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Artificial Intelligence-Generated Content and Consumer Decision-Making: The Roles of Trust, Perceived Risk, and AI Literacy

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ABSTRACT

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Objective: This paper aims to study the effects of generative artificial intelligence (AI), specifically AI-generated images and videos, on consumer trust within digital media and the role of perceived content authenticity as a potential mediator.

Design/methodology/approach: 400 digital media consumers answered a self-administered digital questionnaire and the proposed model was assessed using Partial Least Squares Structural Equation Modelling (PLS-SEM).

Findings*:* According to the results of the structural model, dynamic AI videos have a strong positive and direct influence on consumer trust, while the influence of static AI images is non-significant. Furthermore, the direct influence of content authenticity on consumer trust was also non-significant, thus the indirect mediation effect was also non-significant. Even though both AI media formats are strong enhancers of content realism, consumers are likely to separate that visual authenticity from their trust of the platform.

Practical implications: The study is limited because of the reliance on a cross-sectional report and the lack of segmentation on the online consumer population. Future studies on this topic may implement longitudinal or experimental studies in order to determine actual behavioural shifts, and may include more contextual factors, such as consumer AI understanding or the product in question. To reduce perceived risk, digital marketers and managers of e-commerce platforms must shift resources away from complex static AI imagery and instead support dynamic AI video generation. In addition to the aforementioned factors, organizations must build consumer trust through secure transaction support, real user testimonials, and other operational factors, as modern consumers are pragmatic.

Originality/value*:* By applying Media Richness Theory to synthetic media in conjunction with mainstream marketing, this research identifies the 'artificiality paradox'. This research shows that contemporary digital consumers are able to decouple the authentication of content from the platform's Functionality.

Keywords: Artificial Intelligence, AI-Generated Content, Digital Media, Content Authenticity, Online Consumer Behavior SEM-PLS & Pakistan.

1| INTRODUCTION

Artificial intelligence (AI) has significantly impacted the modern digital media landscape. AI has changed how people create, share, and consume media. AI has created challenges for perception and engagement. Generation of media using AI has improved efficiency for digital marketers, but presents new challenges when considering the effects on the brand (Rosário & Dias, 2023).New visual media created using artificial intelligence can enhance brand communication. New research suggests a paradox exists, and as a result of the rapid use of AI by businesses, consumers will think less of the AI advertising campaigns. Consumers will think AI advertisements are less creative and less authentic than advertisements created by people (Amos & Zhang, 2024; Brüns & Meißner, 2024; Kolinskis & Survilaite, 2025; Yahoo, 2024). Content created using AI may serve to undermine brand trust and affect purchasing intent negatively. Consumers like to perceive content created using AI as authentic, which provides a means for brand trust and will positively affect purchasing intent (Horgby & Galizzi, 2024; American Impact Review, 2026). While consumers using AI may prefer to perceive content as transparent, the use of AI may undermine brand trust if people are not made aware that AI is being used to augment a human created product (Brüns & Meißner, 2024; To et al., 2025). Further, consumers overwhelmingly prefer advertising created by people to advertising created by machines (Getty Images, 2024; MDPI, 2025). There is inadequate understanding of how static images created by AI versus dynamic images created by AI affect consumers. (Belanche et al., 2025; Seo et al., 2025)
AI disclosures have been shown to raise consumer skepticism and diminish trust across many digital contexts (American Impact Review, 2026). Trust and skepticism have been studied in the context of AI images and videos, however, there is a gap in the specific comparative dynamics of trust and skepticism, especially in the developing markets (MDPI, 2025). We cannot generalize Western findings to the developing markets such as Pakistan, which has a vastly different socio-cultural, technological, and economic framework after the implementation of the Digital Nation Pakistan Act 2024 (Golra, 2025; Pakistan Journal of Social Science Review, 2026). Using the Elaboration Likelihood Model (ELM) and Source Credibility Theory, and within the context of consumer trust in Pakistan's emerging digital marketplace, this research attempts to fill significant gaps in academic literature. The study intends to fill these gaps and empirically examine the five main areas identified. To begin with, this research aims to identify the direct effects of AI-generated images and videos on consumer trust in digital media. More specifically, this research aims to examine the effects of content authenticity as a mediator of the aforementioned relationship, and how consumers perceive the authenticity of AI-generated content as compared to human-generated content. This research also aims to identify the specific structural elements of AI visual content that engenders trust through perceived authenticity, and finally, this study aims to assess the functional ability of consumers to recognize genuine AI-generated content as compared to other content across multiple digital media platforms. This research in its entirety endeavors to bridge the gap between structural properties of machine-generated content and the trust of individuals.

From a theoretical standpoint, the study extends the Elaboration Likelihood Model (ELM) and Source Credibility Theory as they pertain to artificial intelligence (AI)-generated visual media to include content authenticity as an input-process-output mediator among distinct generative visual modalities

(American Impact Review, 2026). It also makes a contribution to the theory of authenticity based on Han's (2024) division of objective versus subjective authenticity as they pertain to machine-generated contexts. The findings, from a practical standpoint, provide brand managers and digital marketers with research-based recommendations to assist them in dealing with the AI paradox (Buder et al., 2024). While clearly defining the perimeter of consumer perceptions, this study enables practitioners to design their disclosure policies in a way that safeguards brand equity, while simultaneously avoiding and/or minimizing the risk of consumer push-back. While geographically bounded to individual consumers from Pakistan, the study purposely concentrates on perceived and actual consumer responses to the AI visuals (Dwivedi et al., 2024), and purposely avoids the analysis of macro-level, regulatory, policy-based frameworks, or the evaluation of (purely) algorithmic, technical systems.

