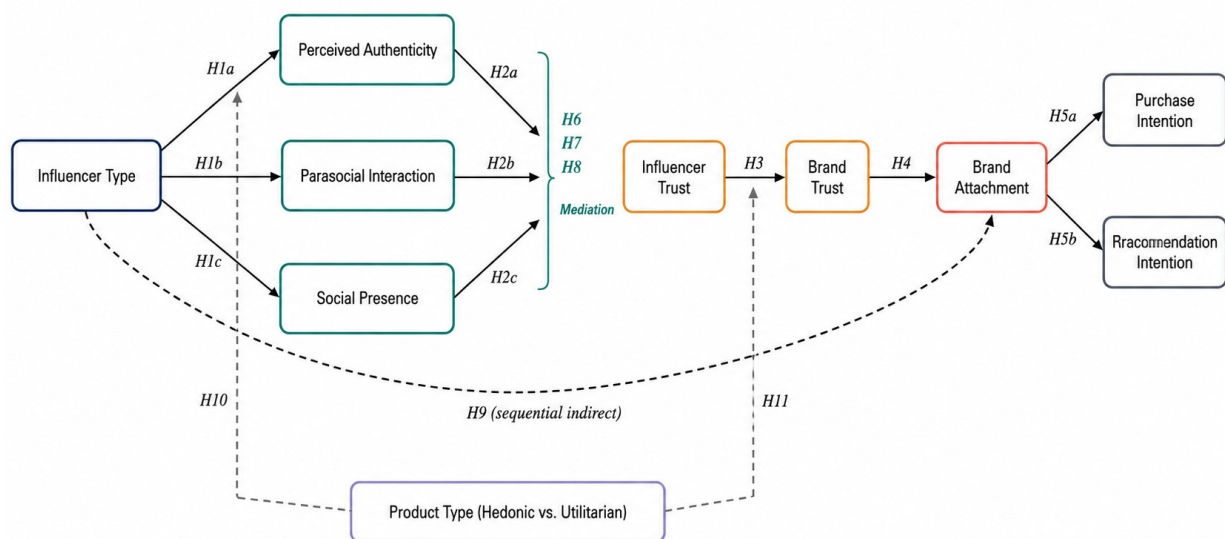


Figure 2. Hypothesized relationships. Solid arrows represent the hypothesized direct paths (H1a–H5b), and dashed arrows represent the hypothesized indirect, sequential, and moderating relationships (H6–H11); the label beside each arrow denotes the corresponding hypothesis.

H1a. Human influencers are associated with higher perceived authenticity than virtual influencers among female consumers.

H1b. Human influencers are associated with higher parasocial interaction than virtual influencers among female consumers.

H1c. Human influencers are associated with higher social presence than virtual influencers among female consumers.

Authenticity, parasocial interaction, and social presence should each be positively associated with influencer trust. Authenticity shows sincerity and reduces suspicion about being completely scripted in terms of endorsement. Parasocial relationship results in relationship familiarity and creates perceived closeness, while social presence makes the influencer seem socially present. Collectively, these create the basis for trust in the influencer as the information source.

H2a. Perceived authenticity is positively associated with influencer trust.

H2b. Parasocial interaction is positively associated with influencer trust.

H2c. *Social presence is positively associated with influencer trust.*

Trust-transfer theory suggests that trust in the influencer can be associated with trust in the endorsed brand when consumers perceive the influencer–brand association as meaningful. Brand trust, in turn, should be associated with brand attachment because trust reduces perceived risk and supports stronger cognitive and affective bonds. Brand attachment should then be associated with purchase intention and recommendation intention.

H3. *Influencer trust is positively associated with brand trust.*

H4. *Brand trust is positively associated with brand attachment.*

H5a. *Brand attachment is positively associated with purchase intention.*

H5b. *Brand attachment is positively associated with recommendation intention.*

The model also proposes indirect mechanisms. If influencer type is associated with authenticity, parasocial interaction, and social presence, and these cues are in turn associated with influencer trust, then the relationship between influencer type and downstream outcomes should be partially transmitted through these cue-based mechanisms and the trust-transfer chain.

H6. *The association between influencer type and influencer trust is partially accounted for by perceived authenticity (indirect association).*

H7. *The association between influencer type and influencer trust is partially accounted for by parasocial interaction (indirect association).*

H8. *The association between influencer type and influencer trust is partially accounted for by social presence (indirect association).*

H9. *Influencer type is indirectly associated with brand attachment and behavioral intentions through the sequential pathway of social cues, influencer trust, brand trust, and brand attachment; this pathway is interpreted as a pattern of associations consistent with, but not demonstrative of, mediation.*

Product type represents a boundary condition in this context. While hedonic products such as beauty, fashion, and lifestyle products are associated with self-expression and symbolic consumption, consumer reliance on authentic and relational source information could be higher in this scenario. Utilitarian products are judged according to their performance and functional aspects to a greater extent than their hedonic aspects. Therefore, the disadvantage of trust transfer resulting from using virtual influencers becomes more apparent in the case of hedonic products than utilitarian products.

H10. *Product type moderates the association between influencer type and perceived authenticity, such that the human-influencer advantage is stronger for hedonic products than for utilitarian products.*

H11. *Product type moderates the broader AI-mediated trust-transfer process, such that the human-influencer advantage in relational cues and trust transfer is stronger in hedonic product contexts than in utilitarian product contexts.*

4. Methodology

4.1. Research Design Overview

The research applies an observational, multi-platform, text-based comparative design that examines AI-based trust transfer in both virtual- and human-influencer marketing. In particular, this design considers female consumers' feedback associated with virtual influencers and their respective human counterparts on Xiaohongshu, Instagram, Weibo, and Douyin platforms. The research uses a 2×2 design involving comparison between influencer type (virtual or human) and product type (hedonic or utilitarian). Since the data used in the study involves observations made on naturally existing social media posts as opposed to data gathered via experimental manipulation, the analysis is treated as evidence of correlation between variables.

Figure 3 summarizes the data-processing pipeline. It includes influencers and platform selection, post-wise identification of brand collaboration-related content, comment extraction, data cleaning, gender filtering, natural language processing (NLP)-based rating, indicator generation using text, and construction of an observable variable path model. This approach allows the study to explore consumer discourse on a larger scale, considering that the analysis of such phenomena involves challenges related to deriving psychological concepts from text.

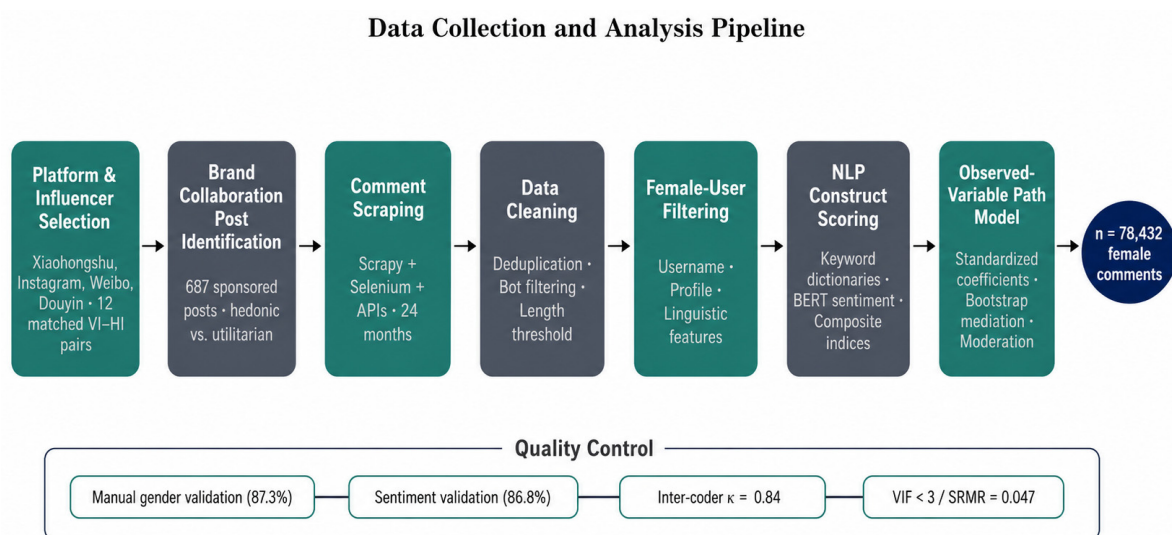


Figure 3. Data collection and analysis pipeline.

