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AIGC Advertising Content and Consumer Responses in Social Media Communication: The Mediating Roles of Perceived Authenticity and Consumer Trust

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Abstract

Purpose: This study examines how consumers' evaluations of artificial intelligence-generated content (AIGC) advertising quality in social media are associated with consumer responses through perceived authenticity and consumer trust. The Persuasion Knowledge Model (PKM) explains how consumers interpret AI-related production and disclosure cues, while Source Credibility Theory explains how authenticity judgments are associated with trust.

Method: A cross-sectional survey of 412 active social media consumers was analysed using partial least squares structural equation modelling (PLS-SEM). Eligibility screening required respondents to be at least 18 years old, to have used social media in the previous three months, and to have encountered social media advertising during that period. The assessment covered measurement quality, structural associations, and the serial indirect pathway. Common-method concerns were addressed procedurally and assessed statistically using Harman's single-factor diagnostic and full-collinearity variance inflation factors (VIFs).

Findings: AIGC advertising content quality was positively associated with perceived authenticity and consumer responses. Perceived authenticity was positively associated with consumer trust, which was positively associated with consumer responses. The serial indirect association through perceived authenticity and consumer trust was also significant.

Originality/Implications: The study conceptualises AIGC as both a production technology and a persuasion cue and separates the measured content-quality construct from AI transparency/disclosure as a contextual cue. It shows that favourable content evaluation alone is insufficient: clear disclosure, human oversight, brand-voice consistency, and claim verification remain central to preserving authenticity and trust.

Keywords: AIGC advertising content quality, AI transparency/disclosure, social media communication, Persuasion Knowledge Model, Source Credibility Theory, perceived authenticity, consumer trust, consumer responses, PLS-SEM

1. Introduction

Generative artificial intelligence enables brands to produce and adapt social media advertising at unprecedented speed. It supports text, images, videos, captions, personalisation, and creative testing, making AIGC an emerging marketing infrastructure rather than a narrow production tool (Davenport et al., 2020; Huang & Rust, 2021). However, scalable automation creates a consumer-side problem: audiences may question whether AI-assisted messages are sincere, transparent, and accountable, particularly when content imitates human creativity or emotion (Brüns & Meißner, 2024; Kirkby et al., 2023).

This tension is pronounced in social media feeds, where personal posts, influencer endorsements, sponsored placements, and algorithmically recommended messages appear together. Consumers often infer advertising intent, authorship, and credibility from disclosure language, visual realism, brand consistency, platform fit, and perceived relevance (Boerman et al., 2017; Eisend et al., 2020). AIGC adds production cues to this persuasion episode because consumers may evaluate not only what a message claims, but also how and why it was created.

Prior research offers competing expectations. AI can improve informativeness, relevance, and creative variation, but consumers may resist machine involvement in communication perceived to require empathy, identity, or human judgment (Castelo et al., 2019; Puntoni et al., 2021). Research on AIGC disclosure and brand voice also indicates that AI involvement does not produce a uniformly positive or negative response; its meaning depends on transparency, task fit, and perceived authenticity (Baek et al., 2024; Brüns & Meißner, 2024).

Recent AI-marketing research indicates that consumer responses depend on agency framing, task fit, and perceived control rather than an invariant preference for human or algorithmic sources (Araujo, 2018; Dietvorst et al., 2018; Dwivedi et al., 2023; Logg et al., 2019; Mariani et al., 2022; Vlačić et al., 2021). Machine authorship can coincide with efficiency and novelty while also being associated with lower credibility when communication appears to simulate human judgment or emotion without sufficient accountability (Hohenstein et al., 2023; Luo et al., 2019; Waddell, 2018). This mixed evidence makes an associative, cue-based explanation more appropriate than a deterministic claim that AIGC itself improves or harms consumer response.

The Persuasion Knowledge Model (PKM) is the primary theoretical lens. It proposes that consumers use knowledge of persuasion agents, tactics, and motives to interpret marketing attempts (Friestad & Wright, 1994). In AIGC advertising, production and disclosure cues can therefore activate inferences about automated persuasion and brand sincerity. Source Credibility Theory complements PKM by explaining why evaluations of expertise, reliability, and trustworthiness shape acceptance of the message (Lou & Yuan, 2019; Ohanian, 1990).