2 | Literature Review

2.1 Theoretical Underpinning

This research combines the Elaboration Likelihood Model (ELM) and Source Credibility Theory with Han's (2024) authenticity framework to analyze the impact of AI-generated visual media on consumer trust. According to ELM, consumers will interpret the realism and structural elements of AI created images and videos along with the sincerity of the messages through the lens of central cognitive elaboration or peripheral heuristics, which may include heuristic cues such as the presence of a disclosure, the visual media’s aesthetic quality, or the label “AI-Generated.” In the presence of AI-generated media, disclosures may serve as peripheral negative cues, triggering persuasive knowledge and skepticism. This friction is counteracted when AI is perceived to be a tool that augments human creativity rather than a replacement (Brüns & Meißner, 2024; American Impact Review, 2026).

When AI is perceived in the way described above, the combination of ELM and Source Credibility Theory suggest that the creativity and the agency of the human element are necessary for the perception of brand expertise and trust, which is especially important in an era where digital trust is in decline (Amos & Zhang, 2024; Srinivas & Rutz, 2024). In the context of a specific input-process-output model, AI visual formats (images vs. videos) are the inputs and consumer brand trust is the output of the model, with perceived content authenticity as the mediating variable (Han, 2024; Dwivedi et al., 2024).

2.2 Consumer Trust

Consumer trust is about an individual's trust in the credibility, reliability, and goodwill of online content and the platforms for its delivery. In AI-moderated settings, trust also includes the authenticity, transparency, and neutrality of the content (Dwivedi et al., 2024). Consumers’ trust in brands and content increases when that content is perceived to be authentic and is AI generated (Bui, 2024; Verma et al., 2024). The present research considers consumer trust to be an attitudinal outcome that captures the disposition of users to trust and use AI-enriched digital media.

2.3 AI-Based Content

AI-based content is digital media of any format, be it text, images or ads that are generated, altered or disseminated via machine learning, natural language processing, or generative algorithms. It represents a shift from conventional interpersonal communication to communication that is mediated through algorithms, and that is optimally efficient and personalized (Dwivedi et al., 2024). As the traditional signs of a human author are increasingly absent, consumers assess AI-based content not only on the information provided, but also on the integration of AI in a context-sensitive manner (Verma et al., 2024). In the current research, AI-based content is used as a technological provocation to stimulate consumer thinking in regard to authenticity and trust in the digital realm.

2.4 AI-generated Videos

AI-generated videos are audiovisual materials that use tools such as text-to-video, digital avatars, and synthetic voice generation, and do not require traditional video capturing and editing (Izani et al., 2025; Shu et al., 2025). Sophisticated generative models take care of the script, narration, and editing, and allow automated workflows for content generation that is, in many cases, disseminated through TikTok and Instagram Reels (Chen et al., 2025; Pellas, 2025). Although there is an increasing commercial application of these videos for brand storytelling, there is little academic literature on video advertisements and consumer behavior concerning them (Gupta et al., 2024; Mogaji & Jain, 2024). This research analyzes AI-generated marketing videos to explore the impact of visual media on consumer trust and perceived authenticity in light of deepfakes (Springer, 2025).

2.5 AI-generated Images

AI-generated Images are still graphics that, similar to traditional photography, can now be created using text descriptions. Advances in tools such as Midjourney, DALL·E, and Adobe Firefly allow marketers to create high-quality graphics at a fraction of the cost, but the quasi-photographic nature of AI Images can result in unexpected complex psychological reactions from the viewer. Although hyperrealistic AI Images can engage the audience, features such as extreme color saturation and artificial imperfections often reveal machine generation and result in lower trust (Nightingale & Farid, 2022). As such, consumers often prefer Images made by humans, unless AI is framed as augmenting human creativity (Arango et al., 2023; Brüns & Meißner, 2024).

2.6 Content Authenticity

Content authenticity is the degree to which consumers feel digital media, regardless of its human or algorithmic production, is truthful, transparent, and genuine. In AI-driven scenarios, the evaluation focus is no longer on the author, but on the disclosure cues, visual realism, contextual coherence, and ethical alignment (Bui, 2024). The psychological process of perceived authenticity is essential, as it allows consumers to comprehend media when there is information asymmetry (Han, 2024). In the case of this study, content authenticity is conceptualized as the primary mediating variable, allowing the initial encounter with AI-created images and videos to be reframed as consumer brand trust beliefs.