4.2. Data Sources and Platform Selection

The platform selection aimed to capture social media environments where influencer marketing, female consumer engagement, and virtual influencers' actions are visible. Xiaohongshu was picked because of its large number of female users and its importance in terms of fashion, beauty, and lifestyle in China. Instagram was selected to provide global exposure to the actions of virtual influencers such as Lil Miquela and Imma. Weibo and Douyin extend the platform setting to include microblog, short-video, and livestreaming settings. For the sample of influencers, there were 24 influencer accounts divided into 12 virtual human pairs. Matching included consideration of fan counts, content domains, brand partnerships, and overlap when possible. Table 1 summarizes the platform characteristics and example accounts, and Table 2 reports the platform-specific collection specifications. The final allocation comprised four matched virtual–human pairs on Xiaohongshu, with four on Instagram, two on Weibo, and two on Douyin (12 pairs; 24 accounts). Matching required both accounts in a pair to fall within the same follower band reported in Table 2

and to share their primary content domain; pair-level characteristics are summarized in Appendix A (Table A1). To preserve the anonymization commitments described in Section 4.10, accounts are identified only by anonymized pair codes (VP01–VP12).

Table 1. Social media platform selection and characteristics.

Platform	Region	Female User Ratio	Virtual-Influencer Examples	Human-Influencer Examples	Primary Content Type	Data Accessibility
Xiaohongshu	China	70–80%	AYAYI, Ling, Liu Yexi	Matched beauty/fashion influencers	Image + short text, video	Web scraping (Selenium)
Instagram	Global	57%	Lil Miquela, Imma, Rozy	Matched lifestyle influencers	Image + stories, reels	application programming interface (API) + web scraping
Weibo	China	54%	Virtual idol accounts	Matched entertainment influencers	Microblog, video	API access available
Douyin	China	52%	Virtual livestreamers	Matched short-video influencers	Short video, livestream	Web scraping (Selenium)

Table 2. Data collection specifications by platform.

Specification	Xiaohongshu	Instagram	Weibo	Douyin
Influencer sample				
Virtual influencers (n)	4	4	2	2
Human influencers (n)	4	4	2	2
Follower range	500 K–5 M	500 K–3 M	1 M–10 M	500 K–5 M
Content sample				
Brand collaboration posts	286	192	112	97
Product categories	Beauty, Fashion, Lifestyle	Fashion, Beauty, Tech	Entertainment, Beauty	Beauty, Fashion
Comment sample				
Initial female-coded comments (after deduplication)	54,350	17,450	6560	9919
Final valid female comments (after bot removal)	48,265	15,686	5854	8627
Time period				
Data collection window	Jan 2023–Dec 2024	Jan 2023–Dec 2024	Jan 2023–Dec 2024	Jan 2023–Dec 2024
Technical approach				
Primary tool	Scrapy + Selenium	Instagram API + Selenium	Weibo API	Selenium
Data storage	MongoDB	MongoDB	MySQL	MongoDB

Note. The initial comment counts in Table 2 refer to the deduplicated, gender-screened female-coded comment pool before bot removal, not to all-gender platform comments. The exclusion chain is: initial female-coded comments after deduplication ($n = 88,279$) → bot removal ($n = 9847$) → final valid female comments ($n = 78,432$). Platform-level counts also reconcile with 687 analyzed brand collaboration posts. Accordingly, Table 2 reports the screened analytical sample used for the cross-platform comparison rather than raw platform-level comment volumes.

4.3. Sample Selection Criteria

The sampling process was conducted at three hierarchical levels: influencer, post, and comment. The selection of virtual influencers took into account that the influencers have human-like appearances, brand collaboration posts, a sufficient number of followers,

and engagement statistics. Whenever possible, the matching of human influencers with their virtual counterparts was performed in terms of content area, number of followers, activity level, and common brand areas. A post-level inclusion required well-defined brand collaboration content, well-defined product type, and a sufficient number of comments. The comment-level filtering process included removing duplicate comments, eliminating automation-generated comments, ensuring comments were of adequate length for analysis, and applying gender-identification methods with the focus on female consumers' discourse. The complete inclusion criteria at each level, together with their rationales, are reported in Table 3.

Table 3. Sample selection criteria across hierarchical levels.

Selection Level	Criterion	Specification	Rationale
Influencer Level			
Virtual Influencer	Anthropomorphic characteristics	Human-like appearance required	Ensure comparability with human influencers
	Follower count	500,000–5,000,000	Adequate engagement while avoiding outliers
	Brand collaboration activity	Minimum of 20 sponsored posts within 24-month period	Sufficient commercial content for analysis
	Content domain	Fashion, beauty, lifestyle	Thematic consistency and female consumer relevance
Human Influencer	Matching protocol	Paired with corresponding virtual influencer	Enable direct comparative analysis
	Follower count variance	Within $\pm 20\%$ of matched virtual influencer	Ensure audience size comparability
	Content domain	Identical to matched virtual influencer	Control for content category effects
	Brand partners	Overlapping collaborations where possible	Minimize brand-specific confounds
	Activity level	Equivalent within same temporal window	Temporal consistency
Post Level			
	Brand disclosure	Explicit collaboration disclosure required	Ensure sponsored content identification
	Product classification	Clear hedonic vs. utilitarian categorization	Enable moderation analysis
	Engagement threshold	Minimum 50 comments	Sufficient data density for natural language processing (NLP) analysis
Comment Level			
	Gender identification	Female users via username, profile, linguistic features	Target population alignment
	Duplicate removal	Exact and fuzzy matching elimination	Data integrity
	Bot filtering	Automated content detection and removal	Analytical validity
	Length threshold	Minimum 10 characters	Meaningful content requirement

4.4. Data Collection and Preprocessing

Data were collected using methods that were relevant for the platform, which included accessing application programming interfaces (APIs) whenever possible and web scraping whenever APIs were not available, along with rate limiting. The dataset contained information on influencer data, post data, category labels, comment content, and engagement indicators. User identifiers were anonymized before analysis. Duplicate comments were removed through exact and fuzzy matching methods. After deduplication, language and length filtering, and gender screening, the female-coded comment pool comprised 88,279 records before bot removal. During final bot screening, 9847 suspected automated

comments were removed, yielding 78,432 final valid female consumer comments. Data were collected over a 24-month window (January 2023–December 2024), and Table 4 reports the technical crawling specifications by phase. Records with failed or incomplete retrievals were discarded before analysis rather than imputed.

