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Responsible AI Influencer Communication in Social Commerce: Perceived Authenticity, Consumer Trust, and Purchase Intention

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Abstract
Purpose: This study examines how consumers evaluate AI-generated influencers in social commerce, focusing on credibility, perceived authenticity, trust, and AI awareness. It asks whether credibility alone builds trust in an artificial communicator, or whether authenticity is the more proximal basis for trust and purchase intention.
Design/methodology/approach: A cross-sectional survey of 283 social-media users aged 18 to 40 in Chongqing, China was analyzed using internal-consistency and factorability diagnostics, multiple regression, mediation, and moderation analysis.
Findings: Authenticity was the strongest predictor of trust (β = .830); credibility was not significant in the full trust model (β = −.013). Trust was the strongest predictor of purchase intention (β = .591); credibility (β = .191) and AI awareness (β = .172) also contributed. Simple mediation through trust was significant but disappeared once authenticity and AI awareness were controlled. The credibility × AI-awareness interaction was nonsignificant.
Research limitations/implications: The study relies on convenience sampling, self-report data, and two-item measures; future work should use multi-item scales and experimental or longitudinal designs.
Practical implications: AI influencer communication should prioritize verifiable information and transparent disclosure over human-like appearance, with stronger oversight in high-risk categories.
Social implications: Responsible practice should protect consumers from deceptive anthropomorphism so novelty is not mistaken for trustworthiness.
Originality/value: The study separates credibility, a source-quality cue, from authenticity, a more proximal judgment of genuineness, showing that a simple credibility–trust–purchase account overstates credibility's role once authenticity is modeled simultaneously.

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Keywords: AI-generated influencers; virtual influencers; authenticity; consumer trust; social commerce; AI awareness

1. Introduction

Artificial intelligence is changing the architecture of digital persuasion. Generative systems can now produce highly realistic characters, images, videos, dialogue and product narratives at a scale and speed that would be difficult for individual human influencers to sustain. In social-commerce environments, these capabilities create a new type of persuasive source: an influencer that can be commercially managed, continuously updated, and personalized while remaining visibly or potentially artificial. The resulting communication problem is not simply whether consumers find AI influencers attractive or novel. It is whether consumers regard the information conveyed by an artificial source as sufficiently credible, authentic and trustworthy to support consequential decisions.

This issue is important because digital persuasion increasingly operates at the boundary between commercial influence and consumer welfare. AI influencer communication therefore matters when research goes beyond engagement or sales efficiency and addresses the conditions under which technologically mediated persuasion supports or undermines informed decision-

making, transparency and responsible consumer outcomes. The present study adopts this broader perspective by treating trust and authenticity not merely as conversion mechanisms but as conditions of responsible persuasion.

Recent scholarship shows that virtual influencers generate a fundamental authenticity paradox. They may be highly controlled and credible while simultaneously lacking the lived experience normally associated with human endorsement. Koles *et al.* (2024) [27] demonstrate that authenticity in virtual-influencer environments is multidimensional and can be expressed through being true to an ideal, true to facts, and true to self. More recent experimental work similarly suggests that credibility and authenticity can coexist in tension: credibility may help consumers resolve doubts created by the artificial nature of the source, while the meaning of authenticity may differ depending on whether consumers evaluate the influencer's identity or the truthfulness of the product claim (Zhou *et al.*, 2026) [49]. This literature indicates that treating credibility and authenticity as interchangeable predictors is theoretically insufficient.

The present study therefore examines an integrated process in which AI influencer credibility represents a conventional source-quality cue, perceived authenticity captures the consumer's evaluation of whether the communication feels genuine and coherent, consumer trust represents the proximal relational mechanism, and purchase intention represents a downstream behavioural intention. AI awareness is introduced as a potential boundary condition because consumers may evaluate an artificial source differently when they consciously recognize its technological origin. The model is grounded primarily in Source Credibility Theory (Ohanian, 1990) [36] and the Elaboration Likelihood Model (Petty and Cacioppo, 1986) [39], while drawing on contemporary authenticity and virtual-influencer research to explain why source cues may not operate in the same way when the source is artificial.

The research objectives and research questions are deliberately integrated rather than presented as repetitive lists. The study aims to determine whether AI influencer credibility is associated with consumer trust and purchase intention; to establish whether perceived authenticity provides a distinct and more proximal explanation of trust; to examine whether consumer trust statistically transmits the association between credibility and purchase intention; to assess whether AI awareness changes the credibility–trust relationship; and to translate these findings into implications for transparent, consumer-centred AI influencer communication. Accordingly, the study asks: How does AI influencer credibility relate to consumer trust and purchase intention? Does perceived authenticity provide a more proximal basis for trust toward an artificial influencer? Does consumer trust account for part of the credibility–purchase relationship? Does AI awareness alter the relationship between credibility and trust? And, taken together, what do these relationships imply for responsible AI-mediated consumer decision-making?

The study contributes in three ways. First, it extends source-credibility reasoning by examining an environment in which competence and trustworthiness can be simulated without conventional human experience. Second, it positions authenticity as a theoretically meaningful trust mechanism rather than a generic positive attitude toward influencers. Third, it connects AI influencer research to the practical and social-marketing question of how digital persuasion can remain effective without weakening consumer autonomy, transparency or confidence in the information environment.

The paper proceeds as follows. Sections 2 through 4 develop the theoretical model, hypotheses, and survey method; Sections 5 through 8 report and discuss the survey findings and their practical and social-marketing implications. Because a single cross-sectional survey can establish association but not causation, Section 9 specifies — as a pre-registered design rather than as completed research — an experimental method for testing the central authenticity-versus-credibility pattern under random assignment, and Section 10 concludes.