2.7 The Impact of AI-Generated Content on Perceived Authenticity

The rising prevalence of artificial intelligence (AI) in digital media has fundamentally transformed how consumers evaluate the veracity of marketing and informational messages. Unlike human-created media, which reflects individual motives and emotional depth, AI content generation relies on automated algorithms, data trends, and programmatic logic. Consequently, consumers judge the authenticity of AI-driven media based on external indicators—such as transparency, realism, visual coherence, and contextual fit—rather than authorial origin (Möller et al., 2024). Recent literature suggests that AI content does not inherently erode consumer perceptions of authenticity; instead, the impact depends heavily on how the media is designed and presented. Consumers are inclined to view AI content as genuine when explicit authenticity cues are present, including transparent disclosure, ethical framing, and alignment with brand identity (Dwivedi et al., 2023; Verma et al., 2024). Conversely, content perceived as hyper-artificial, deceptive, or misaligned with consumer expectations triggers skepticism and lowers perceived authenticity (Longoni & Cian, 2024). Advances in generative models have enabled highly realistic visual outputs that positively influence authenticity evaluations when the material is contextually relevant and informative (Luo et al., 2024). However, technical quality alone is insufficient; without clear signals of moral intent and structural transparency, consumers continue to question the credibility of AI-generated media.

2.8 Perceived Authenticity as a Driver of Consumer Trust

In digitally mediated environments, content authenticity serves as a critical determinant of consumer trust, reflecting perceptions of truthfulness, candor, and alignment with social standards. Empirical research indicates that authenticity cues act as robust predictors of trust outcomes across online platforms (Möller et al., 2024). High perceived authenticity encourages consumers to view messages as credible and well-intentioned, thereby increasing engagement and reinforcing confidence in both the brand and the channel (Verma et al., 2024). In contrast, misleading, manipulated, or irrelevant content undermines perceived authenticity and severely damages consumer trust (Longoni & Cian, 2024). This dynamic is particularly pronounced in AI-mediated contexts, where the absence of traditional human authorship renders consumers more sensitive to authenticity signals. Psychologically, perceived authenticity functions as a reassurance mechanism that mitigates consumer uncertainty and perceived risk in digital communications (Dwivedi et al., 2023). Specific indicators—such as transparent AI disclosures, context-appropriate messaging, and alignment with core brand values—reassure audiences of a firm's integrity and diminish concerns regarding hidden motives (Bui, 2024).

2.9 Content Authenticity as a Mediating Mechanism

The relationship between AI-generated content and consumer trust in digital media is increasingly understood as indirect, operating through consumer cognitive and perceptual evaluations rather than direct mechanical effects. Although AI offers unprecedented scalability and personalization, its ultimate influence on trust hinges on whether consumers perceive the underlying media as authentic (Möller et al., 2024). When content feels overly automated, opaque, or detached, trust diminishes; conversely, when AI-generated media incorporates structural signals of transparency, realism, ethical framing, and contextual relevance, perceived authenticity rises, subsequently fostering brand trust (Bui, 2024; Verma et al., 2024). Positioned as a core mediating variable, content authenticity clarifies the inconsistent findings present in prior literature, where automated AI disclosures sometimes diminish trust and other times yield neutral or positive responses (Longoni & Cian, 2024; Luo et al., 2024). Conceptualizing authenticity as a mediating mechanism explains these mixed outcomes: exposure to AI-generated images or videos triggers psychological evaluations of authenticity, which then dictate whether consumer trust is established or eroded in digital environments.

H1: There is a relationship between AI based Videos and consumer Trust.

H2: There is a relationship between AI based images and consumer Trust.

H3: There is a relationship between content authenticity and consumer Trust.

H4: Content Authenticity mediates the relationship between AI based Videos and consumer Trust.

H5: Content Authenticity mediates the relationship between AI based Images and consumer Trust.