Table 4. Data crawling technical specifications.

Crawling Phase	Data Elements	Technical Approach	Storage Solution
Phase 1: Influencer Profile			
	Follower count	API query/Web scraping	MySQL
	Account metadata	Profile extraction	MySQL
	Post archives	Historical content retrieval	MySQL
Phase 2: Post Level			
	Brand collaboration content	Content identification algorithms	MySQL
	Engagement metrics	Like, comment, share extraction	MySQL
	Publication timestamps	Metadata parsing	MySQL
	Textual descriptions	Caption and hashtag extraction	MongoDB
Phase 3: Comment Level			
	User identifiers	Anonymized ID extraction	MongoDB
	Comment text	Full text capture	MongoDB
	Timestamps	Comment timing data	MongoDB
	Interaction indicators	Like and reply count	MongoDB
Technical Infrastructure			
Primary Tools	—	Scrapy 2.11.2, Selenium WebDriver 4.27.0 (Python 3.11)	—
API Integration	—	Instagram Graph API, Weibo Open Platform	—
Rate Limiting	—	Randomized delays (3–8 s)	—
IP Management	—	Proxy cycling protocol	—
Error Handling	—	Automated retry mechanisms	—
Collection Period	—	24 months (Jan 2023–Dec 2024)	—

4.5. Unit of Analysis and Data Structure

The unit of observation was the comment-level record linked to influencer, post, platform, and product-type metadata. Comments are therefore not fully independent: they are nested within posts, influencers, platforms, and product categories. The path model reported in Section 5 was estimated at the comment level and does not explicitly model this nested structure, which means that conventional standard errors would be understated. For this reason, we interpret the reported coefficients as descriptive standardized associations, refrain from emphasizing significance tests, and treat the overall pattern of associations—rather than any individual test statistic—as the unit of interpretation. Re-estimation with multilevel or cluster-robust specifications was not possible within this revision because the raw comment-level records could not be re-accessed under the platforms’ data-retention terms after anonymization and aggregation; we register this explicitly as a limitation in Section 7. Future studies should employ multilevel models, influencer fixed effects, or experimental designs.

4.6. Variable Measurement

Since this study uses social media comments that are not from a survey, they can be considered text-based observed variables rather than multi-item latent variables. For each construct, we constructed standardized composite indices from linguistic traces in user comments, including construct-relevant keyword density, sentiment orientation, direct-address patterns, and manually validated product and source classifications. Continuous indicators were standardized before model estimation to improve comparability across platforms and constructs. For descriptive reporting, some variables are presented as normalized 1–5 indices; these values should not be interpreted as Likert-scale survey responses. Concretely, each construct indicator combined (a) the density of construct-relevant dictionary terms per comment (term count normalized by comment length), (b) the valence weighting of those terms derived from the sentiment classifier, and (c) construct-specific linguistic patterns, such as direct-address forms for parasocial interaction. The components were z-standardized and averaged to form each construct composite. Table 5 reports the operationalization of every variable; the construction of the underlying dictionaries is described in Section 4.7 and Table 6.

Table 5. Variable operationalization and measurement approaches.

Variable	Type	Operationalization	Measurement Method	Data Source
Independent Variable				
Influencer Type	Categorical	Virtual influencer = 0; Human key opinion leader (KOL) = 1	Binary coding	Influencer profile
Mediating Variables				
Perceived Authenticity	Continuous	Authenticity-related keyword frequency + sentiment score	Lexicon matching + Bidirectional Encoder Representations from Transformers (BERT) sentiment	Comment text
Parasocial Interaction	Continuous	Intimacy expressions + direct-address frequency + emotional engagement indicators	Keyword density + linguistic pattern analysis	Comment text
Social Presence	Continuous	Human warmth expressions + sociability indicators + interaction depth	Dictionary frequency, sentiment orientation, and standardized composite scoring	Comment text
Influencer Trust	Continuous	Trust keyword density + positive sentiment ratio (influencer-directed)	Text-derived composite index: lexicon + sentiment	Comment text
Brand Trust	Continuous	Trust keyword density + positive sentiment ratio (brand-directed)	Text-derived composite index: lexicon + sentiment	Comment text
Brand Attachment	Continuous	Emotional connection + brand-self identification + behavioral loyalty expressions	Multi-dimensional keyword analysis	Comment text
Dependent Variables				
Purchase Intention	Continuous	Purchase-related expression frequency/total comments	Normalized frequency count	Comment text
Recommendation Intention	Continuous	Recommendation expression frequency/total comments	Normalized frequency count	Comment text
Moderating Variable				

Table 5. *Cont.*

Variable	Type	Operationalization	Measurement Method	Data Source
Product Type	Categorical	Hedonic = 0; utilitarian = 1	Manual coding based on product characteristics	Post content
Covariates (not included in estimated path model)				
Follower Count	Continuous	Log-transformed follower number	Direct extraction	Influencer profile
Post Engagement	Continuous	(Likes + comments + shares)/followers	Engagement rate calculation	Post metrics
Brand Familiarity	Continuous	Brand mention frequency in platform	Platform-level brand search volume	Platform data
Comment Length	Continuous	Average character count per comment	Text length calculation	Comment text

Table 6. Keyword dictionary construction for variable measurement.

Construct	Dimension	Positive Indicators (Examples)	Negative Indicators (Examples)	Dictionary Size
Perceived Authenticity				
	Genuineness	real, genuine, authentic, natural, sincere	fake, artificial, staged, inauthentic	78 terms
	Transparency	honest, transparent, heartfelt, candid	deceptive, hidden agenda, scripted	52 terms
Parasocial Interaction				
	Perceived Intimacy	bestie, sister, friend, babe, dear	distant, cold, unfamiliar	65 terms
	Emotional Connection	love you, adore, support, always with you	indifferent, don't care	71 terms
	Identification	like me, understands me, same as me, relatable	unlike me, doesn't understand	48 terms
Social Presence				
	Human Warmth	warm, kind, gentle, caring, approachable	cold, robotic, mechanical	56 terms
	Sociability	interactive, responsive, engaging, communicative	unresponsive, one-sided	43 terms
Influencer Trust				
	Competence Trust	professional, reliable, expert, credible, knowledgeable	unprofessional, amateur, unreliable	82 terms
	Benevolence Trust	sincere recommendation, honest review, genuinely cares	just for money, scam, deceiving	67 terms
Brand Trust				
	Brand Reliability	trustworthy brand, good quality, reliable	bad brand, untrustworthy, quality issues	74 terms
	Brand Integrity	authentic, official, guaranteed	counterfeit, fake, false advertising	58 terms
Brand Attachment				
	Emotional Connection	love, adore, heart, obsessed, devoted	indifferent, dislike, hate	69 terms
	Brand-Self Connection	represents me, my style, perfect for me, made for me	not for me, doesn't suit me	54 terms
	Brand Prominence	must-have, can't live without, always use, go-to	optional, occasionally, whatever	47 terms

Table 6. *Cont.*

Construct	Dimension	Positive Indicators (Examples)	Negative Indicators (Examples)	Dictionary Size
Purchase Intention	Intention Expression	want to buy, ordered, purchased, getting it, take my money	won't buy, pass, not interested	63 terms
	Urgency Indicators	immediately, right now, must have, need it	later, maybe, will think about it	38 terms
Recommendation Intention	Sharing Willingness	recommend, share, tell friends, spread the word	won't recommend, don't bother, avoid	57 terms
	Advocacy Expression	must buy, blind buy, highly recommend, absolute must	don't buy, disappointing, removing from wishlist	51 terms