This study models AIGC advertising content quality, perceived authenticity, and consumer trust as sequentially related constructs associated with consumer responses. The measured AIGC construct captures informativeness, creativity, visual attractiveness, personal relevance, and product-benefit clarity. AI transparency/disclosure is conceptually separated as a production-related persuasion cue rather than being included in the content-quality scale. Perceived authenticity captures whether the message appears genuine, sincere, realistic, and consistent with the brand. Consumer trust reflects confidence in the honesty and reliability of the brand and its communication. Consumer responses include favourable attitudes, engagement, information-search intention, purchase consideration, and electronic word-of-mouth.

The study addresses three connected gaps. Existing AI marketing research has emphasised organisational applications more than consumer interpretation; disclosure research has focused mainly on sponsorship rather than AI-assisted production; and source-credibility research has rarely examined a distributed human-AI source. By integrating PKM and Source Credibility Theory, the study examines how AIGC content-quality evaluations are associated with consumer responses through authenticity and trust while maintaining the claim boundary of a cross-sectional design.

The theoretical contribution lies in a division of explanatory labour. PKM accounts for how production and disclosure cues activate inferences about persuasive intent, fairness, and brand accountability, whereas Source Credibility Theory accounts for how authenticity judgments align with perceived trustworthiness and response (Friestad & Wright, 1994; Hovland & Weiss, 1951; Ohanian, 1990). This integration treats the effective source of AIGC advertising as distributed across the brand, human reviewers, AI systems, and the platform rather than as a single human communicator.

2. Literature Review

Critical synthesis: AI agency, disclosure, authenticity, and credibility

Disclosure scholarship shows that recognition of persuasive intent and evaluation of the message are distinct. Disclosures may improve recognition of commercial or automated intent while also activating scepticism; associations vary with wording, position, similarity to ordinary posts, and perceived fairness (Beckert et al., 2021; Campbell & Grimm, 2019; De Veirman & Hudders, 2020; Evans et al., 2017; Naderer et al., 2021; van Reijmersdal et al., 2016; Wojdynski & Evans, 2016). Accordingly, AI transparency/disclosure should not be collapsed into the measured content-quality construct.

Authenticity and source credibility are related but distinct. Authenticity concerns perceived genuineness, sincerity, continuity, and identity consistency (Duffek et al., 2025; Moulard et al., 2016; Napoli et al., 2016; Yang & Battocchio, 2021), whereas source credibility concerns expertise, reliability, and trustworthiness (Hovland & Weiss, 1951; Ohanian, 1990). Social-media research further indicates that source fit, message value, parasocial identification, and creator-brand alignment are associated with trust and response (De Veirman et al., 2017; Hudders et al., 2021; Ki & Kim, 2019; Kim & Kim, 2021; Lou & Xie, 2021; Pan et al., 2025; Schouten et al., 2020; Ünalmış et al., 2024).

AIGC advertising content quality and perceived authenticity

AIGC advertising content quality may be positively associated with authenticity when it provides relevant, informative, creative, visually attractive, and platform-appropriate communication. Consumers can interpret such content as responsive and brand-consistent, particularly when the surrounding production context remains transparent and human accountability is visible (Davenport et al., 2020; Kshetri et al., 2024). In this study, the measured predictor therefore captures consumer evaluation of content quality; AI transparency/disclosure is discussed separately as a contextual PKM cue.

The opposite association is also plausible because machine-produced communication can be linked to artificiality or perceived loss of human creativity. Evidence indicates that generative AI use may coincide with lower brand authenticity, although disclosure and brand voice condition this relationship (Brüns & Meißner, 2024; Kirkby et al., 2023). PKM suggests that consumers evaluate whether AI supports legitimate communication or conceals automated persuasion. More favourable evaluations of AIGC content quality are therefore expected to be associated with stronger authenticity judgments, without implying that AI use itself causes authenticity.

H1. AIGC advertising content quality is positively associated with perceived authenticity.

Perceived authenticity and consumer trust

Perceived authenticity is expected to be positively associated with consumer trust because authentic communication signals sincerity, continuity, and integrity. Brand-authenticity research links these perceptions with credibility and trust, while social media research shows that audiences respond more favourably when commercial communication remains consistent with the communicator's identity (Fritz et al., 2017; Portal et al., 2019).