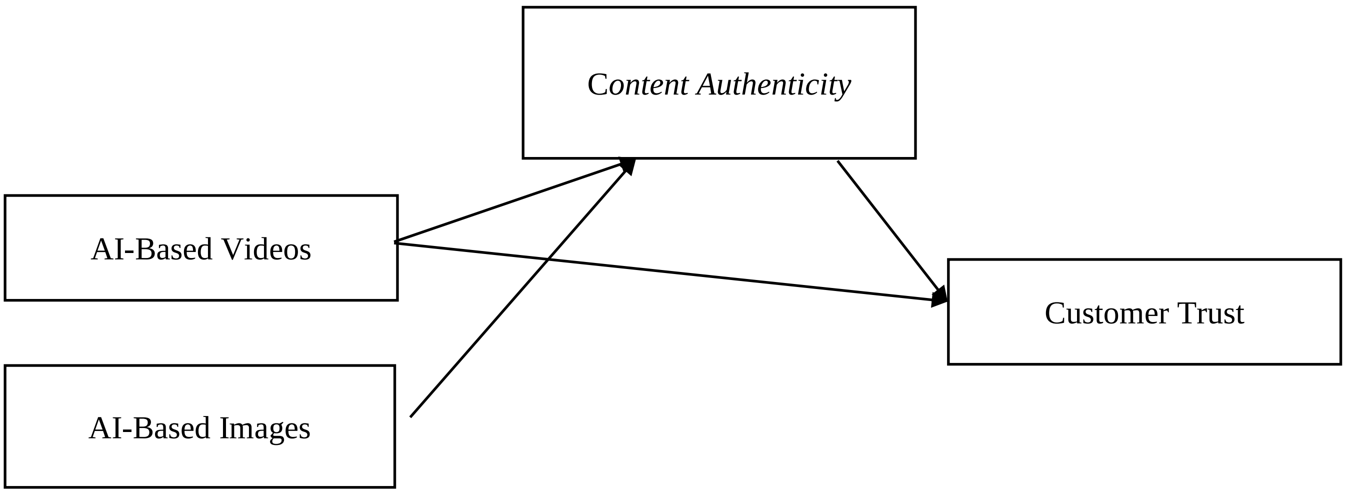

Figure-1 Conceptual Framework

3 | Research Methodology Research Design and Sample

In this research, a positivist philosophy is combined with a deductive, quantitative methodology to analyze the connections among AI-generated visual media, the authenticity of digital content, and consumer trust from an objective perspective. Empirical testing of a theory with this research philosophy places an emphasis on the objective measurement of consumer perceptions and on the precision and replicability of this measurement (Saunders et al., 2019; Hair et al., 2024). Because of this, a cross-sectional survey is designed to collect consumer attitudes toward AI-generated visual content at a specific moment in time, which facilitates the efficient evaluation of mediation effects in PLS-SEM (Saunders et al., 2019; Hair et al., 2024).

The sample population consists of active digital consumers and social media users in Pakistan who come in contact with AI-based marketing on Facebook, Instagram, TikTok, YouTube, and other e-commerce sites. This age group is digitally competent enough to assess the authenticity of the content critically and develop trust-based perceptions that affect their online shopping. A self-administered digital survey was designed through primary data collection and a convenience sampling method, which is well accepted in digital marketing studies due to its extensive reach and low cost (Saunders et al., 2019; Hair et al., 2024). A screening questionnaire was designed to restrict survey participants to those who are familiar with AI-based media, and a preliminary test with 20 to 30 respondents was conducted to check the clarity and the first level of reliability of the test items.

The proposed measurement instrument is a structured questionnaire that incorporates closed-ended items and consists of four multi-item constructs. These four constructs are based on previous research and recognized measurement scales in the literature (Bui, 2024; Dwivedi et al., 2024; Verma et al., 2024). AI-Based Videos, AI-Based Images, Content Authenticity, and Consumer Trust each include five items. All items are measured on a 5-point Likert scale, where 1 is “Strongly Disagree” and 5 is “Strongly Agree”.

For the assessment of the proposed conceptual model, PLS-SEM is the selected statistical technique. PLS-SEM is the appropriate statistical modeling technique when structural models are more intricate (i.e., those which comprise mediation relationships and latent constructs). PLS-SEM is the preferred statistical modeling technique as it allows for both the measurement and structural models to be assessed concurrently (Hair et al., 2024; Sarstedt et al., 2023). For the objective of this study, PLS-SEM will be used to analyze the reliability and validity of the constructs. Following this, the bootstrapping procedure will be used for the significance testing of the estimations.

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4 |Results and Discussion

4.1 Respondent’s Profile

Demographic Profile of Respondents

Demographic variable	Category	Frequency	Percent (%)
Gender	Male	169	42.1
	Female	232	57.9
Marital status	Single	243	60.6
	Married	158	39.4
Age group	Below 25	52	13
	25 – 30	277	69.1
	31 – 40	57	14.2
	41 – 50	15	3.7
Educational background	Diploma	5	1.2
	Under-Graduate	10	2.5
	Graduate	190	47.4
	Masters	186	46.4
	PhD	10	2.5

For the sample studied (N = 401), the demographic description offers a representative image of active digital media consumers in Pakistan regarding the sample's gender, marital status, age, and level of education. The survey was completed by 232 females (57.9%) and 169 males (42.1%). There are more women than men in digital content creation and consumption in South Asia (statista, 2024). This survey also tries to maintain a fair representation of gender in South Asia. Of those surveyed, 243 were single (60.6%) and 158 (39.4%) were married. Of the respondents, 27.0% (n= 156) were under 25 and 60.2% (n= 327) were between 25 and 40. (n= 15) respondents were aged 41-50. 69.1% (n= 277) of respondents were in the 25-30 age bracket. This survey most respondents were between the ages of 25 (or younger) and 40 (or older). This concentration in younger cohorts is favorable because these respondents most likely have greater exposure and use of digital creation and editing platforms than older users. The age bracket of 25-30 also has the highest representation, this cohort has the highest propensity to use social networks that are engagement centers for generative videos and images for digital content (Lou & Copeland, 2025; Xu et al., 2024). Further, the respondents were highly educated. 47.4% (n= 190) were graduates and 46.4% (n= 186) held Master's Degrees. 2.5% (n= 10) held Doctorates, 2.5% (n= 10) held Bachelor's Degrees, and 1.2% (n= 5) held Diplomas. Higher education denotes a greater ability of digital users to assess the quality of AI generated digital content and their capacity to critically evaluate the depth of Trust and authenticity of the content of their judgments (Kučinskas & Survilaite, 2025; Liu et al., 2025).