4.7. Keyword Dictionary and NLP Scoring

The keyword dictionaries were developed through seed-term generation, bilingual expansion, corpus inspection, and expert review. Separate dictionaries were constructed for perceived authenticity, parasocial interaction, social presence, influencer trust, brand trust, brand attachment, purchase intention, and recommendation intention. Sentiment classification was used to distinguish positive and negative expressions and to weight construct-relevant terms by orientation. The resulting scores were aggregated into construct-level observed indicators. The NLP pipeline should be interpreted as a transparent measurement procedure for public linguistic traces, not as a complete substitute for psychometric scale validation. The development proceeded in four stages. First, seed terms for each construct were generated deductively from the definitional literature (e.g., authenticity: genuine, sincere; parasocial interaction: address terms and intimacy markers; social presence: warmth and responsiveness markers). Second, the seed lists were expanded bilingually (simplified Chinese and English), including platform-typical colloquialisms, with forward and back translation to verify equivalence of meaning. Third, candidate terms were screened against a random sample of the corpus, and terms with high false-positive rates in context (e.g., polysemous terms matching unrelated usages) were removed. Fourth, the resulting dictionaries were reviewed by independent coders, with disagreements resolved by discussion; inter-coder reliability for the manually coded validation categories reached Cohen's kappa = 0.84. Example positive and negative indicators and dictionary sizes for each construct dimension are reported in Table 6, and the full dictionaries, coding rules, scoring scripts, and validation protocol are available to the editor and reviewers as stated in the Data Availability Statement. We emphasize that these procedures support the transparency and reliability of the scoring pipeline; they do not establish construct validity in the psychometric sense, a point we return to in Section 7.

4.8. Analytical Strategy

The empirical model was estimated as an observed-variable path model using standardized text-derived composite indicators. This terminology is important. Because the constructs were not measured with multiple reflective survey items, conventional latent-variable measurement statistics such as average variance extracted (AVE), composite reliability (CR), and heterotrait-monotrait ratio (HTMT) are not directly applicable in the same way as in survey-based structural equation modeling (SEM). Instead, the analysis evaluates the pattern of standardized associations among observed indicators. Indirect associations were examined using nonparametric bootstrapping with 5000 resamples. Product-type moderation was assessed through interaction terms and product-condition comparisons.

The results are reported as standardized coefficients and should be interpreted as associations consistent with the proposed theoretical account. Two clarifications are warranted. First, because the constructs enter the model as single observed composites, measurement-model statistics (AVE, CR, HTMT) have no estimable analog here; reporting them would imply a latent measurement structure that was not estimated. Second, the fit statistics that are reported (standardized root mean square residual (SRMR), comparative fit index (CFI), and root mean square error of approximation (RMSEA)) evaluate only the overidentifying restrictions of the structural path configuration—that is, the consistency of the hypothesized pattern of paths with the observed covariance matrix among the composites. They carry no information about measurement quality and should not be read as validating the constructs themselves. Finally, as noted in Section 4.5, the model treats comments as independent observations, and the coefficients are accordingly interpreted as descriptive associations rather than formal inferential tests.

4.9. Data Quality Control

Several checks were used to assess data quality. Gender identification was manually verified on a random profile subsample. Performance of the sentiment classification models was tested on manually coded posts. Interrater reliability was calculated for the human-coded categories. Bot and duplication checks were used to eliminate low-quality cases before building the models. These checks help support the reliability of the data-processing procedure; nevertheless, they do not guarantee the construct validity of complex psychological phenomena such as trust, attachment, or parasocial interaction. That is why the results of the study can be considered only as proxies for the phenomena studied.

4.10. Ethical Considerations

The research was conducted using social media content that was accessible publicly and without any interaction with social media users. User identifiers were anonymized by removing all identifiable data before analysis. The procedures for data gathering included rate limiting and platform-specific limitations. The research was carried out under the institutional guidelines that govern ethical standards. Social media data in their raw form are not shared because of the platform stipulations that govern such data; however, the processed and anonymized materials—including the keyword dictionaries, coding rules, and scoring scripts—are available to the editor and reviewers upon request and will be deposited in a public repository upon acceptance, subject to platform terms and user privacy, as stated in the Data Availability Statement.

5. Results

5.1. Descriptive Statistics

After data collection and preprocessing, the analysis data set included 78,432 comments from female consumers corresponding to 24 influencer profiles, classified into 12 matched virtual–human pairs. The virtual influencer subset involved 35,847 comments, and the human influencer subset contained 42,585 comments. Xiaohongshu was the highest source of comments, followed by Instagram, Douyin, and Weibo. Comments on hedonic products amounted to 45,892, while those on utilitarian products amounted to 32,540. Descriptive statistics reveal that there is sufficient variability among the observed indicators obtained from texts. The normalized 1–5 values in Table 7 are provided for presentation only and should not be interpreted as direct survey scale responses. Figure 4 summarizes the sample composition across influencer type, platform, and product type.

Table 7. Descriptive statistics of sample characteristics and key variables.

Category	Specification	n/Mean	%/SD
Sample Overview			
Total Valid Comments	Female consumers	78,432	100.0%
Total Influencer Accounts	Virtual + human matched	24	—
Total Brand Collaboration Posts	Analyzed posts	687	—
Data Collection Period	January 2023–December 2024	24 months	—
Influencer Type Distribution			
Virtual-Influencer Comments	VI subsample	35,847	45.7%
Human-Influencer Comments	HI subsample	42,585	54.3%
Platform Distribution			
Xiaohongshu	Primary platform	48,265	61.5%
Instagram	Secondary platform	15,686	20.0%
Douyin	Supplementary platform	8627	11.0%
Weibo	Supplementary platform	5854	7.5%
Product Type Distribution			
Hedonic Products	Fashion, beauty, lifestyle	45,892	58.5%
Utilitarian Products	Electronics, functional goods	32,540	41.5%
Influencer Account Characteristics			
Virtual-Influencer Follower Count	Mean (log-transformed)	14.21	0.89
Human KOL Follower Count	Mean (log-transformed)	14.35	0.92
Virtual-Influencer Post Engagement Rate	Mean	4.82%	2.15%
Human KOL Post Engagement Rate	Mean	5.47%	2.68%
Key Variables (Continuous)		Mean	SD
Perceived Authenticity	Normalized index (1–5, presentation only)	3.18	1.22
Parasocial Interaction	Normalized index (1–5, presentation only)	3.35	1.15
Social Presence	Normalized index (1–5, presentation only)	3.27	1.19
Influencer Trust	Normalized index (1–5, presentation only)	3.42	1.18
Brand Trust	Normalized index (1–5, presentation only)	3.28	1.24
Brand Attachment	Normalized index (1–5, presentation only)	3.15	1.31
Purchase Intention	Normalized index (1–5, presentation only)	3.08	1.28
Recommendation Intention	Normalized index (1–5, presentation only)	2.95	1.25
Comment Characteristics		Mean	SD
Comment Length (Characters)	Average per comment	42.6	28.4
Sentiment Score	Range: –1 to +1	0.34	0.52
Distribution Properties		Skewness	Kurtosis
Perceived Authenticity	—	–0.42	0.18
Parasocial Interaction	—	–0.38	0.24

Table 7. Cont.