2. Literature Review and Hypothesis Development

2.1. AI-generated and Virtual Influencers in Contemporary Social Commerce

Virtual influencers are not simply digital substitutes for human celebrities. They are constructed communicators whose visual identities, biographies, speech patterns and interactions can be designed or modified by creators, agencies, platforms and brands. Earlier work identified the strategic appeal of virtual influencers in terms of controllability, consistency and novel forms of audience engagement (Arsenyan and Mirowska, 2021; Sands *et al.*, 2022) [4, 41], and more recent evidence suggests that AI-powered virtual influencers can, under some conditions, outperform their human counterparts on engagement and cost-efficiency metrics (Allal-Chérif *et al.*, 2024) [3]. More recent research has moved beyond the novelty question and has examined how consumers interpret the meaning of an artificial source. For example, Lou *et al.* (2023) [32] show that consumers can respond positively to virtual influencers while simultaneously recognizing that their authenticity is constructed. AI influencer research has also identified multiple attributes — including anthropomorphism, artificiality, attractiveness, quality, trendiness and perceived threat — that shape acceptance of AI influencers as endorsers.

This evolution matters for social commerce because the persuasive encounter is often compressed into short videos, livestreams, recommendation posts or product demonstrations. Consumers therefore use source cues to reduce uncertainty. Yet AI-generated influencers complicate the usual inference from source cue to trust: the communicator may appear expert without having personal experience, and it may appear socially responsive while being substantially controlled by a commercial organization. Recent evidence reinforces this concern. Experimental research finds that AI versus human endorsement can reduce perceived brand trustworthiness and purchase intentions under some conditions, suggesting that artificiality can carry downstream consequences for the brand rather than merely the influencer (Ozdemir *et al.*, 2023) [37].

2.2. Source Credibility Theory and AI-mediated Persuasion

Source Credibility Theory proposes that persuasion depends partly on perceptions of the source, particularly expertise and trustworthiness, with attractiveness and related source characteristics often incorporated into endorsement models (Ohanian, 1990) [36]. In influencer marketing, credibility can reduce perceived uncertainty and increase acceptance of branded information (Lou and Yuan, 2019; Sokolova and

Kefi, 2020; Casaló *et al.*, 2020) [8, 31, 43], and has been shown to shape purchase decisions even in the relatively low-information environment of an Instagram profile (Djafarova and Rushworth, 2017) [15]. The mechanism is intuitively powerful: when a source is believed to possess relevant knowledge and to communicate reliably, consumers have less reason to discount the message, and observable social-media activity itself can function as a signal of that reliability (Cheung *et al.*, 2014) [9].

AI-generated influencers, however, create a boundary condition for conventional credibility theory. Expertise can be algorithmically produced and displayed through fluent explanations, polished demonstrations and immediate responses. Trustworthiness can also be signalled through consistency and apparent confidence. What cannot be inferred automatically is lived experience. An AI influencer may provide accurate information about a product without having used the product, experienced its benefits, or independently chosen to recommend it. The credibility cue is therefore potentially decoupled from experiential authenticity. This problem is increasingly visible in the literature: Zhou *et al.* (2026) [49] argue that credibility can function as a psychological repair mechanism when consumers encounter authenticity deficits, while other work finds that virtual endorsement can reduce perceptions of brand authenticity (Song *et al.*, 2024) [44].

The implication is not that credibility becomes irrelevant. Rather, credibility may perform different functions across stages of the persuasion process. It can make a product message easier to evaluate or accept, while a deeper judgment about whether the communicator is genuine may determine whether consumers are willing to place trust in it. This distinction motivates the first hypothesis that AI influencer credibility will be positively associated with consumer trust, while the separate direct relationship with purchase intention is also expected.

2.3. Perceived Authenticity as a Distinct Construct

Authenticity is conceptually different from credibility. Credibility concerns whether a source is believable, knowledgeable or trustworthy; authenticity concerns whether the source and its communication are perceived as genuine, congruent and true to the identity it presents. This distinction has deep roots in brand and marketing research more broadly, where authenticity is treated as a judgment of sincerity and fidelity to a claimed identity rather than a simple factual property (Beverland, 2005) [6]. In human influencer research, authenticity has been linked to transparency, consistency, sincerity and resistance to overly commercialized self-presentation (Audrezet *et al.*, 2020) [5]. Morhart *et al.* (2015) [35] similarly conceptualize authenticity as a multidimensional consumer evaluation rather than a simple factual property.

In virtual-influencer environments, authenticity requires further refinement because consumers already know — or may suspect — that the source is not a human being. Koles *et al.* (2024) [27] show that virtual-influencer authenticity can take several forms, including being true to an ideal, true to facts, and true to self. This means that authenticity does not necessarily require consumers to believe that the influencer is literally human. Instead, consumers may judge whether the influencer behaves consistently with its stated identity, whether product claims are congruent with available evidence, and whether the communication avoids manipulative contradictions. Thompson *et al.* (2025) [45] further demonstrate that audiences actively construct meaning around virtual-influencer identities through interaction and interpretation rather than simply receiving a pre-defined persona.

This conceptualization is particularly relevant to trust. If credibility answers the question "Can this source provide useful or believable information?", authenticity addresses the question "Does the way this source communicates appear genuine and congruent with what it claims to be?" In AI-mediated communication, the second question may become more important because the artificial origin is itself salient. Thus, perceived authenticity is hypothesized to have a positive relationship with consumer trust.

2.4. Consumer Trust as the Proximal Mechanism

Trust is central to online exchange because consumers frequently make decisions under conditions of incomplete information and uncertainty (Gefen *et al.*, 2003; Pavlou, 2003) [19, 38]. In social commerce specifically, trust can emerge from source credibility, platform cues, prior experience, social proof, observational learning, and information quality (Wang and Yu, 2017) [47]. For influencer-mediated communication, trust represents a willingness to rely on the influencer's information despite uncertainty about the promoted product and the commercial relationship.

The AI influencer context makes trust particularly consequential. A consumer can recognize that a virtual influencer is artificial and still decide that the information is dependable. Conversely, a highly realistic influencer can attract attention without producing confidence. Recent work using configurational analysis shows that no single factor is sufficient to generate high trust in AI influencers; instead, combinations of attractiveness, authenticity, expertise and congruence can form different trust-producing configurations (Alboqami, 2023) [2]. This supports a process-oriented view in which trust is an outcome of multiple source and relational evaluations rather than a mechanical consequence of one credibility cue.