4.2 Descriptive Analysis of the Latent Constructs

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
AI-BV	344	1	5	3.3069	0.705
AI-BI	344	1	5	3.3083	0.813
CA	344	1	5	3.2456	0.776
CT	344	1	5	3.4159	0.690

Note: AI-BV= Artificial Intelligence based video, AI-BI= Artificial Intelligence based Images CA= Content Authenticity & CT= Customer Trust

Descriptive statistics were conducted for four constructs (N = 400) using a 5-point Likert scale. Results show participant ratings across constructs were moderately positive. The highest mean was determined for Consumer Trust (M = 3.4159, SD = 0.690). The highest mean score for Consumer Trust also had the lowest standard deviation, indicating that the digital media confidence response was the most uniform. American Impact Review (2026) observed the results of the mean value for Consumer Trust. AI-Based Images (M = 3.3083, SD = 0.813) recorded slightly higher results than AI-Based Videos (M = 3.3069, SD = 0.705). However, AI-Based Images reported a higher degree of variability in the response (Zhang & Hur, 2025). Ratings for the Content Authenticity measure had the lowest mean score (M = 3.2456, SD = 0.776). Responses to this item suggest that consumers are more skeptical about the genuine intentions of machines (Han, 2024). The mean scores demonstrated a more negative response within the range 3.24 to 3.42. Overall, results suggest a more cautious and less positive.

4.3 Measurement of the Model Analysis

In assessing the structural and measurement models, the study adopted the Ringle et al. (2005) method. Ringle et al. (2005) suggested the variance-based method incorporates both models at the same time and is more beneficial than covariance-based SEM when dealing with complex frameworks of latent-variable. PLS-SEM was useful in such instances as it dealt with constructs like content authenticity and consumer trust, which, in this study, were indirectly measured through reflective indicators. SmartPLS version 4.0.8 was used in this study. This study adopted the model evaluation criteria given by Hair et al. (2019). The measurement model was assessed prior to the evaluation of the structural model.

Convergent validity was assessed using three criteria. The four constructs' Average Variance Extracted (AVE) scores ranged from 0.55 to 0.927, indicating satisfactory convergent validity and were assessed against the Fornell and Larcker (1981) recommendation that the AVE be greater than 0.50. The evaluation of Composite Reliability was undertaken using the threshold of 0.70 established by Gefen, Straub and Boudreau (2000), who noted that it was a better estimation than Cronbach's alpha. The assessment of Cronbach's alpha was performed using Nunnally's (1978) benchmark of 0.70, which all constructs satisfied. Item loadings were assessed as per the recommendations provided by Hair et al. (2014), which suggested an item should load at 0.50 as a minimum (0.70 preferred). Items with low loadings were removed to enhance the fit and reliability of the constructs.

Factor loadings, Cronbach's alpha, composite reliability and AVE

Constructs	Items	Loading	AVE	Composite Reliability	Cronbach Alpha
AI-BI	AI_BI_1	0.912	0.754	0.965	0.921
	AI_BI_2	0.911			
	AI_BI_3	0.847			
	AI_BI_4	0.809			
	AI_BI_5	0.858			
AI-BV	AI_BV_1	0.852			

	AI_BV_2	0.739			
	AI_BV_3	0.782	0.647	0.872	0.864
	AI_BV_4	0.804			
	AI_BV_5	0.841			
	CA_1	0.710			
	CA_2	0.832			
CA	CA_3	0.761	0.604	0.846	0.836
	CA_4	0.870			
	CA_5	0.698			
	CT_1	0.730			
	CT_2	0.829			
CT	CT_3	0.811	0.597	0.863	0.836
	CT_4	0.840			
	CT_5	0.884			

Note: AI-BV= Artificial Intelligence based video, AI-BI= Artificial Intelligence based Images CA= Content Authenticity & CT= Customer Trust

The results of convergent validity for four constructs—AI-based images (AI-BI), AI-based videos (AI-BV), content authenticity (CA), and consumer trust (CT)—demonstrated reliability and validity for all three criteria: outer loadings, AVE, and composite reliability.

All constructs demonstrated outer loadings above the minimum recommended value of 0.50 (Hair et al., 2014), and most of the constructs demonstrated outer loadings above the most preferred value of 0.70. AI-BI attained the highest outer loadings followed by AI-BV, CA, and CT.

All constructs attained the required level of AVE (0.50) (Fornell and Larcker, 1981). AI-BI achieved the highest level at 0.754, followed by AI-BV, CA and CT at 0.647, 0.604, and 0.597 respectively. Although CA and CT were only slightly above the cutoff value, they still achieved the required level of convergent validity within the accepted range of consumer behavior studies (Fornell & Larcker, 1981).

All values of composite reliability exceeded the recommended value of 0.70 (Gefen et al., 2000). The highest value of composite reliability was achieved for AI-BI (0.965), and AV-BV, CA and CT ranged from 0.863 to 0.872.

Finally, all constructs met Nunnally's (1978) threshold of 0.70 for Cronbach's alpha, with AI-BI achieving the highest at 0.921, followed by AI-BV, CA and CT at 0.864, 0.836, and 0.836 respectively.

Discriminant Validity

Discriminant validity ensures that different constructs in a model are conceptually different from each other (Farrell & Rudd, 2009). Discriminant validity was examined in this study using the Fornell-Larcker criterion. This criterion stipulates that the square root of a construct's AVE should be higher than the correlations with the other constructs in the model. This definition means that the construct of interest should be unique and not overlap with the other constructs (Fornell & Larcker, 1981). In line with the convergent validity criterion, the AVE was set to at least 0.50 as the minimum threshold. When the square root of the AVE of a construct exceeds the correlations with the other constructs in the model, discriminant validity is demonstrated. Conversely, if the inter-construct correlations exceed the square root of the AVE, then discriminant validity is compromised, and the construct of interest might need to be redefined or the items associated with the construct might need to be removed from the model.