This relationship is especially important for AIGC because consumers may be uncertain about authorship, emotional representation, and accountability. Transparent AI use can signal responsible innovation, whereas undisclosed synthetic communication can create a credibility violation. Authenticity therefore provides a relational cue associated with judgments about whether the brand's AI-assisted message is trustworthy (Choung et al., 2023; Glikson & Woolley, 2020; Lou & Yuan, 2019).

H2. Perceived authenticity is positively associated with consumer trust.

Consumer trust and consumer responses

Consumer trust is associated with lower uncertainty and greater willingness to rely on advertising claims. In social media environments, trusted branded content is more likely to coincide with favourable attitudes, engagement, purchase consideration, and recommendation (Lou & Yuan, 2019; Weismueller et al., 2020). Trust is particularly relevant for AIGC because realistic synthetic content can appear persuasive even when consumers cannot immediately verify its origin or accuracy.

Source Credibility Theory proposes that messages from sources perceived as reliable and trustworthy are more likely to be accepted. PKM adds that recognised persuasion does not necessarily produce rejection; consumers may respond favourably when a persuasive attempt appears fair and credible. Consumer trust should therefore be positively associated with favourable responses to AIGC communication (Eisend et al., 2020; Sokolova & Kefi, 2020).

H3. Consumer trust is positively associated with consumer responses.

AIGC advertising content quality and consumer responses

AIGC advertising content quality may also be directly associated with consumer responses. Social media messages are often processed quickly, and informative, entertaining, visually attractive, or personally relevant content can coincide with clicking, saving, sharing, or further search before a fully developed trust judgment is reported (Campbell et al., 2020; Voorveld et al., 2018).

This direct association is not assumed to be unconditional. AI-related cues can activate scepticism when content appears generic, emotionally hollow, or insufficiently accountable. The present hypothesis therefore concerns favourable evaluations of usefulness, creativity, visual appeal, personal relevance, and platform fit; authenticity and trust are tested separately to represent the relational pathway, while AI transparency/disclosure remains a contextual cue (Kirkby et al., 2023; Puntoni et al., 2021).

H4. AIGC advertising content quality is positively associated with consumer responses.

Serial mediation of perceived authenticity and consumer trust

The central mechanism is represented as a serial indirect pathway. AIGC content-quality evaluations are associated with perceived authenticity; authenticity judgments are associated with consumer trust; and trust is associated with consumer responses. This ordering is theory-guided and statistical rather than evidence of temporal or causal sequencing in the cross-sectional data. PKM explains the interpretation of production and persuasion cues, whereas Source Credibility Theory explains the credibility logic linking authenticity, trust, and response.

This serial ordering is consistent with evidence that authenticity is associated with trust and that trust is associated with social media engagement and purchase intention (Audrezet et al., 2020; Lou & Yuan, 2019). It also avoids treating AI disclosure as a sufficient explanation by itself. Disclosure can activate persuasion knowledge, but its downstream meaning is associated with whether consumers view the brand's use of AI as transparent, responsible, and consistent with its identity.

H5. The association between AIGC advertising content quality and consumer responses includes a significant serial indirect pathway through perceived authenticity and consumer trust.