Trust should also have a direct relationship with purchase intention, consistent with the broader behavioural-intention literature in which intention functions as the most proximal predictor of subsequent action (Ajzen, 1991) [1]. When consumers trust the source and its information, perceived uncertainty and informational risk should fall, making purchase-related action more acceptable. Accordingly, the study hypothesizes that consumer trust will positively predict purchase intention and will statistically mediate the relationship between credibility and purchase intention.

2.5. AI Awareness, Disclosure and the Boundary Conditions of Persuasion

AI awareness refers here to consumers' recognition that an influencer or its content is generated or substantially mediated by artificial intelligence. Awareness is conceptually distinct from disclosure. A consumer may know that a character is artificial, but may not know who controls it, whether the content was generated automatically, whether a human reviewed the claims, or whether the persona's product experiences are fictional. Treating these issues as one variable risks obscuring important mechanisms.

Theoretically, higher AI awareness could weaken the credibility–trust relationship because awareness may trigger greater scrutiny of the source. Alternatively, awareness may have little effect if consumers regard artificiality as expected

and instead evaluate communication quality, transparency and usefulness. Current evidence supports this ambiguity. Research on disclosure and virtual influencers suggests that origin disclosure and emotional narratives can affect perceived credibility and the parasocial processes classically associated with sustained media-personality relationships (Horton and Wohl, 1956; Lim and Lee, 2023) [23, 29], while newer work emphasizes that disclosure effects depend on how consumers interpret the artificial source. The systematic literature review by Khalfallah and Keller (2025) [24] similarly identifies authenticity, transparency, ethics and cultural context as interconnected determinants of trust and engagement.

The present study therefore treats AI awareness as a theoretically plausible moderator rather than assuming that awareness must reduce persuasion. The corresponding hypothesis is that AI awareness moderates the positive relationship between AI influencer credibility and consumer trust.

2.6. Social-Marketing and Consumer-Welfare Perspective

This perspective changes the interpretation of the model. Trust is valuable not only because it can increase conversion but also because it can support informed behavioural choice when information is accurate and transparent. Emerging social-marketing scholarship similarly frames virtual influencership through a "desire to model" lens, in which younger audiences look to influencers, human or artificial, as templates for behaviour rather than merely as sources of product information (Sharma *et al.*, 2026) [42]. The paper therefore interprets purchase intention through a broader lens of responsible, consumer-centred digital influence.

2.7. Hypothesis Development

H1. AI influencer credibility is positively associated with consumer trust.

H2. AI influencer credibility is positively associated with purchase intention.

H3. Consumer trust is positively associated with purchase intention.

H4. Consumer trust mediates the positive relationship between AI influencer credibility and purchase intention.

H5. Perceived authenticity is positively associated with consumer trust.

H6. AI awareness moderates the positive relationship between AI influencer credibility and consumer trust.

3. Conceptual Model and Research Logic

The conceptual model integrates Source Credibility Theory with an authenticity-based account of trust formation in AI-mediated persuasion. The model distinguishes four functional roles. AI influencer credibility represents the primary source cue; perceived authenticity represents a parallel evaluation of whether the artificial communicator's presentation is genuine and coherent; consumer trust represents the proximal psychological mechanism linking source evaluations to purchase intention; and AI awareness is specified as a potential boundary condition on the credibility–trust relationship.

The model deliberately retains both a direct credibility-to-purchase path and an indirect credibility-to-purchase path through trust. This allows the analysis to distinguish two forms of persuasive effectiveness. The direct path captures the possibility that credible source cues facilitate product evaluation without requiring deep relational confidence. The mediated path captures the possibility that credibility works because it produces trust. Perceived authenticity enters the trust model independently because an artificial source can be evaluated as credible while still being perceived as insufficiently genuine. AI awareness is positioned as a moderator because conscious recognition of artificiality may change how consumers interpret credibility signals.

Figure 1. Conceptual Framework

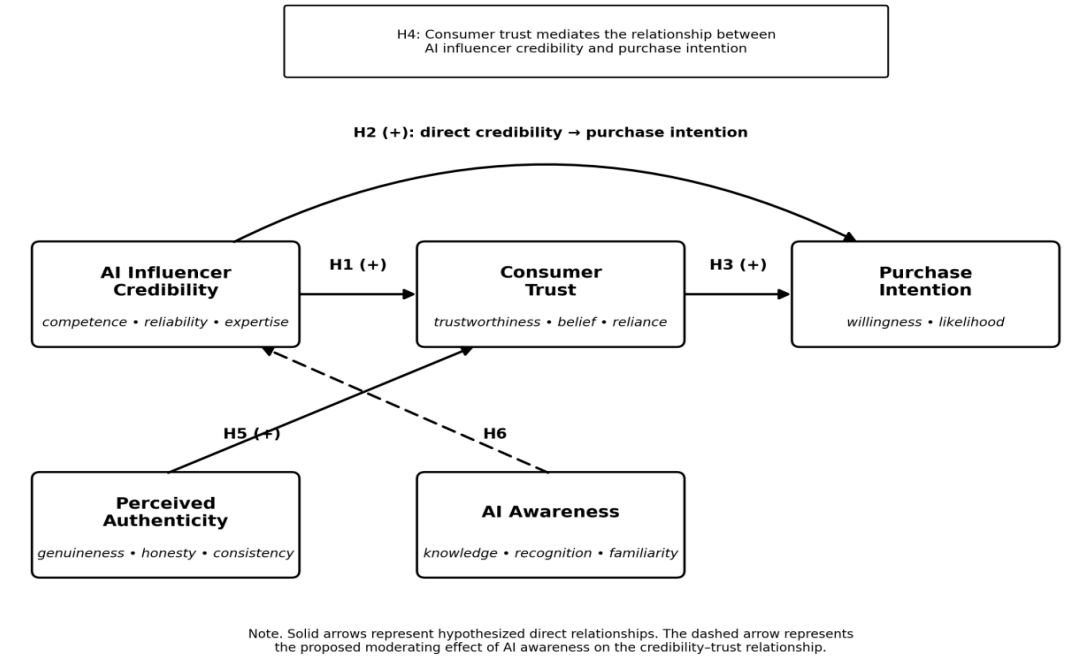


Fig 1: Conceptual framework. Solid arrows represent hypothesized direct relationships; the dashed arrow represents the proposed moderating effect of AI awareness on the credibility–trust relationship.