The findings of this study show that all four constructs—AI-based images, AI-based videos, content authenticity, and consumer trust—demonstrated discriminant validity as the square root of the AVE was greater than the off-diagonal inter-construct correlations. These results, in addition to the AVE of greater than 0.50 and the previously mentioned thresholds of reliability, demonstrated both convergent and discriminant validity of the measurement model (Hair et al., 2019; Fornell & Larcker, 1981). This set of results provided the necessary grounds for the assessment of the structural model.

Forrnell –Larcker

	AI_BI	AI_BV	AUTH	CI
AI_BI	**0.868**			
AI_BV	0.454	**0.805**		
CA	0.487	0.461	**0.777**	
CT	0.338	0.597	0.329	**0.821**

Note: AI-BV= Artificial Intelligence based video, AI-BI= Artificial Intelligence based Images CA= Content Authenticity & CT= Customer Trust

The Fornell-Larcker criterion evaluated the discriminant validity of the four latent constructs as proposed by Fornell and Larcker (1981) and Hair et al. (2019). The diagonal was populated by AVE square roots and, along the diagoal, were inter-construct correlation values.

AI-based images, discriminant validily confirmed, showed an AVE square root of 0.868, greater than the correlation values of AI-based videos (0.454), content authenticity (0.487), and consumer trust (0.338). AI-based videos demonstrated an AVE square root of 0.805, also, and exceeded all of the correlation values, including the highest one with consumer trust (0.597), which agrees with the findings that the video-based AI content has a stronger effect in cultivating consumer trust than the AI-based images (Xu et al., 2024).

The AVE square root of content authenticity (0.777) was greater than its correlation with AI-based images (0.487), AI-based videos (0.461), and consumer trust (0.329). The low correlation of authenticity and trust also supports the proposed mediating effect of content authenticity in the model (Han, 2024; Fornell & Larcker, 1981). The square root of consumer trust (0.821) also was greater than the correlation values of (0.338, 0.597, 0.329), showing that consumer trust is a separate construct.

The Fornell-Larcker criterion was satisfied across the four constructs reviewed, and, in combination with the convergent validity results, support the measurement model validity and readiness for the structural path analysis (Hair et al., 2019)

Heterotraitmonotrait (HTMT)

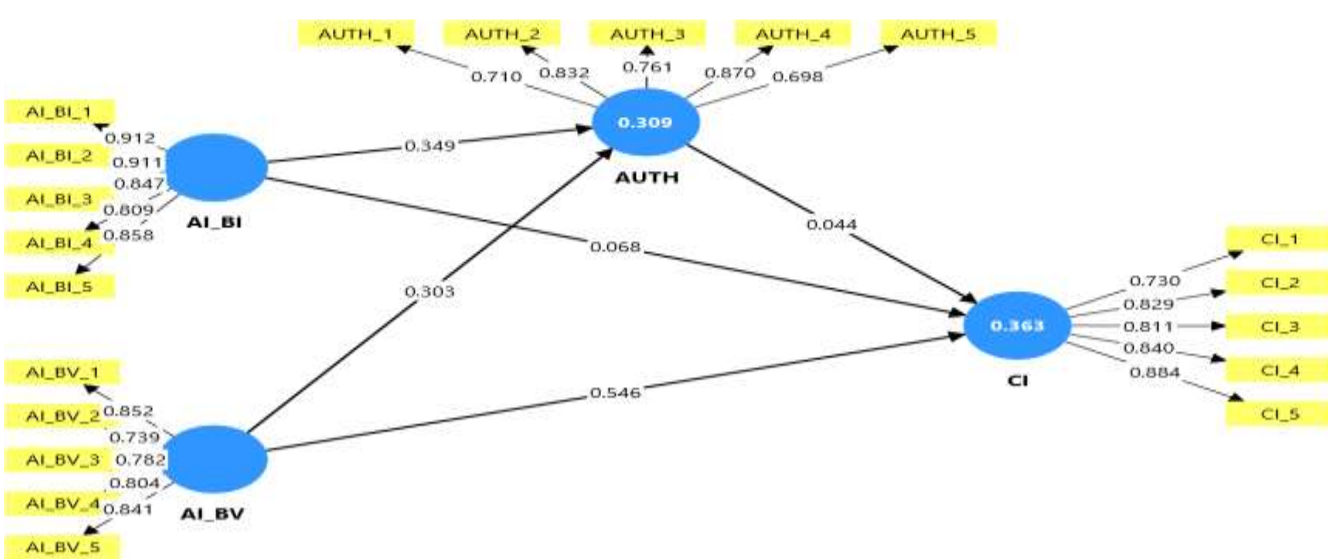
	AI_BI	AI_BV	AUTH	CT
AI_BI				
AI_BV	0.473			
CA	0.504	0.506		
CT	0.337	0.666	0.368	

Note: AI-BV= Artificial Intelligence based video, AI-BI= Artificial Intelligence based Images CA= Content Authenticity & CT= Customer Trust

The Heterotrait-Monotrait (HTMT) ratio was applied in this study as part of a more rigorous measurement standard for discriminant validity, as described in Henseler et al. (2015). Kline (2016) and Gold et al. (2001) confirmed that discriminant validity was satisfied for HTMT values when they were less than the strict criterion of 0.85, or when they were less than the relaxed criterion of 0.90.