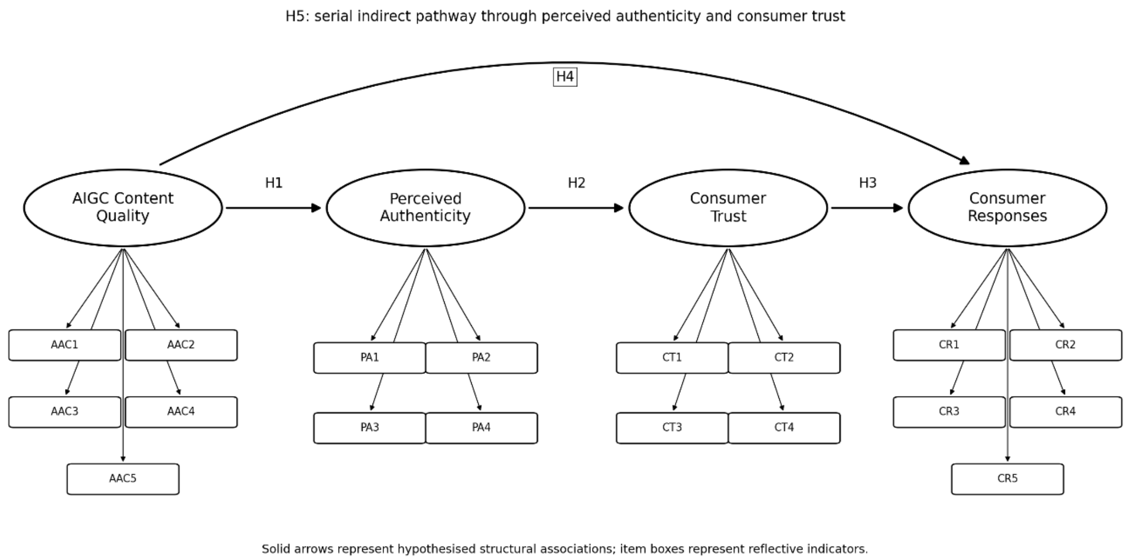

Figure 1. Theoretical and measurement structure of the PLS-SEM model

Note. The empirical predictor is AIGC advertising content quality. AI transparency/disclosure is conceptually distinguished as a contextual persuasion cue and is not estimated as a separate latent construct in the reported model.

3. Methodology

The study used a cross-sectional quantitative survey of active social media consumers who had encountered brand advertising disclosed, suspected, or described as AIGC-supported. Eligibility was determined through prespecified screening criteria: respondents had to be at least 18 years old, have used social media during the previous three months, and have encountered social media advertising during that period. After eligibility and data-quality screening, 412 complete cases were retained. The obtained sample is not presented as a probability sample of all social media consumers; inference is limited to the respondents represented in the analytic sample.

The questionnaire began with screening questions and then asked respondents to evaluate either a recently encountered AIGC-supported social media advertisement or the study scenario. The four core constructs were measured with multi-item five-point Likert scales (1 = strongly disagree; 5 = strongly agree). The empirical AIGC predictor measured content quality through informativeness, creativity, visual attractiveness, personalisation, and product-benefit clarity. AI transparency/disclosure was treated as a conceptually separate contextual cue and was not included in the AIGC content-quality score. All retained items were positively keyed, none was reverse-coded, and wording was contextualised to AIGC social-media advertising. Appendix A provides the exact retained item wording and adaptation notes.

PLS-SEM was used because the study examines latent constructs and a serial indirect mechanism within a prediction-oriented model. Following established reporting guidance, the analysis assessed indicator loadings, Cronbach's alpha, rho_A, composite reliability, average variance extracted, HTMT, structural paths, effect sizes, explained variance, predictive relevance, and bootstrapped indirect associations (Benitez et al., 2020; Hair et al., 2019, 2020, 2022; Henseler et al., 2016; Sarstedt et al., 2022; Voorhees et al., 2016).

Common method concerns were addressed procedurally through anonymity, clear wording, separated construct sections, and reduced evaluation apprehension. Statistical assessment was also conducted using Harman's single-factor diagnostic and full-collinearity variance inflation factors (VIFs) (Kock, 2017). These diagnostics were interpreted as supplementary checks rather than proof that common method bias was absent. Because the data are cross-sectional and self-reported, the findings are interpreted as theory-guided associations rather than definitive causal effects.

The study was conducted in accordance with the ethical principles outlined in the Declaration of Helsinki. All participants provided informed consent prior to participating in the survey. The survey was completely anonymous, and no personally identifiable data were collected, ensuring the confidentiality and privacy of all respondents.