4. Methodology

4.1. Research Design and Sampling

The study used a cross-sectional survey design (Creswell and Creswell, 2018) [11], administered as an online questionnaire. The target population comprised university students and young social-media users familiar with digital content and online shopping. Data were collected in Chongqing, China, from respondents aged approximately 18 to 40 years. Convenience sampling was used because respondents were recruited on the basis of accessibility and willingness to participate; this is a widely used approach for exploratory research on emerging consumer phenomena, though it carries recognized trade-offs against population-level representativeness (Etikan *et al.*, 2016) [16]. A total of 283 valid responses were available for analysis. This sampling strategy is suitable for an exploratory empirical investigation of a rapidly developing phenomenon but limits population-level generalization. The sample should therefore be interpreted as evidence about the studied respondent group rather than as a representative estimate of all social-commerce consumers, and findings should not be generalized beyond this cultural and demographic context without replication.

4.2. Measures and Operationalization

The questionnaire contained demographic/screening items followed by ten focal items measured on five-point Likert-type scales from 1 (strongly disagree) to 5 (strongly agree). AI influencer credibility was measured with Q3–Q4; perceived authenticity with Q5–Q6; consumer trust with Q7–Q8; purchase intention with Q9–Q10; and AI awareness with Q11–Q12. Composite scores were formed by averaging the corresponding items. The limited number of indicators is a methodological constraint relative to standard scale-development practice, which recommends multiple indicators per construct to support dimensionality and discriminant-validity assessment (DeVellis, 2017) [14]: internal consistency can be assessed, but a rigorous latent measurement model cannot be established from the present item structure alone.

4.3. Data-Analysis Strategy

The analysis proceeded in four stages. First, Cronbach's alpha (Cronbach, 1951) [12] was used to assess internal consistency. Second, the KMO statistic and Bartlett's test of sphericity were used to evaluate whether the item correlation matrix was factorable. Third, multiple regression models were estimated for consumer trust and purchase intention, following standard multivariate diagnostic practice for coefficient interpretation and collinearity assessment (Hair *et al.*, 2019; Field, 2018) [17, 20]. Fourth, mediation and moderation analyses were examined to evaluate the proposed process and boundary condition, using indirect-effect and bootstrapping logic consistent with established guidance for mediation analysis in the behavioural and social sciences (Preacher and Hayes, 2008; Hayes, 2022) [22, 40]. Multicollinearity diagnostics were also reviewed using tolerance and variance-inflation statistics available in the reported SPSS output. The interpretation emphasizes standardized effects, explained variance, statistical uncertainty, and the change in the mediation result when theoretically relevant covariates are introduced.

4.4. Ethics and Informed Consent

This study was conducted by the author as independent research and was not reviewed by a formal institutional ethics review board. Data were collected via an online questionnaire. Prior to participation, respondents were informed of the purpose of the study, that participation was voluntary and anonymous, that their responses would be used only for research purposes, and that they could withdraw at any time without penalty. Informed consent was obtained from all respondents, via an online consent screen, before they proceeded to the questionnaire. Data were collected in Chongqing, China, from respondents aged approximately 18 to 40 years. No personally identifying information was collected. The absence of independent ethics committee review is acknowledged as a limitation of the present study.

4.5. Research Integrity and Reproducibility

Because the available evidence consists of aggregate SPSS results rather than the original respondent-level dataset, the analysis reported in Section 5 is limited to statistics that can be verified from the available output: model-level F statistics, R^2 and adjusted R^2, unstandardized and standardized coefficients, t tests, significance levels, multicollinearity diagnostics, the available indirect effects and confidence intervals, and interaction tests. Statistics that would require reconstruction of the raw data — such as CFA loadings, composite reliability, AVE, HTMT, latent-variable fit indices, or newly generated bootstrap distributions — are not reported. This is acknowledged as a limitation in Section 8.

5. Results

The results are reported in a table-led sequence consistent with empirical journal conventions. The analysis first establishes measurement reliability and factorability, then evaluates the two multivariable regression models, followed by collinearity diagnostics, mediation, moderation, and the overall hypothesis pattern. Because the respondent-level dataset was not available, the analysis is restricted to statistics documented in the available SPSS output; no CFA, CR, AVE, HTMT, latent-variable fit, or new bootstrap statistics are reported.

5.1. Measurement Quality and Factorability

Table 1 reports the internal-consistency results for the five focal constructs. According to Table 1, Cronbach's alpha coefficients range from .743 to .909. AI influencer credibility records the lowest coefficient (α = .743), while perceived authenticity records the highest (α = .909). Consumer trust (α = .856), purchase intention (α = .800), and AI awareness (α = .801) also demonstrate acceptable internal consistency. The overall alpha of .885 further indicates strong consistency across the focal measurement set. Given that each construct was measured with two items, these coefficients should be interpreted as evidence of internal consistency rather than as proof of full construct dimensionality.

The factorability diagnostics further support multivariate analysis. The KMO statistic is .840, indicating that the correlation matrix is suitable for factor-analytic investigation, while Bartlett's test of sphericity is significant, $\chi^2(45) = 2019.960$, $p < .001$. Thus, the item correlation structure is sufficiently interrelated for the subsequent regression-based analysis.