The current study reported HTMT values between 0.337 and 0.666. The highest association was between AI-based Videos and Consumer Trust (AI_BV-CT) at 0.666, followed by Content Authenticity and AI-based Videos (CA-AI_BV) at 0.506, and Content Authenticity and AI-based Images (CA-AI_BI) at 0.504. The lowest association was between Consumer Trust and AI-based Images (CT-AI_BI) at 0.337.

As all HTMT values remained below all acceptable thresholds, the empirical distinctiveness of each construct was evidenced. Consequently, the results substantiated that discriminant validity was satisfied, and that the measurement model was adequate and free of multicollinearity concerns. This confirmed the model was ready to proceed with structural path .



According to Hair et al. (2017), 30.9% variance in content authenticity and 36.3% variance in consumer trust ($R^2 = 0.309$ and 0.363) presents a moderate level of explanation. AI Images content moderately impacted content authenticity ($\beta = 0.349$) and almost had no effect on consumer trust ($\beta = 0.068$). AI Videos exerted the strongest impact in all the instances, impacting content authenticity ($\beta = 0.303$) and consumer trust ($\beta = 0.546$). The direct unmediated influence of content authenticity on consumer trust was also almost negligible ($\beta = 0.044$). This means that the effect of content authenticity on consumer trust is almost indirect.

Structural Model Analysis

Path coefficients

Relations	***β***	***Mean***	***SD***	***T-Stast***	***P Values***	***Status***
AI_BI -> CA	0.349	0.353	0.041	8.445	0.000	Accepted
AI_BI -> CT	0.068	0.070	0.055	1.246	0.213	**Rejected**
AI_BV -> CA	0.303	0.305	0.048	6.278	0.000	Accepted
AI_BV -> CT	0.546	0.545	0.053	10.224	0.000	Accepted
CA -> CT	0.044	0.047	0.064	0.678	0.498	**Rejected**

Note: AI-BV= Artificial Intelligence based video, AI-BI= Artificial Intelligence based Images CA= Content Authenticity & CT= Customer Trust

Hypothesis testing was conducted as per Hair et al. (2017), employing a critical t-value of 1.96, with a significance level set at $p < 0.05$. Sample mean and standard deviation were used to determine the direction and magnitude of effects.

AI-based videos significantly and directly impacted customer trust ($\beta = 0.546$, $t = 10.224$, $p = 0.000$), confirming H1. AI-based images, on the other hand, did not impact customer trust, therefore H2 is rejected ($\beta = 0.068$, $t = 1.246$, $p = 0.213$). Content authenticity also did not significantly impact customer trust, therefore H3 is also rejected ($\beta = 0.044$, $t = 0.678$, $p = 0.498$).

All AI-based images ($\beta = 0.349$, $t = 8.445$, $p = 0.000$) and AI-based videos ($\beta = 0.303$, $t = 6.278$, $p = 0.000$) significantly predicted content authenticity. This pattern of strong antecedent paths with a non-significant CA–CT link sets the stage for a mediation analysis (H4, H5).

Discussion

This study analyzes the effects of AI-generated imagery and video on consumer trust and examines perceived content authenticity as a possible mediator. The data provided strong support for H1. Results indicated consumer trust increased when AI-generated videos were used. Videos are helpful in providing information cues when compared to static media, and thus, reduce perceived risk due to the information asymmetry of the digital marketplace. This is in agreement with Daft and Lengel's (1986) Media Richness Theory. The results of this study are positioned alongside Bleier et al. (2019), where the authors cite dynamic and vivid media as hallmarks of increased consumer trust, and

Davenport et al. (2020), who argue that highly sophisticated AI visuals decrease the perception of content being "artificial" for consumers.

In H2, the results indicated that AI-generated imagery had no significant direct impact on consumer trust. This is perhaps due to the increasing skepticism among consumers toward static images due to the awareness of AI and manipulated imagery, in line with Appel et al. (2022). Since images are of lower media richness, it may be the case that they lack the depth needed to reduce perceived risk. This is similar with Guo et al. (2020), who explain that images found in online marketplaces are often perceived as generic stock images and are therefore not trust indicators.

H3 was also not supported. Similar to H2, the results of this study suggest that trust and not perceived content authenticity was impacted. In this case perceived trust was linked to site utility, safety, and the integrity of the transactions, which is in agreement with Gillespie et al. (2021) and Pavlou (2003).

Mediation analysis showed that AI images and videos positively influenced perceived authenticity. However, increased trust did not follow since the authenticity–trust link remained weak. This supports Kietzmann et al. (2021) and the "artificiality paradox." AI-generated content can appear authentic and still not create trust, meaning the trust in AI-based videos relies on richness and utility over authenticity.