Category	Specification	n/Mean	%/SD
Social Presence	—	−0.45	0.31
Influencer Trust	—	−0.52	0.27
Brand Trust	—	−0.48	0.35
Brand Attachment	—	−0.56	0.42
Purchase Intention	—	−0.61	0.38
Recommendation Intention	—	−0.58	0.29

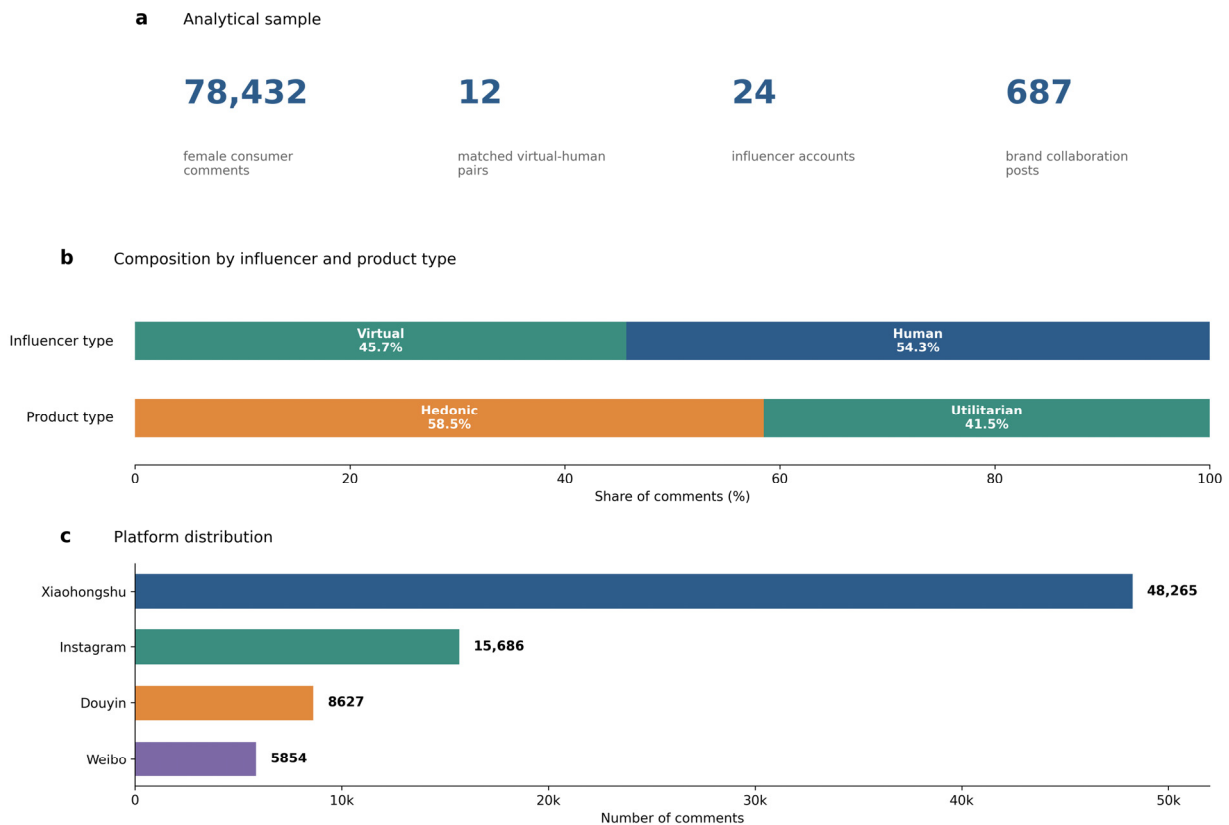


Figure 4. Sample composition and analytical context. Note. Bars show within-category shares in the final analytical dataset. This figure is descriptive and does not imply causal identification. (a) Key counts for the analytical sample; (b) composition by influencer type (virtual vs. human) and product type (hedonic vs. utilitarian); (c) distribution of comments across platforms.

5.2. Data Quality Assessment

The data quality checks indicate acceptable performance of the classification and filtering procedures. The gender-identification validation reached 87.3% accuracy, and the sentiment classification validation reached 86.8% accuracy. Inter-coder reliability for manually coded categories reached Cohen's kappa of 0.84. Bot detection removed 9847 suspected automated comments from the initial female-coded comment pool, yielding the final valid sample of 78,432 comments. These results support the reliability of the preprocessing pipeline while leaving room for the construct-validity limitations discussed later. Table 8 reports the complete set of quality metrics against their acceptance thresholds.

Table 8. Data quality assessment results.

Assessment Category	Metric	Value	Threshold	Status
Gender-Identification Validation				
Manual Verification Sample	n	2500	—	—
Overall Accuracy	%	87.3%	≥80%	✓ Acceptable
Precision	Coefficient	0.89	≥0.80	✓ Acceptable
Recall	Coefficient	0.85	≥0.80	✓ Acceptable
F1-Score	Coefficient	0.87	≥0.80	✓ Acceptable
Sentiment Analysis Validation				
Validation Sample	n	3000	—	—
Classification Accuracy	%	86.8%	≥85%	✓ Acceptable
Precision	Coefficient	0.87	≥0.80	✓ Acceptable
Recall	Coefficient	0.86	≥0.80	✓ Acceptable
F1-Score	Coefficient	0.86	≥0.80	✓ Acceptable
Inter-Coder Reliability				
Manual Coding Sample	n	1500	—	—
Cohen’s Kappa	Coefficient	0.84	≥0.70	✓ Substantial
Percent Agreement	%	91.2%	≥85%	✓ Acceptable
Bot Detection Results				
Initial Female-Coded Sample (after deduplication)	n	88,279	—	—
Detected Bot Comments	n	9847	—	—
Bot Removal Rate	%	11.2%	—	—
Final Valid Female Sample	n	78,432	—	—
Multicollinearity Diagnostics				
Perceived Authenticity	variance inflation factor (VIF)	1.87	<10	✓ Acceptable
Parasocial Interaction	VIF	2.15	<10	✓ Acceptable
Social Presence	VIF	1.92	<10	✓ Acceptable
Influencer Trust	VIF	2.43	<10	✓ Acceptable
Brand Trust	VIF	2.87	<10	✓ Acceptable
Brand Attachment	VIF	2.56	<10	✓ Acceptable
Product Type	VIF	1.24	<10	✓ Acceptable
Influencer Type	VIF	1.31	<10	✓ Acceptable
Normality Assessment				
Kolmogorov–Smirnov Test	Max D statistic	0.047	—	—
Shapiro–Wilk Test (subsample)	W statistic	0.968	>0.90	✓ Acceptable
Skewness Range	All variables	−0.61 to −0.38	Absolute value < 2	✓ Acceptable
Kurtosis Range	All variables	0.18 to 0.42	Absolute value < 7	✓ Acceptable

Note. A check mark (✓) indicates that the corresponding data-quality metric meets or exceeds the predefined acceptable threshold.

5.3. Correlation Analysis

The bivariate association matrix provides descriptive evidence consistent with the proposed trust-transfer account. Perceived authenticity was positively correlated with influencer trust ($r = 0.58$) and brand trust ($r = 0.47$). Parasocial interaction was positively correlated with influencer trust ($r = 0.62$), social presence ($r = 0.54$), and brand attachment ($r = 0.51$). The strongest reported bivariate association was between influencer trust and brand trust ($r = 0.67$). Brand trust was also positively correlated with brand attachment ($r = 0.59$), purchase intention ($r = 0.53$), and recommendation intention ($r = 0.49$). These correlations should be interpreted as initial evidence of association rather than causal effects. Table 9 reports the full lower-triangular matrix for the descriptive association analysis.