Table 1. Questionnaire Profile

Construct / analytical role	Item pool and retained codes	Operationalisation, adaptation, and source basis
AIGC advertising content quality (measured predictor)	Six-item pool; AAC1-AAC5 retained	Five positively keyed items on informativeness, creativity, visual appeal, personal relevance, and product-benefit clarity. Contextualised to AIGC social-media advertising; no retained item was reverse-coded. Adapted from Campbell et al. (2020), Davenport et al. (2020), and Lou and Yuan (2019).
Perceived authenticity (mediator 1)	Five-item pool; PA1-PA4 retained	Items assess genuineness, sincerity, brand consistency, and realism. Contextualised to AIGC advertising; no retained item was reverse-coded. Adapted from Fritz et al. (2017), Moulard et al. (2016), Napoli et al. (2016), and Portal et al. (2019).
Consumer trust (mediator 2)	Five-item pool; CT1-CT4 retained	Items assess confidence in product information, brand confidence, claim dependability, and willingness to rely on the message. Contextualised to AIGC advertising; no retained item was reverse-coded. Adapted from Choung et al. (2023), Glikson and Woolley (2020), and Lou and Yuan (2019).
Consumer responses (outcome)	Six-item pool; CR1-CR5 retained	Items assess click, interaction, follow, purchase-consideration, and recommendation intentions. Contextualised to AIGC advertising; no retained item was reverse-coded. Adapted from Sokolova and Kefi (2020), Voorveld et al. (2018), and Weismueller et al. (2020).
AI transparency/disclosure (contextual PKM cue; not a latent construct)	Not included in the retained structural measure	Conceptually separated from content quality. It concerns disclosure of AI involvement and visible human/brand accountability. It was not assigned a latent-variable score or structural coefficient in the reported model.

Appendix A reports the exact wording of the 18 retained indicators and the adaptation/coding notes. The reported structural estimates apply to the content-quality construct; AI transparency/disclosure is retained as a separate theoretical and contextual cue.

Table 2. Empirical Sample Profile

Profile dimension	Category	Frequency	Percentage
Gender	Female	218	52.9%
Gender	Male	182	44.2%
Gender	Prefer not to say	12	2.9%
Age Group	18-24	168	40.8%
Age Group	25-34	139	33.7%
Age Group	35-44	73	17.7%
Age Group	45+	32	7.8%
Platform	Facebook	58	14.1%
Platform	Instagram	91	22.1%
Platform	Other	32	7.8%
Platform	TikTok/Douyin	110	26.7%
Platform	Xiaohongshu/RED	51	12.4%
Platform	YouTube	70	17.0%

4. Results

The PLS-SEM results are reported in evidence-chain order: sample profile, common-method diagnostics, measurement quality, discriminant validity, structural associations, explanatory and predictive assessment, and bootstrapped hypothesis tests. The estimated model contains AIGC advertising content quality, perceived authenticity, consumer trust, and consumer responses.

The final sample comprised 412 valid cases. Respondents were concentrated in the 18-24 and 25-34 age groups and represented TikTok/Douyin, Instagram, YouTube, Facebook, Xiaohongshu/RED, and other platforms. Table 2 summarises the sample profile.

Common-method variance was assessed statistically using Harman's single-factor diagnostic and full-collinearity VIFs for AIGC content quality, perceived authenticity, consumer trust, and consumer responses. These statistical diagnostics were considered alongside the procedural safeguards described in the Methodology and were treated as sensitivity checks rather than definitive evidence that common method bias was absent.

Table 3. Construct Reliability and Convergent Validity

Construct	Dijkstra-Henseler's rho (rhoA)	Joreskog's rho (rhoC)	Cronbach's alpha	AVE
AIGC advertising content quality	0.888	0.898	0.858	0.638
Perceived authenticity	0.886	0.900	0.851	0.693
Consumer trust	0.910	0.919	0.882	0.739
Consumer responses	0.874	0.887	0.841	0.612

Table 3 shows acceptable internal consistency and convergent validity. Cronbach's alpha ranged from 0.841 to 0.882, composite reliability from 0.887 to 0.919, rho_A from 0.874 to 0.910, and AVE from 0.612 to 0.739. All values met commonly applied PLS-SEM guidelines (Hair et al., 2019, 2020, 2022).

Table 4. Measurement Item Loading Statistics

Indicator	AIGC content quality	Perceived authenticity	Consumer trust	Consumer responses
AAC1	0.805			
AAC2	0.777			
AAC3	0.825			
AAC4	0.811			
AAC5	0.775			
PA1		0.836		
PA2		0.842		
PA3		0.837		
PA4		0.815		
CT1			0.878	
CT2			0.869	
CT3			0.846	
CT4			0.845	
CR1				0.826
CR2				0.814
CR3				0.781
CR4				0.736
CR5				0.751

As shown in Table 4, retained loadings ranged from 0.775 to 0.825 for AIGC advertising content quality, 0.815 to 0.842 for perceived authenticity, 0.845 to 0.878 for consumer trust, and 0.736 to 0.826 for consumer responses. The indicators therefore provided adequate representation of their intended constructs.