5 | Conclusion and Recommendations

This study explored how deep tech media specifically AI-generated images and videos — impacts consumer trust and the perceived content authenticity as a mediating or moderating variable. Following the guidance of Hair et al. (2017), the study employed Partial Least Squares Structural Equation Modelling (PLS-SEM). Data were collected from 400 participants and, in accordance with the systematic validation procedures put forth by Henseler et al. (2015), the researchers ascertained the measurement model's internal consistency, convergent validity, and discriminant validity. Following that, a bootstrapping method with 5,000 resamples was employed to assess the pathways of the study's hypotheses. The framework built from this study demonstrates that media generated by AI and its diverse forms affect customer trust in unique and fundamental ways. The study's results confirmed Hypothesis 1 (H1) with a significant and strong positive relation of trust in AI-generated videos ($\beta = 0.546$, $p < 0.05$). Hypothesis 2 (H2), stating that AI-generated images would build a substantial level of trust, was not supported ($\beta = 0.068$, $p > 0.05$). The video versus image discrepancy aligns with Media Richness Theory (Daft and Lengel, 1986), suggesting that in a digital space, a consumer's trust gap can be closed with rich and dynamic video content, whereas a high quality and polished still image is insufficient. Hypothesis 3 (H3) was also rejected as the perceived content authenticity-consumer trust direct relationship was statistically non-significant ($\beta=0.044$, $p>0.05$). This indicates that the average digital consumer prioritizes practical, operational trust indicators (i.e., the security of a transaction, the reliability of the platform) over the authenticity of marketing content, which is consistent with Pavlou (2003).

Hypotheses 4 and 5 were also rejected as content authenticity was shown not to mediate the AI media formats-consumer trust relationship. Referring to the mediation approach of Preacher and Hayes (2008), as mediation is defined by the existence of a significant relationship between a mediating variable and an outcome variable, the authenticity-trust relationship was non-existent, therefore mediation was not possible. Interestingly, AI images and videos both had significant, positive relationships with perceived content authenticity ($\beta=0.349$ and $\beta=0.303$, respectively, $p<0.05$). This indicates that the use of AI, at least in image and video format, can create an enhanced perceived realism. However, increased perceived authenticity of marketing content does not increase trust, therefore the relationship was both indirect and non-existent

6 |IMPLICATIONS

6.1 Theoretical Implications

The study provides three main theoretical advancements. First, it extends the Media Richness Theory (Daft & Lengel, 1986) to include the emerging area of synthetic media, showing that richness and vividness are still required for trust to be established when content is AI-generated.

Second, this research adds complexity to how we understand perceived authenticity in digital environments. Traditionally, authenticity has been at the core of consumer trust. However, this research demonstrates a gap between perceived authenticity and trust, adding to Kietzmann et al. (2021) synthetic realism and artificiality paradox concepts. Consumers can assess a brand as being more authentic through the use of AI-generated content, and this will not necessarily lead to greater trust in the brand.

Third, this research adds to the PLS-SEM methodology by documenting a case in which a mediating variable is strongly influenced by the independent variables, and is unrelated to the dependent variable allowing the development of the concept of structural chain collapse in mediation.

6.2 Practical Implications

For digital marketers and platform developers, the study’s findings suggest the need for the prioritization of AI-generated Video content over static AI images, as images alone do not reinforce confidence in the brand. The focus should be on AI-enhanced interactive product demonstrations, walkthroughs, and personalized video messaging, as these help to manage perceived risk and enhance trust.

Furthermore, since the role of authenticity in trust is diminishing, e-commerce managers should stop constructing marketing authenticity narratives and focus more on trust frameworks and reliable services. Consumers seem to welcome AI-generated content, especially if it serves a purpose and adds value.

6.3 Limitations

Several study limitations were identified. First, the cross-sectional design means consumer sentiment was captured only once. As generative AI was anticipated to be further embedded in the digital environment, this study was unable to identify how attitudes toward digital AI media may change over time. In this case, a longitudinal study would be more appropriate to capture the long-term causal dimensions

Second, the regional and contextual dimensions of the study limited its scope. Findings were especially challenged by the trust dynamics and risk thresholds in various cultures and marketplaces. Therefore, the findings on the non-significance of content authenticity and the presence of static images may differ in other cultural and e-commerce studies.

Third, the self-respondent study design, even with its ease to reach digital platform users, incurs self-selection and social desirability biases. This design captures trust and authenticity perceptions, which may differ from the social and economic behaviors that support and amplify trust (e.g. click-through rates, transaction data). Finally, the limited scope of the structural model excluded important dimensions such as brand familiarity, the involvement continuum (high/low and personal) and disposition trust. This limits the model's scope to capture the consumer trust ecosystem's full complexity.

6.4 Future Recommendations and Conclusion

It is recommended that future studies include boundary conditions and moderators such as consumer tech literacy, age-group-based segments and varying degrees of product involvement to determine the varying importance of AI images and/or the issue of authenticity. Additionally, Media Richness Theory-based alternative pathways that consider content quality, cognitive engagement and interaction with the video may better illuminate the video-trust pathway. A variety of cross-industry studies that include both high (e.g. financial, medical) and low threat marketplaces (e.g. fast fashion) are warranted along with experimental and longitudinal studies that incorporate behavioral-based trust measures. the study finds that AI videos are more effective than still AI images in mitigating the perceived risk among consumers, decreasing consumer skepticism, and building trust. While still images generated by AI are increasingly criticized and negatively perceived, videos generated by AI are viewed less skeptically and more positively. The study also takes issue with the marketing assumption that consumers are looking for genuine, unedited content. In fact, synthetic videos that are aesthetically pleasing and do not increase trust of consumers are viewed positively. Rather, trust of consumers is rooted in the perceived safety of the transaction and the service and media used. This suggests that, especially with the growing use of AI, trust is built from the integration of transparency and the depth of information, as compared to the overt priority of the visual accuracy of the content.

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