Table 9. Reported bivariate correlations among text-derived indicators.

Variable	1	2	3	4	5	6	7	8
1. Perceived authenticity	1							
2. Parasocial interaction	0.49	1						
3. Social presence	0.52	0.54	1					
4. Influencer trust	0.58	0.62	0.55	1				
5. Brand trust	0.47	0.50	0.48	0.67	1			
6. Brand attachment	0.44	0.51	0.46	0.57	0.59	1		
7. Purchase intention	0.39	0.43	0.41	0.50	0.53	0.55	1	
8. Recommendation intention	0.36	0.40	0.38	0.46	0.49	0.52	0.60	1

Note. Values are zero-order (bivariate), lower-triangular Pearson correlations among the eight text-derived observed composites ($N = 78,432$); they are not partial correlations. The matrix summarizes bivariate relationships among the observed indicators and is interpreted descriptively in line with the study's observational design.

5.4. Main Associations

The observed-variable path model indicates that influencer type is associated with the three proposed social-cue indicators. Human influencers were associated with higher perceived authenticity ($\beta = 0.42$), parasocial interaction ($\beta = 0.38$), and social presence ($\beta = 0.35$) than virtual influencers, consistent with H1a–H1c. Perceived authenticity ($\beta = 0.31$), parasocial interaction ($\beta = 0.36$), and social presence ($\beta = 0.28$) were each positively associated with influencer trust, consistent with H2a–H2c. The trust-transfer path from influencer trust to brand trust was the strongest reported path in the model ($\beta = 0.58$), consistent with H3. Brand trust was positively associated with brand attachment ($\beta = 0.52$), consistent with H4. Brand attachment was positively associated with purchase intention ($\beta = 0.49$) and recommendation intention ($\beta = 0.45$), consistent with H5a and H5b. The full set of standardized path estimates is displayed in Figure 5. The variables listed under covariates in Table 5 were considered as descriptive covariates only and were not entered into the estimated path model—this is because they are defined at the influencer or post level rather than at the comment level at which the model is estimated and because the raw comment-level records could no longer be re-accessed to reconstruct them as comment-level covariates; accordingly, no control coefficients are reported.

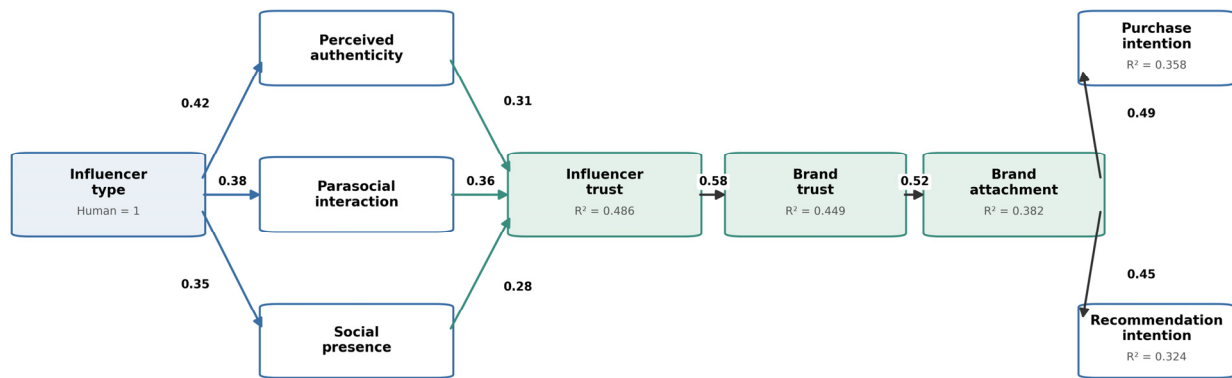


Figure 5. Artificial intelligence (AI)-mediated trust-transfer path model. Note. Values are standardized coefficients reported in Section 5.4. Constructs are text-derived observed indicators. The model is presented as an observed-indicator path model rather than a reflective measurement model.

5.5. Indirect Associations

The bootstrapped indirect association analysis yields estimates consistent with the postulated indirect structure. In particular, the indirect association between the type of influencer and influencer trust as mediated by authenticity was $\beta = 0.14$, 95% confidence interval (CI) [0.11, 0.17]. The indirect association through social presence was $\beta = 0.10$, 95% CI [0.07, 0.13]. Furthermore, the chain of events in which authenticity serves as the link between influencer type, influencer trust, brand trust, and brand attachment is distinguishable from zero in descriptive terms ($\beta = 0.08$, 95% bootstrap CI [0.06, 0.11], excluding zero). Collectively, these results are consistent with H6–H9 and suggest that the association between influencer type and brand outcomes operates partly through the proposed social-cue and trust pathways. These indirect associations are visualized in Figure 6.

Direct and indirect associations

Reported coefficients visualized with a common scale

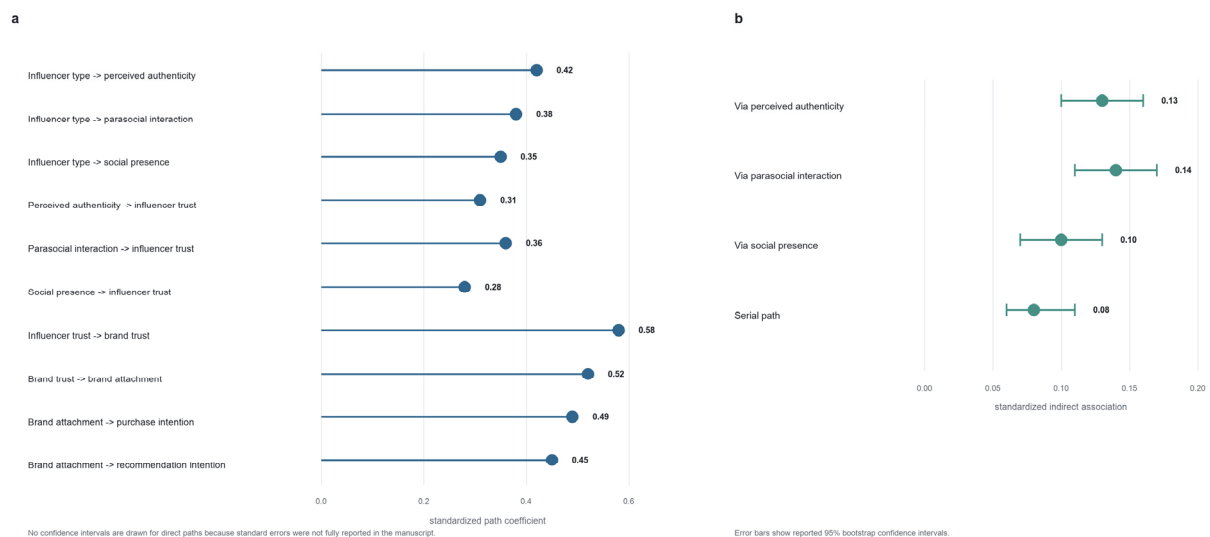


Figure 6. Direct and indirect associations. Note. Direct paths are shown as reported point estimates; indirect associations include reported 95% bootstrap confidence intervals. (a) Standardized direct path coefficients; (b) standardized indirect associations with reported 95% bootstrap confidence intervals.