Table 5. Discriminant Validity: Heterotrait-Monotrait Ratio of Correlations (HTMT)

Construct	1	2	3	4
AIGC content quality				
Perceived authenticity	0.762			
Consumer trust	0.495	0.683		
Consumer responses	0.555	0.556	0.659	

All HTMT values in Table 5 were below the conservative 0.85 criterion. The highest value, between AIGC advertising content quality and perceived authenticity, was 0.762. The four constructs were therefore empirically distinguishable despite their theoretically related roles.

Table 6. Structural Path Overview

Path	Beta	Indirect effects	Total effect	Cohen's f2
AIGC content quality -> Perceived authenticity	0.652		0.652	0.739
Perceived authenticity -> Consumer trust	0.593		0.593	0.541
Consumer trust -> Consumer responses	0.445		0.445	0.262
AIGC content quality -> Consumer responses	0.280	0.172	0.452	0.104

Table 6 indicates positive associations from AIGC advertising content quality to perceived authenticity (beta = 0.652), perceived authenticity to consumer trust (beta = 0.593), consumer trust to consumer responses (beta = 0.445), and AIGC advertising content quality to consumer responses (beta = 0.280). The serial indirect association was 0.172, while the total association between AIGC content quality and consumer responses was 0.452.

Table 7. Explanatory and Predictive Assessment

Construct	Coefficient of determination (R2)	Adjusted R2	Q2predict	RMSE	MAE
Perceived authenticity	0.425	0.423	0.420	0.762	0.597
Consumer trust	0.351	0.350	0.346	0.809	0.646
Consumer responses	0.384	0.381	0.376	0.790	0.630
Overall composite model	SRMR = 0.056	NFI = 0.918	d_ULS = 0.643	d_G = 0.218	

The model explained 42.5% of the variance in perceived authenticity, 35.1% in consumer trust, and 38.4% in consumer responses (Table 7). Positive Q2predict values indicated predictive relevance within the reported PLS-SEM assessment; they are not interpreted as guaranteed out-of-sample forecasting performance.

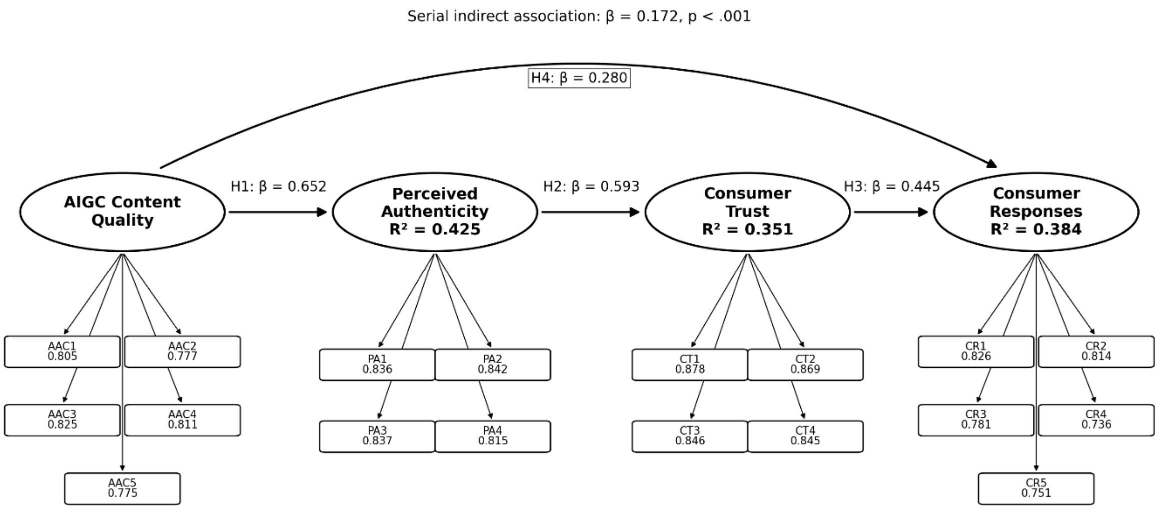

Figure 2. PLS-SEM measurement and structural model estimates

Figure 2 presents the reported structural coefficients, R-square values, and retained outer loadings from the completed PLS-SEM analysis. The estimates apply to AIGC content-quality evaluations; AI transparency/disclosure was not estimated as a separate construct. The direct association between AIGC content quality and consumer responses remained significant alongside the serial indirect association, a pattern consistent with partial statistical mediation but not with temporal causality.