Table 1. Reliability and factorability evidence

Construct / diagnostic	Items	Result
AI influencer credibility	Q3–Q4	Cronbach's α = .743
Perceived authenticity	Q5–Q6	Cronbach's α = .909
Consumer trust	Q7–Q8	Cronbach's α = .856
Purchase intention	Q9–Q10	Cronbach's α = .800
AI awareness	Q11–Q12	Cronbach's α = .801
Overall scale	10 focal items	Cronbach's α = .885
KMO	—	.840
Bartlett's test	—	χ^2 = 2019.960, df = 45, p < .001

5.2. Determinants of Consumer Trust

The first multivariable model examines whether AI influencer credibility, perceived authenticity, and AI awareness are uniquely associated with consumer trust. As reported in Table 2, the overall regression model is statistically significant, F(3, 279) = 184.851, p < .001, and explains 66.5% of the variance in consumer trust (R^2 = .665; adjusted R^2 = .662). This represents a substantial level of explained variance for the trust outcome.

According to Table 2, perceived authenticity is by far the strongest unique predictor of consumer trust (B = .747, β = .830, t = 17.715, p < .001). In contrast, AI influencer credibility is not significant after authenticity and AI awareness are entered simultaneously (B = −.012, β = −.013, t = −.262, p = .793). AI awareness is likewise nonsignificant (B = −.029, β = −.036, t = −.997, p = .319). The contrast is theoretically important: the results suggest that consumers' trust judgments are more closely associated with perceived authenticity than with a general credibility cue when the constructs are considered together.

Accordingly, H1 is not supported in the full multivariable trust model, whereas H5 is supported. The magnitude of the authenticity coefficient should nevertheless not be interpreted causally because the data are cross-sectional.

Table 2. Multivariable regression predicting consumer trust

Predictor	B	β	t	p
AI influencer credibility	−.012	−.013	−.262	.793
Perceived authenticity	.747	.830	17.715	< .001
AI awareness	−.029	−.036	−.997	.319

Note: F (3, 279) = 184.851, p < .001; R^2 = .665, adjusted R^2 = .662.

5.3. Determinants of Purchase Intention

The second multivariable model shifts the dependent variable from trust to purchase intention and simultaneously includes credibility, authenticity, trust, and AI awareness. According to Table 3, the overall model is statistically significant, F(4, 278) = 133.901, p < .001, explaining 65.8% of the variance in purchase intention (R^2 = .658; adjusted R^2 = .653).

As shown in Table 3, consumer trust is the strongest unique predictor of purchase intention (B = .624, β = .591, t = 9.753, p < .001), supporting H3. AI influencer credibility also retains a significant positive association with purchase intention (B = .187, β = .191, t = 3.949, p < .001), supporting H2. AI awareness has a smaller but statistically significant positive association with purchase intention (B = .146, β = .172, t = 4.739, p < .001). By contrast, perceived authenticity is not a significant direct predictor of purchase intention once trust, credibility, and AI awareness are controlled (B = .058, β = .061, t = .879, p = .380).

The contrast between Tables 2 and 3 is particularly informative. Authenticity dominates the explanation of trust, whereas trust dominates the explanation of purchase intention. This pattern is consistent with a proximal-mechanism interpretation in which authenticity contributes to trust formation, and trust is more immediately connected to downstream purchase intention.

Table 3. Multivariable regression predicting purchase intention

Predictor	B	β	t	p
AI influencer credibility	.187	.191	3.949	< .001
Perceived authenticity	.058	.061	.879	.380
Consumer trust	.624	.591	9.753	< .001
AI awareness	.146	.172	4.739	< .001

Note: F (4, 278) = 133.901, p < .001; R^2 = .658, adjusted R^2 = .653.

5.4. Collinearity and Coefficient Stability

The VIF and tolerance diagnostics are reported alongside the regression results to assess whether multicollinearity could materially distort the coefficient pattern. As reported in Table 4, the trust model has tolerance values of .528, .547, and .932 and corresponding VIF values of 1.896, 1.829, and 1.073 for credibility, authenticity, and AI awareness, respectively. In the purchase-intention model, tolerance values are .527, .257, .335, and .929, with VIF values of 1.896, 3.886, 2.988, and 1.077 for credibility, authenticity, trust, and AI awareness. These values do not indicate severe multicollinearity, although the VIF of 3.886 for authenticity indicates that the authenticity–trust relationship deserves interpretive caution. The coefficient pattern should therefore be understood as a set of unique associations conditional on the other predictors rather than as independent zero-order effects.

Table 4. Collinearity diagnostics

Model	Predictor	Tolerance	VIF
Trust	Credibility	.528	1.896
Trust	Authenticity	.547	1.829
Trust	AI awareness	.932	1.073
Purchase intention	Credibility	.527	1.896
Purchase intention	Authenticity	.257	3.886
Purchase intention	Trust	.335	2.988
Purchase intention	AI awareness	.929	1.077

5.5. Mediation Analysis: The Role of Trust

The mediation analysis evaluates whether consumer trust provides a mechanism linking AI influencer credibility to purchase intention. Table 5 reports a significant indirect effect in the simple mediation specification: the indirect effect is .328 with a 95% confidence interval of [.248, .414]. Because the confidence interval does not include zero, the simple mediation pathway is statistically significant.

However, as also reported in Table 5, the indirect effect is not robust when perceived authenticity and AI awareness are controlled. The controlled indirect effect is −.007, with a 95% confidence interval of [−.097, .068], which includes zero. Therefore, H4 should not be described as definitive

mediation. A more defensible interpretation is that the evidence for mediation is model-dependent: credibility is associated with purchase intention through trust in the simpler specification, but this pathway disappears when the theoretically relevant competing predictors are included.

This distinction is important because a significant indirect effect in a simpler model does not establish a unique mechanism once overlapping explanatory constructs are controlled. The result instead suggests that authenticity may account for a substantial part of the credibility–trust relationship.

5.6. Moderation Analysis: AI Awareness as a Boundary Condition

The moderation analysis tests whether AI awareness changes the strength of the credibility–trust relationship. According to Table 5, the credibility × AI-awareness interaction is nonsignificant (B = .055, p = .301). Thus, H6 is not supported. When perceived authenticity is additionally controlled, the interaction becomes negative and approaches conventional significance (B = −.067, p = .069), but this does not meet the conventional p < .05 criterion and should therefore be treated only as a suggestive pattern rather than evidence of moderation.