5.6. Product-Type Moderation

Product type was associated with differences in the strength of the influencer-type associations. The interaction term between influencer type and product type on perceived

authenticity was $\beta = 0.18$: the association between influencer type and perceived authenticity was stronger in hedonic contexts ($\beta = 0.51$) than in utilitarian contexts ($\beta = 0.33$), a difference of 0.18 standardized units. Product type was similarly associated with the strength of the influencer type–parasocial interaction association (interaction $\beta = 0.14$) and with the trust-transfer path (interaction $\beta = 0.11$). These patterns are consistent with H10–H11 and suggest that virtual influencers are not uniformly disadvantaged; rather, the gap relative to human influencers is most visible in product categories that depend strongly on emotional, symbolic, and identity-relevant source cues. Figure 7 visualizes these moderation patterns together with the explained-variance summary.

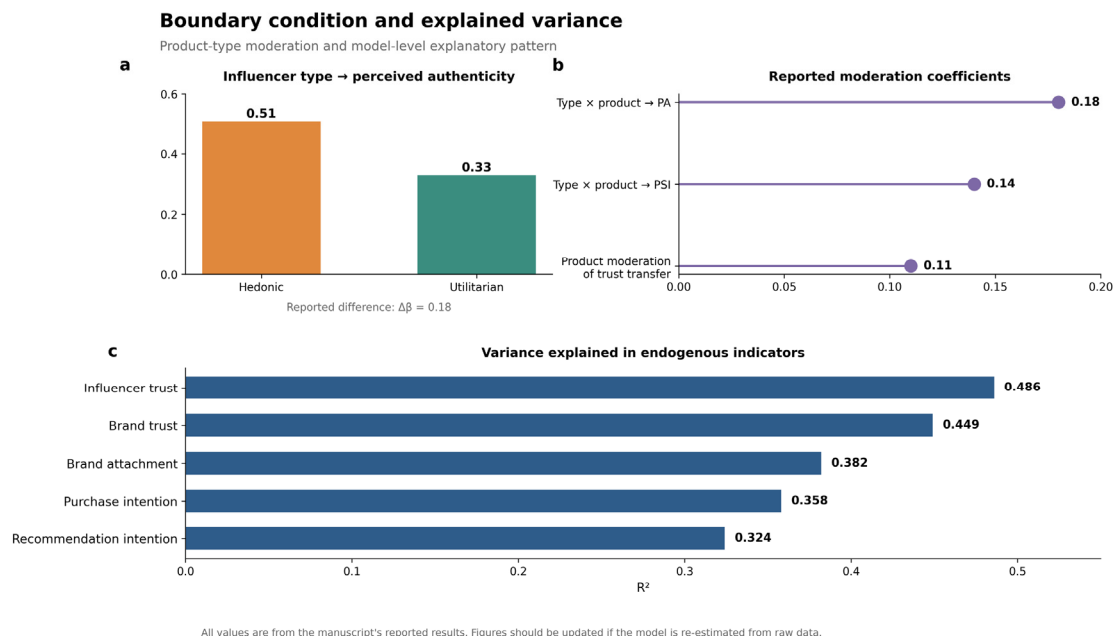


Figure 7. Product-type boundary condition and explained variance. Note. The figure visualizes reported product-type moderation coefficients, product-condition differences, and R² values. (a) Product-type difference in the influencer-type-to-perceived-authenticity path; (b) reported product-type moderation coefficients; (c) variance explained (R²) in the endogenous indicators.

5.7. Overall Model Pattern

The full observed-indicator path model shows a coherent pattern of standardized associations. The model explains variance in influencer trust ($R^2 = 0.486$), brand trust ($R^2 = 0.449$), brand attachment ($R^2 = 0.382$), purchase intention ($R^2 = 0.358$), and recommendation intention ($R^2 = 0.324$). Model-fit statistics reported for the path model are within acceptable ranges ($SRMR = 0.047$, $CFI = 0.951$, $RMSEA = 0.048$). These indices describe the overidentified observed-variable path model (paths constrained as in Figure 5) and are not latent-variable measurement-fit statistics. Overall, the results are consistent with a conditional, descriptive AI-mediated trust-transfer account: human influencers are associated with higher authenticity, parasocial, and social-presence indicators, and these cues are associated with influencer trust, brand trust, brand attachment, and behavioral intentions. Product type is associated with how strongly this pattern favors human influencers over virtual influencers.

6. Discussion

The findings are consistent with an AI-mediated trust-transfer account of virtual-influencer marketing. Human influencers were associated with stronger authenticity, parasocial interaction, and social-presence indicators, suggesting that female consumers

more readily express relational and humanizing cues when responding to human endorsers. Furthermore, the core process involved more than the nature of the influencer alone. The strongest reported association was observed between trust in the influencer and trust in the brand, suggesting that once trust in the source was expressed, it was also associated with trust in the endorsed brand. The implication is that the core difficulty for virtual influencers appears to lie not in transferring trust but in generating the social and authenticity cues associated with earning it in the first place.

The results highlight the notions of source credibility and trust transfer in AI-based endorsement. In conventional models of endorsement, source credibility is often viewed as a characteristic of the endorsing party. In the case of virtual endorsers, credibility can be described as being partly designed and partly constructed by consumers through social signals. The virtual influencer may display both esthetic sophistication and consistency, but these characteristics do not necessarily imply authenticity or relational proximity. Hence, the theory proposed by the researchers assumes that trust transfer depends not only on the presence of the connection between the influencer and the brand, but also on consumer perception regarding its social and relational credibility.

These findings can be situated against prior empirical evidence in three ways. First, the human-influencer advantage in perceived authenticity and relational cues is consistent with experimental results reporting lower authenticity and stronger skepticism or uncanniness responses toward virtual endorsers [7,10,12]. Second, the present results extend this literature by shifting the locus of explanation: in our data, the influencer-to-brand link ($\beta = 0.58$) mirrored classical trust-transfer accounts [15–18], suggesting that what differs across source types is not the transfer mechanism itself but the upstream formation of source trust. This stage-wise descriptive decomposition is not visible in outcome-comparison designs and is offered here as a descriptive reframing rather than the identification of a causal mechanism. Third, the product-type boundary condition aligns with and generalizes to field data, with experimental findings showing that virtual influencers perform relatively better for functional or low-sensory products [13,14] and that perceived artificiality and disclosure matter most where experiential claims are central [8,11]. Where prior work has largely relied on single-platform experiments with forced exposure, the present multi-platform observational evidence indicates that these patterns also emerge in naturally occurring consumer discourse, albeit with the associational caveats discussed in Section 7.

The product-type moderation offers an additional qualification to the discussion. The human-influencer association was more pronounced for hedonic products, whose consumption involves stronger emotional components. Therefore, the conclusion can be made that virtual influencers may have more trouble when endorsing products involving personal experience. The disadvantage associated with the use of virtual influencers is much smaller (descriptively near zero) in utilitarian settings, where consumers attach more importance to information transparency, coherence, and functionality of products. Taken together, the results argue against framing the decision as simple substitution: virtual and human influencers occupy partly different effectiveness domains.