Table 8. Bootstrapped Path Analysis

Hypothesis / Path	Original Sample	STDEV	T Statistics	P Values
H1: AACQ → PA	0.652	0.038	17.190	p < .001
H2: PA → CT	0.593	0.036	16.529	p < .001
H3: CT → CR	0.445	0.042	10.603	p < .001
H4: AACQ → CR	0.280	0.041	6.835	p < .001
H5: AACQ → PA → CT → CR	0.172	0.023	7.626	p < .001

Bootstrapping supported all hypotheses (Table 8). H1 (beta = 0.652, t = 17.190), H2 (beta = 0.593, t = 16.529), H3 (beta = 0.445, t = 10.603), and H4 (beta = 0.280, t = 6.835) were significant at $p < .001$. The serial indirect association in H5 was also significant (beta = 0.172, t = 7.626, $p < .001$). These results support the serial indirect pattern without implying temporal or causal ordering beyond the cross-sectional design.

5. Discussion

The findings show that evaluations of AIGC advertising content quality are associated with consumer responses both directly and through perceived authenticity and consumer trust. The model therefore shifts attention from the fact of AI use to how consumers interpret message quality and the relational meaning of AI-assisted communication. AI transparency/disclosure remains a separate contextual cue rather than a component of the measured content-quality construct. This pattern is consistent with PKM and Source Credibility Theory, which respectively explain persuasion-cue interpretation and credibility-based response (Friestad & Wright, 1994; Lou & Yuan, 2019).

H1 indicates that more favourable evaluations of AIGC content quality were associated with stronger perceived authenticity. This qualifies evidence that generative AI use may coincide with lower brand authenticity: the issue is not machine assistance alone but whether the resulting message appears generic, inconsistent, or insufficiently accountable (Brüns & Meißner, 2024; Kirkby et al., 2023). From a PKM perspective, content-quality evaluations operate alongside, rather than replace, inferences prompted by disclosure and production cues.

H2 and H3 clarify the relational associations. Perceived authenticity was positively associated with consumer trust, and trust was positively associated with consumer responses. In an AIGC setting, authenticity can signal that the brand remains accountable for the message despite technological mediation. Trust is correspondingly associated with lower uncertainty and more favourable engagement, information-search, purchase-consideration, and recommendation intentions (Choung et al., 2023; Glikson & Woolley, 2020; Portal et al., 2019).

H4 shows that content-quality evaluations also retained a direct association with consumer responses. Useful, visually attractive, and platform-appropriate messages may coincide with immediate interaction even before deeper relational evaluations are reported. However, this path should not be interpreted as evidence that surface-level quality replaces authenticity. Attention associated with creative automation may be fragile when brand voice, disclosure, or claim integrity is weak (Puntoni et al., 2021; Voorveld et al., 2018).

H5 provides the central theoretical contribution. The significant serial indirect association aligns with a sequence in which content-quality evaluations covary with perceived authenticity, authenticity covaries with trust, and trust covaries with consumer responses. The cross-sectional data do not establish that these judgments occurred in that temporal order. PKM explains interpretation of AI production and disclosure cues, while Source Credibility Theory explains the credibility logic linking authenticity, trust, and response. The two theories therefore have a clear division of labour rather than serving as parallel labels.

The results also suggest that AI disclosure should be treated as part of a broader authenticity strategy rather than as a component of content quality. A label may activate persuasion knowledge but does not by itself explain what AI produced, whether humans reviewed the content, or whether claims were verified. More favourable trust judgments are likely when disclosure is clear, brand voice remains coherent, and human accountability is visible (Baek et al., 2024; Van Reijmersdal et al., 2023).

For practice, the findings support a three-stage governance process: proportionate disclosure of material AI involvement, human review of factual claims and brand voice, and documented verification of provenance and product claims. Performance dashboards should separate attention metrics, such as clicks and views, from credibility metrics, such as perceived authenticity, trust, complaints, and correction rates. This distinction reduces the risk of treating high short-term engagement as evidence of durable consumer confidence (Grewal et al., 2025; Kumar et al., 2025).