The null interaction is theoretically informative. It indicates that merely being aware that an influencer is AI-generated does not necessarily change the association between perceived credibility and trust. AI awareness may be better understood as a transparency or consumer-literacy condition than as a simple amplifier or attenuator of source credibility. This interpretation is consistent with research showing that virtual-influencer effectiveness depends on how consumers interpret authenticity, realism, and credibility rather than on artificiality alone (Koles *et al.*, 2024; Zhou *et al.*, 2026) [27, 49].

Table 5. Mediation, moderation, and integrated hypothesis evidence

Test	Estimate	95% CI / p	Interpretation
Simple indirect effect: Credibility → Trust → Purchase	.328	[.248, .414]	Significant
Controlled indirect effect	−.007	[−.097, .068]	Nonsignificant
Credibility × AI awareness → Trust	.055	p = .301	Nonsignificant
Controlled interaction	−.067	p = .069	Suggestive, not supported

5.7. Overall Hypothesis Assessment

Table 6 summarizes the hypothesis-testing decisions. H2, H3, and H5 are supported by the full multivariable results. H1 and H6 are not supported in their respective full models. H4 receives model-dependent evidence rather than robust support because the significant simple indirect effect is eliminated after theoretically relevant controls are added.

Taken together, the results describe a differentiated persuasion structure rather than a uniformly positive credibility model. As summarized in Table 6, authenticity is the dominant predictor of trust, trust is the dominant predictor of purchase intention, and credibility retains a direct association with purchase intention even though its unique association with trust becomes nonsignificant. This distinction provides the empirical basis for the discussion of responsible AI influencer communication that follows.

Table 6. Hypothesis-testing summary

Hypothesis	Relationship	Evidence	Decision
H1	Credibility → Trust	β = −.013, p = .793 in full model	Not supported
H2	Credibility → Purchase intention	β = .191, p < .001	Supported
H3	Trust → Purchase intention	β = .591, p < .001	Supported
H4	Trust mediates Credibility → Purchase	Simple indirect significant; controlled indirect nonsignificant	Model-dependent
H5	Authenticity → Trust	β = .830, p < .001	Supported
H6	Credibility × AI awareness → Trust	p = .301; controlled p = .069	Not supported

6. Discussion

The findings provide a more nuanced account of how AI influencers can shape consumer responses in social commerce. Rather than showing that credibility automatically generates trust and purchase intention, the results indicate that different constructs play different roles in the persuasion process. The strongest trust-related result is perceived authenticity (Table 2), whereas the strongest purchase-intention predictor is consumer trust (Table 3). At the same time, credibility retains a direct relationship with purchase intention but not with trust in the full trust model. This pattern supports a distinction between source evaluation, trust formation, and downstream behavioural intention.

6.1. Authenticity Is the Central Trust-Building Resource

The most consequential result is the strength of perceived authenticity as a predictor of trust. As shown in Table 2, authenticity has β = .830, substantially exceeding the standardized coefficients for credibility and AI awareness. This finding extends recent virtual-influencer research that treats authenticity as multidimensional rather than as a simple synonym for credibility. Koles *et al.* (2024) [27], for example, show that authenticity in virtual-influencer contexts can involve being true to an ideal, true to facts, and true to oneself. The present evidence suggests that these authenticity concerns may be especially consequential at the trust-formation stage.

The finding also helps explain why H1 is not supported once authenticity is entered into the trust model. A conventional source-credibility perspective would predict a positive credibility–trust association. However, in an AI-mediated context, consumers may evaluate whether a source appears genuine, transparent, and internally consistent before translating perceived expertise or credibility into trust. The result therefore suggests that responsible AI influencer design should not treat polished credibility cues as substitutes for authenticity.

6.2. Trust Is the Proximal Predictor of Purchase Intention

The second major finding is the role of trust in purchase intention. According to Table 3, trust has the largest standardized coefficient (β = .591), exceeding credibility (β = .191), AI awareness (β = .172), and authenticity (β = .061). This suggests that consumer confidence is more immediately connected to purchase intention than authenticity itself. The result is consistent with established social-commerce research in which trust reduces perceived uncertainty and facilitates online purchasing (Hajli, 2015; Pavlou, 2003) [21, 38].

Importantly, authenticity should therefore not be interpreted as irrelevant to purchase behaviour. Rather, Tables 2 and 3 suggest a sequential interpretation: authenticity is especially important for establishing trust, while trust is more directly associated with the intention to purchase. This provides a more precise theoretical account than treating every persuasion construct as an equivalent direct predictor of purchase intention.

6.3. Credibility Operates Differently at the Trust and Purchase Stages

The divergence between H1 and H2 is one of the most interesting features of the model. As reported in Table 2, credibility does not make a unique contribution to trust after authenticity and AI awareness are controlled. Yet Table 3 shows that credibility remains positively associated with purchase intention (β = .191, p < .001). One possible interpretation is that credibility functions partly as an information-quality cue at the decision stage: consumers may use perceived expertise or competence to evaluate whether a promoted product appears useful or appropriate, even when credibility alone does not determine whether the AI influencer is trusted.

This interpretation is compatible with research suggesting that virtual influencers can generate positive consumer responses when distinctive characteristics compensate for concerns surrounding trustworthiness and authenticity (Volles *et al.*, 2024) [46]. The present results add an important qualification: credibility should not be treated as a single universal mechanism. Its association may depend on the stage of the consumer decision process and on the simultaneous presence of authenticity and trust.

6.4. Why the Mediation Result Is Model-Dependent

The mediation analysis provides a useful warning against overly strong mechanism claims. The simple indirect effect is significant, but the controlled indirect effect is not. Therefore, the evidence does not justify claiming that credibility reliably produces purchase intention through trust under all model specifications. Instead, the disappearance of the indirect effect after adding authenticity and AI awareness indicates that the credibility–trust–purchase pathway overlaps with other explanatory processes.

From a theoretical perspective, this result strengthens rather than weakens the contribution of the study. It shows that credibility and authenticity should not be treated as interchangeable source evaluations. The evidence points toward a more conditional model in which authenticity is particularly important for trust formation, while credibility may retain a more direct informational role in purchase evaluation.