This research draws a clear distinction among the roles of authenticity perception, parasocial interaction, and social presence. The aforementioned concepts are related, but are separate dimensions of consumer reactions. Authenticity concerns the genuineness of an influencer; parasocial interaction involves expression of consumer imagination about relationship or closeness to the influencer; and social presence concerns the impression of social accessibility of the influencer. Viewing them as separate phenomena helps explain why humans are able to perform better than virtual influencers in different aspects. A virtual influencer may be visually salient and human-looking yet still lack the ability

to convey authentic influence; alternatively, it may appear authentic within a branded environment but be unable to create a parasocial bond.

For managers, the findings imply that the influencer choice should be based on both the nature of the products and goals for the campaign. It remains the case that human influencers remain important where the authenticity, identity-related aspects, emotional appeals, and experiential elements play important roles in the success of a marketing campaign. Virtual influencers are better alternatives where there is an emphasis on message control, visual cohesion, innovation messaging, product demonstration, or functional communication. Virtual influencers cannot be viewed as a cheaper alternative to human influencers. Their value depends on the fit among the persona, the product category, and the form of trust the campaign needs to build.

7. Limitations and Future Research

Several limitations should be mentioned. First, this is an observational study based on social media data; therefore, one should treat the relationships presented as correlational rather than necessarily causal. While the theoretical model assumes directionality, the empirical analysis is unable to reject reverse causation, omitted variables, platform-level influences, or self-selection biases inherent in influencer-brand collaborations.

Second, the measures are derived from text-based cues within comments. Although dictionary searches, sentiment analysis, and manual checks improve their transparency, these measures can never be viewed as identical to conventional measurement techniques using multiple-item questionnaires as they might reflect only those aspects of authenticity, trust, attachment, and intention that have been expressed publicly. Future research needs to compare textual-based measures with psychometric scales through validation studies that use either mixed methods research or small sample surveys. A related concern is classification error: the gender-identification procedure reached 87.3% accuracy and the sentiment classifier 86.8% (Table 8), so roughly one in eight records may be misclassified on these dimensions. Such error is likely to be predominantly random with respect to the hypotheses and would then attenuate rather than inflate the reported associations; however, systematic misclassification (for example, gendered language styles that differ across platforms) cannot be ruled out, and the female consumer framing of the sample should be read with this margin of error in mind. Because the anonymized analytical dataset no longer contains the raw profile information needed to re-run classification under alternative thresholds, formal sensitivity analyses for gender, sentiment, and bot-classification error could not be conducted in this revision and remain a priority for future validation work.

Third, commentary is embedded in the context of posts, influencers, platforms, and product categories. Platform cultures might affect how users convey their trust, attachment, or intentions to recommend; influencer traits might affect both the makeup of the audience and the response. Future studies should use multilevel modeling, fixed effects on influencers, or experiments when possible to better control for variation from these sources. In the present data, re-estimation with multilevel or cluster-robust specifications was not feasible for the reasons stated in Section 4.5, so the results should be read at the level of descriptive associations rather than formal hypothesis tests.

Fourth, the focus on female consumers holds theoretical relevance in terms of influencer marketing settings where beauty, fashion and lifestyle concerns predominate, but at the same time, the scope of application for other gender segments and products is limited. Future research should consider whether the phenomenon of AI-facilitated trust transfer is comparable across diverse gender, generational, and cultural segments of society.

Finally, virtual influencers are a diverse group. Some display high levels of human resemblance; some are stylistic representations or animations; and yet others are explicitly created AI characters for brands. Future studies could categorize different types of virtual influencers and study how transparency, anthropomorphism, autonomy, and tactics used with human–AI collaborations affect trust transfer and brand attachment.

8. Conclusions

This study examined AI-mediated trust transfer by comparing virtual and human influencers among female consumers across four social media platforms. Using text-derived observed indicators constructed from 78,432 comments and 12 matched virtual–human-influencer pairs, the study found that human influencers were associated with stronger perceived authenticity, parasocial interaction, and social presence. These cues were associated with influencer trust, which was in turn associated with brand trust, brand attachment, purchase intention, and recommendation intention. Product type qualified the pattern: the human-influencer advantage was stronger in hedonic contexts and less pronounced in utilitarian contexts.

The findings suggest that virtual influencers should not be understood as universal replacements for human influencers. Their effectiveness depends on whether an AI-mediated persona can generate the social and authenticity cues that are linguistically associated with trust transfer in a specific product context. By reframing virtual-influencer effectiveness as a conditional trust-transfer process, this study contributes to a more nuanced understanding of how artificial social actors participate in brand relationships and how brands should strategically deploy human and virtual endorsers. The boundary conditions of these conclusions should remain explicit: the evidence comes from four platforms with distinct cultures, from Chinese- and English-language discourse, from female-coded commenters, and from text-derived linguistic indicators that serve as proxies rather than validated psychometric constructs; generalization beyond these conditions and confirmation against established psychometric measures require further validation.

Author Contributions: Conceptualization, Q.Z.; methodology, Q.Z.; software, Q.Z.; validation, Q.Z.; formal analysis, Q.Z.; investigation, Q.Z.; resources, Q.Z.; data curation, Q.Z.; writing-original draft preparation, Q.Z.; writing-review and editing, Q.Z.; visualization, Q.Z.; supervision, Q.Z. and F.A.; project administration, Q.Z. and F.A.; funding acquisition, Q.Z. and F.A. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: Upon review, this manuscript reports a retrospective textual analysis drawing on publicly accessible social media comment data. Because this study relies exclusively on publicly accessible, de-identified social media comment data and discloses no personally identifiable information, individual informed consent and publication consent are not applicable and may be waived. Based on those reasons, this study qualifies as a minimal-risk, non-interventional public-data research project. Under applicable institutional ethics management requirements, it is eligible for exemption from full ethics review, and individual informed consent may be waived.

Informed Consent Statement: Informed consent was waived because the study analyzed publicly available data and did not involve direct interaction with participants.

Data Availability Statement: Processed and anonymized materials, variable codebooks, keyword dictionaries, scoring scripts, and the validation protocol are available to the editor and reviewers upon request and will be deposited in a public repository (e.g., OSF/Zenodo) upon acceptance, subject to platform terms of service and user-privacy requirements. Raw social media data cannot be publicly redistributed because of platform restrictions and user privacy protection.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Appendix A reports the anonymized structure of the 12 matched virtual–human–influencer pairs. Account names are withheld in accordance with the anonymization procedure described in Section 4.10.

Table A1. Matched virtual–human–influencer pairs (anonymized).

Pair Code	Platform	Primary Content Domain	Follower Band	Product Categories Covered
VP01	Xiaohongshu	Beauty	500K–5M	Hedonic and utilitarian
VP02	Xiaohongshu	Fashion	500K–5M	Hedonic and utilitarian
VP03	Xiaohongshu	Lifestyle	500K–5M	Hedonic and utilitarian
VP04	Xiaohongshu	Beauty/lifestyle	500K–5M	Hedonic and utilitarian
VP05	Instagram	Lifestyle	500K–3M	Hedonic and utilitarian
VP06	Instagram	Fashion	500K–3M	Hedonic and utilitarian
VP07	Instagram	Beauty	500K–3M	Hedonic and utilitarian
VP08	Instagram	Lifestyle/fashion	500K–3M	Hedonic and utilitarian
VP09	Weibo	Entertainment/lifestyle	1M–10M	Hedonic and utilitarian
VP10	Weibo	Fashion/entertainment	1M–10M	Hedonic and utilitarian
VP11	Douyin	Short-video/ livestream commerce	500K–5M	Hedonic and utilitarian
VP12	Douyin	Beauty/livestream commerce	500K–5M	Hedonic and utilitarian

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