6. Conclusion

This study estimated a serial indirect model linking AIGC advertising content quality with consumer responses through perceived authenticity and consumer trust. All five hypotheses were supported as associations. AIGC content-quality evaluations were positively associated with authenticity and consumer responses; authenticity was positively associated with trust; trust was positively associated with consumer responses; and the serial indirect association was significant.

The central conclusion is that AIGC advertising is a credibility-sensitive communication practice rather than merely a creative production technique. Brands may benefit from AI-assisted relevance and variation, but favourable consumer responses are associated with transparent use, coherent brand voice, human oversight, and claim verification. Because the design is cross-sectional, these findings represent theory-guided associations rather than definitive causal or temporal effects.

Theoretical and Practical Implications

Theoretically, the study extends PKM by treating AI involvement as production-related persuasion knowledge while explicitly separating content-quality evaluation from transparency/disclosure. Consumers evaluate not only whether content is advertising, but also how it was created, whether AI use is disclosed, and whether the brand remains accountable. This extends disclosure research beyond sponsorship recognition to the interpretation of human-AI production.

The study also positions perceived authenticity as a situational judgment associated with trust. In AIGC communication, authenticity is not a fixed brand asset; it is negotiated through content quality, disclosure, voice consistency, and perceived integrity. Source Credibility Theory is correspondingly extended to a distributed source comprising the brand, human creators, AI systems, and the platform.

For managers, AIGC should enhance rather than replace accountable brand communication. Human review is needed for factual claims, tone, cultural sensitivity, and ethical risk. Disclosure should identify the role of AI in language drafting, visualisation, translation, or personalisation where relevant, while making clear that the brand remains responsible for the final message (Grewal et al., 2025; Kumar et al., 2025).

Platform fit also matters. AIGC can adapt creative formats across TikTok/Douyin, Instagram, YouTube, Facebook, and Xiaohongshu/RED, but rapid variation should not fragment brand voice. Platforms and policymakers can support responsible practice through clear labels, provenance tools, advertiser verification, and reporting mechanisms for misleading synthetic content.

Limitations and Further Research Directions

Cross-sectional design, self-reporting, and common-method limitations

The cross-sectional self-report design limits causal and temporal inference and may not fully capture actual behaviour. The significant indirect association is consistent with statistical mediation, but it does not establish that authenticity judgments preceded trust or that trust produced later behaviour. Statistical common-method diagnostics were used as sensitivity checks; such tests cannot rule out method bias. Experiments can manipulate AI disclosure, human oversight, content quality, and product category, while longitudinal studies can examine whether repeated exposure is associated with normalisation or scepticism.

Construct scope and contextual heterogeneity

The empirical AIGC predictor captures content quality rather than a general perception that combines quality with disclosure. Future studies should measure AI transparency/disclosure as a separate latent construct and distinguish AI-written text, generated images, synthetic voices, virtual influencers, AI-edited human content, and personalised recommendations. Associations may differ across hedonic, identity-related, and high-risk categories (Castelo et al., 2019; Longoni et al., 2019).

Cultural, demographic, and platform contexts may also condition authenticity and trust. The present study did not compare structural paths across age, gender, or platform groups because measurement invariance was not established for those subgroups. Comparative research should assess measurement invariance before applying multigroup analysis across TikTok/Douyin, Instagram, YouTube, Facebook, and Xiaohongshu/RED, while also examining regulatory environments, AI literacy, advertising scepticism, privacy concerns, brand familiarity, and platform trust. Behavioural measures such as click-through, dwell time, sharing, and verified purchase records could further strengthen validation of the observed association pattern.

Data Availability Statement

The respondent-level data supporting this study are not contained in the article. Data-access requests may be directed to the corresponding author and will be considered in accordance with applicable ethical and privacy requirements.

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Author contributions

Xiaowei Cong was solely responsible for the conceptualization and design of the study, literature review, methodology, data collection, formal analysis, interpretation of the findings, preparation of the original manuscript, and subsequent review and revision. The author has read and approved the final manuscript and accepts full responsibility for the accuracy and integrity of the work.

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Obtained.

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Data availability statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.

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