6.5. AI Awareness Is Not Equivalent to Transparency

The nonsignificant moderation result in Table 5 indicates that AI awareness does not significantly alter the credibility–trust relationship in the present sample. This does not mean that disclosure or transparency is unimportant. Instead, awareness of artificiality and meaningful transparency are conceptually different. A consumer may know that an influencer is AI-generated without knowing who controls the account, whether product claims are independently verified, how commercial content is generated, or whether the influencer simulates personal experience.

This distinction is particularly relevant to responsible marketing. Recent research shows that virtual influencers create an authenticity challenge precisely because artificial sources can appear credible while lacking human experience (Zhou *et al.*, 2026) [49]. Consequently, responsible communication should move beyond a minimal "AI-generated" label toward disclosures that are understandable, prominent, and relevant to the consumer's decision.

6.6. Implications for Social Marketing and Consumer Welfare

The findings also extend beyond commercial social commerce. AI influencers may be used to promote health, environmental protection, financial literacy, public-interest information, and other socially desirable behaviours. In these contexts, trust becomes particularly important because inaccurate or simulated expertise can produce welfare costs. Consumer-welfare concerns extend beyond the accuracy of claims to how AI influencer platforms collect and use behavioural data to personalize persuasion, an issue distinct from but related to authenticity and disclosure (Liyanaarachchi *et al.*, 2024; Zhang *et al.*, 2016) [30, 48]. The strong relationship between trust and purchase intention in Table 3 suggests a broader principle: persuasive effectiveness should be evaluated together with the quality and verifiability of the information that generates consumer confidence.

7. Practical Implementation and Managerial Implications

The empirical pattern can be translated into an implementation framework for firms, agencies, platforms, and social-marketing organizations using AI influencers. The central implication is that AI influencer governance should be organized around the sequence of authenticity, trust, and behavioural response rather than around visibility or credibility alone.

7.1. Implementation Principle 1: Design for Verifiable Authenticity

Because Table 2 identifies authenticity as the strongest predictor of trust, organizations should operationalize authenticity through verifiable communication rather than through simulated human experience. AI influencers should distinguish clearly between generated content and genuine human experience, avoid fabricated personal stories, and provide evidence for product or behavioural claims. Where a claim depends on expert knowledge, the underlying human or institutional source should be identifiable.

7.2. Implementation Principle 2: Build Trust Before Optimizing Conversion

Table 3 shows that trust is the strongest predictor of purchase intention. Campaign managers should therefore evaluate

trust-building metrics before optimizing conversion metrics. Pre-launch testing can assess whether consumers perceive claims as reliable, whether disclosures are understood, and whether the influencer's recommendations appear consistent with available evidence. A campaign that generates clicks without justified trust should not be treated as a successful responsible-communication outcome.

7.3. Implementation Principle 3: Use Credibility as an Information-Quality Cue

The positive direct relationship between credibility and purchase intention indicates that credibility remains useful, but it should be operationalized carefully. Firms should prioritize demonstrable expertise, accurate product information, source citations, and transparent commercial relationships rather than relying only on polished visual realism or authoritative language. This approach reduces the risk that artificial presentation quality is mistaken for genuine expertise.

7.4. Implementation Principle 4: Make AI Disclosure Meaningful

The nonsignificant moderation result means that simply increasing awareness of AI origin is unlikely, by itself, to guarantee a different trust response. Disclosure should therefore be expanded from a binary label into meaningful transparency. Depending on the context, this can include the fact that the influencer is AI-generated, who operates the account, whether content is sponsored, whether claims have been verified, and whether the influencer is representing lived experience that it cannot actually possess.

7.5. Implementation Principle 5: Introduce a Responsible AI Influencer Decision Gate

A practical governance process can use four decision gates. First, assess whether the communication task requires genuine lived experience; if so, a human or human–AI hybrid communicator may be preferable. Second, verify the factual basis of substantive claims. Third, test whether consumers understand the AI origin and commercial purpose of the communication. Fourth, evaluate trust and consumer welfare outcomes alongside engagement and conversion. This sequence aligns campaign implementation with the empirical finding that trust, rather than attention alone, is the critical downstream mechanism.

7.6. Implementation Principle 6: Protect Higher-Risk Consumer Decisions

The implementation framework should be stricter in high-consequence categories such as health, finance, safety, and other domains in which misleading confidence can cause substantial harm. In such settings, organizations should require stronger evidence, clearer disclosure, human oversight, and escalation procedures before AI influencer content is published. The objective is not simply to make AI influencers more persuasive, but to ensure that persuasive effects are grounded in accurate and appropriately qualified information.

8. Limitations and Future Research

First, the convenience sample of 283 respondents, drawn from a single city (Chongqing, China) and a bounded age range (18 to 40 years), limits external validity. The findings should not be generalized to other regions, cultural contexts, or age groups without replication. Future research should replicate the model with probability-based or quota-based samples across different demographic and cultural settings, including cross-national comparisons, given that authenticity and trust judgments may themselves be culturally contingent.

Second, the cross-sectional design limits causal inference. The regression and mediation results identify statistical associations consistent with the proposed framework but cannot establish temporal causality. Experiments, longitudinal studies, and field studies could test whether changes in authenticity, disclosure, or credibility actually produce changes in trust and behaviour.

Third, each focal construct was measured with only two items. This creates a measurement constraint and limits assessment of construct dimensionality and discriminant validity. The original respondent-level dataset was not available for the present revision, so CFA, composite reliability, AVE, HTMT, and latent-variable model-fit statistics cannot be responsibly added. Future research should use multi-item validated scales and conduct CFA and measurement-invariance testing before estimating a more complete structural model.

Fourth, the study relies on self-reported purchase intention rather than observed behaviour. Future studies should incorporate click-through rates, product-page visits, actual purchases, repeat purchases, or experimentally observed choice behaviour to determine whether the trust pathway extends beyond stated intentions.

Fifth, the model does not systematically distinguish platforms, product categories, or types of AI-generated influencer. Future work should test whether human-like versus cartoon-like presentation (Franke and Groeppel-Klein, 2024) [18] — including the uncanny-valley effects long documented for near-human but imperfect artificial agents (Mori, 2012) [34] — platform affordances, product risk, and degree of behavioural and form realism (Kim *et al.*, 2024) [26] change the observed relationships.

Finally, AI awareness should be distinguished from disclosure quality, AI literacy, perceived control, and perceived manipulation. Future studies should test these variables separately and compare competing models in which transparency, authenticity, trust, and credibility occupy different positions in the causal sequence.

A Proposed Experimental Extension (Study 2)

The single-study, cross-sectional design constrains all causal language above. Section 9 specifies a pre-registered experimental design intended to test, under random assignment, whether authenticity's dominance over credibility as a predictor of trust replicates causally. No data collection for that design has occurred; it is presented as a concrete next step rather than as a completed study.

9. Study 2: Proposed Experimental Method

No data have been collected for the study described in this section. It is reported here, ahead of data collection, as a fully specified and pre-registerable method — consistent with the paper's broader emphasis on evidential transparency (Section 4.5) — so that the design, measures, and analysis plan are fixed before any results exist. No findings, statistics, or outcomes for Study 2 are reported anywhere in this manuscript.

9.1. Purpose and Design

Study 1 shows that perceived authenticity is a stronger correlate of consumer trust than AI influencer credibility, and that this pattern does not survive as a mediated credibility-to-purchase pathway once authenticity and AI awareness are controlled. Because Study 1 is cross-sectional and self-report, it cannot establish that authenticity's association with trust is causal, nor rule out that the pattern reflects shared method variance between the two source-evaluation measures. Study 2 is designed to address both limitations directly. It uses a 2 (credibility cue: high vs. low) × 2 (authenticity cue: high vs. low) between-subjects factorial design. AI origin is disclosed to all participants and held constant across conditions, consistent with the paper's focus on persuasion by a communicator known to be artificial rather than a comparison between human and AI sources.

9.2. Participants

Participants would be recruited from a quality-controlled online panel (e.g., Prolific), screened for English fluency and prior familiarity with social media influencer content, with attention-check and speeding exclusions specified in advance. A target of approximately 160 valid respondents per cell (640 total) is proposed, based on a power analysis (G*Power or equivalent) for detecting a small-to-medium interaction effect ($f = 0.15$, per Cohen's, 1988, conventions) [10] at 80–90% power and $\alpha = .05$ in a 2 × 2 between-subjects ANOVA; this figure should be finalized against the pretested effect size of the manipulations (Section 9.3) rather than treated as fixed in advance.

9.3. Stimuli and Manipulations

The stimulus is a single fictional AI-generated influencer profile in a short-form social media format (image, bio, and one product-recommendation post), held constant in visual presentation across all four cells. Only the caption and bio text vary by condition. The credibility manipulation varies the presence of specific, verifiable expertise claims and sourcing (high) versus generic, unsupported enthusiasm (low). The authenticity manipulation varies whether the copy is transparent and consistent about what an AI persona can and cannot claim to have experienced (high) versus whether it uses fabricated first-person sensory or experiential claims typical of human-influencer copy (low). Both manipulations would be pretested independently (target $n \approx 40–60$, drawn from a separate sample) to confirm that each moves its intended construct without materially shifting the other, before the main study is fielded.

9.4. Measures

Perceived credibility and perceived authenticity are measured as manipulation checks using established multi-item scales (credibility: Ohanian, 1990; authenticity: Morhart *et al.*, 2015, adapted to an influencer-endorsement context) [35, 36]. Consumer trust is measured with a validated multi-item scale (e.g., the trusting-beliefs subscale in McKnight *et al.*, 2002) [33], addressing the two-item measurement constraint noted for Study 1. Purchase intention is measured with a standard multi-item purchase-intention scale, to be confirmed against its original source before fielding. Perceived manipulative intent (adapted from Campbell, 1995) [7] is included as a covariate to test whether any effect of the authenticity manipulation on trust survives controlling for the rival explanation that it operates only by reducing perceived manipulation.

9.5. Procedure

Participants would be randomly assigned to one of the four conditions, view the stimulus, complete the manipulation-check and outcome measures, pass an attention check, and complete brief demographic items before debriefing. Exclusion criteria (failed attention check, failed manipulation check on both dimensions, completion time below a pre-set floor) are specified in advance rather than applied post hoc.

9.6. Planned Analysis

The planned analysis is a 2 × 2 ANOVA on consumer trust and on purchase intention, followed by a formal contrast comparing the standardized effect size of the authenticity manipulation against that of the credibility manipulation on trust — directly testing, under experimental control, whether the asymmetry observed in Study 1 (H1 unsupported, H5 supported) replicates causally. Mediation of the authenticity manipulation's effect on purchase intention through trust would be tested with bootstrapped indirect effects (e.g., Hayes' PROCESS Model 4 or an equivalent structural approach), and the authenticity-to-trust effect would be re-estimated controlling for perceived manipulative intent to assess whether it survives this rival-mechanism check.

10. Conclusion

This study examined how AI influencer credibility, perceived authenticity, consumer trust, and AI awareness relate to purchase intention in social commerce. The evidence points to a differentiated persuasion structure. According to Table 2, authenticity is the dominant predictor of trust, while Table 3 shows that trust is the strongest predictor of purchase intention. Credibility also retains a significant direct association with purchase intention, but it does not uniquely predict trust after authenticity is controlled. The mediation evidence is model-dependent, and the proposed moderating role of AI awareness is not supported.

The central contribution is therefore not that AI influencers are inherently effective or ineffective. Rather, effectiveness depends on how consumers interpret authenticity, trust, and information quality. For responsible AI-mediated persuasion, organizations should prioritize verifiable authenticity, justified trust, meaningful disclosure, and consumer welfare. These principles provide a practical basis for designing AI influencer communication that is not only persuasive, but also transparent and responsible.

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