

How Perceptions Variance Shapes Brand Culture: Deconstructing Consumer Cognition Through a Comparison of Generative AI and Human-generated Texts

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Abstract: This study investigated how differences in consumer perceptions of content origin—specifically between Gen-AI and human creation—influence brand culture, with a focus on addressing the underexplored connection between content authorship and brand cultural formation. Drawing on the Elaboration Likelihood Model (ELM), brand signal theory, and cultural consistency theory, two empirical studies were carried out to unpack the cognitive and affective mechanisms underlying this relationship. Study 1 compared consumer perceptions across four dimensions—brand authenticity, credibility, electronic word-of-mouth (EWOM) intentions, and brand attitudes. Findings indicated no significant differences in these perceptions between the two AI tools. Study 2 further explored the impact of human-generated versus DeepSeek-generated texts on brand culture. Results revealed that human-authored narratives significantly outperformed AI-generated content in enhancing perceptions of authenticity, credibility, EWOM intentions, brand attitudes, and brand culture. Brand credibility is the only factor with a significant positive effect on brand culture. Additionally, text origin (human vs. AI) played a moderating role, with human authorship strengthening the resonance between perceptual dimensions and brand culture. The AI origin functions as a negative peripheral cue under the ELM framework triggered heuristic skepticism. The study offered practical insights for marketers on integrating Gen-AI into brand communication while preserving cultural coherence.

Keywords: Generative AI, human-generated text, brand culture, consumer perception, cultural consistency.

1. Introduction

In the rapidly evolving landscape of digital marketing, artificial intelligence (AI) is reshaping how brand communicate. AI-driven language models now support tasks from creative writing to customer service [1]. As digital platforms proliferate, GenAI tools such as ChatGPT and DeepSeek have been increasingly adopted to produce persuasive marketing messages, challenging traditional human-generated narratives [1, 2]. Concurrently, scholars have highlighted the importance of consumer cognition and affective responses in driving brand loyalty and culture [3, 4]. Despite the rapid advancement of natural language processing (NLP) technologies, consumers' perceptions of AI-authored content versus human-authored texts remain understudied in terms of their consequent impact on brand culture.

Although several studies have compared linguistic features and persuasive effectiveness between AI and human-generated marketing texts [1, 2], there is scant research linking perception variance elicited by these different content origins to broader brand cultural constructs. Recent empirical evidence shows that when brands fail to account for how AI-generated contents are differently perceived, consumer trust and engagement can decline significantly, undermining loyalty and diluting cultural coherence [5]. Understanding this gap is therefore crucial for designing AI-driven narratives that not only persuade but also reinforce the cultural values central to sustainable brand equity. Bibliometric analyses have mapped relationships between brands and linguistics [6], and investigations into storytelling and signaling theory have explored how corporate narratives shape consumer behavior [7]. Yet, an integrative examination of how discrepancies in

consumer cognition toward GenAIs versus human texts inform brand culture formation is missing. This oversight is significant because without insights into how perception variances alter brand meaning and identity, marketers cannot effectively tailor AI-driven narratives to reinforce cultural values, risking misalignment between brand messages and consumer expectations [8, 9]. Furthermore, earlier works on consumer psychology from Babu [10] and brand-consumer behavior relationships from Kootenaie and Kootenaie [11] provided rich theoretical frameworks but does not address AI-moderated content creation nuances. Addressing this gap is imperative, as advancements in AI-driven communication demand robust theoretical frameworks to predict and interpret how algorithmically crafted messages shape consumer emotional responses and cognitive processing, ultimately influencing the trajectory of brand culture [12, 13]. From the perspective of psychology, brand signal theory contributes to strengthening this link by brand storytelling, which is important in shaping positive corporate brand perception and emotional attachment [7]. However, the relationship between customers and brands is facing great challenges in the AI era.

This study makes several key contributions to the identified research gaps. First, based on Elaboration Likelihood Model (ELM), cultural consistency and brand signal theory, by decomposing customer perceptions into four distinct dimensions—brand authenticity, brand credibility, EWOM intentions, and brand attitudes—it provides a granular understanding of the cognitive and affective mechanisms through which content origin influences consumer responses. By situating brand culture as the dependent outcome variable, the research links micro-level perceptual variances to macro-level cultural constructs, elucidating how different messaging sources shape collective brand meaning. Second, by

introducing AI-generated versus human-generated text as a moderating variable, the study offers practitioners nuanced guidance on when and how to deploy generative AI tools to preserve or enhance cultural coherence and loyalty. By Study 1 and Study 2, we seek to reveal the mechanisms by which perception differences inform brand storytelling, authenticity judgments, and cultural resonance. Together, these empirical and theoretical contributions equip scholars and managers with a robust framework for predicting and managing the cultural consequences of AI-mediated brand communications.

The remainder of this article is organized as follows. Section 2 reviews relevant literature on ELM, brand signal theory, brand culture and cultural consistency. Respectively, Section 3 and Section 4 details hypotheses participants, methodological designs, procedures, results and discussions. Section 5 discusses general discussions of two studies, including theoretical and managerial implications, highlighting strategies for integrating GenAIs in brand communication while preserving cultural coherence. Finally, Section 6 concludes with limitations and directions for future research.

2. Literature Reviews

The Elaboration Likelihood Model (ELM) offers a foundational framework for understanding how consumers process persuasive brand communications via two distinct routes: the central route—characterized by high cognitive effort and thoughtful evaluation of message arguments—and the peripheral route, which relies on ancillary cues such as source characteristics or aesthetic appeal [14]. In contemporary digital marketing contexts, source cues have gained heightened importance [15]. Chen et al. find that when messages are identified as machine-generated, consumers disproportionately rely on peripheral heuristics, leading to reduced cognitive elaboration and weaker attitude change [16]. Complementing this, Lütjens, et al., demonstrated in their meta-analysis that automated content triggers less sustained engagement, thereby attenuating the persuasive impact on brand-related judgments [8]. Together, these studies suggest that variations in perceived brand authenticity and credibility will exert differential effects on brand culture depending on the processing route activated by message origin [17-19].

Brand signal theory, first articulated by Spence, explains how visible indicators help brands bridge the information gap with consumers [20]. Empirical work has since identified source disclosure and storytelling depth as key markers of a brand's honesty—when companies openly share origins and processes, trust tends to rise [21-23]. Conversely, messages labeled as “AI-generated” often carry less evident human purpose, which audiences interpret as reduced sincerity and that, in turn, dampens persuasive impact [24, 25]. From this foundation, we propose that the nature of text authorship signals will alter how strongly consumer perceptions translate into brand culture.

Brand culture is cultivated when brand expressions resonate consistently with consumers' shared values and contribute to the construction of collective meaning over time. According to Holt, brands became cultural icons when they tapped into prevailing ideological tensions and maintain symbolic alignment with their audiences [26]. Extending this, Amaral and Torelli suggested that alignment between brand-stated values and consumers' self-identity reinforces cultural identification, fostering deeper emotional bonds [27].

Similarly, Suo and Huang highlighted that authenticity congruence—that is, perceived harmony between brand behavior and consumer expectations—enhances community cohesion and participatory engagement [28]. However, the emergence of AI-generated brand content introduced potential dissonance, as algorithmic messaging may disrupt familiar narrative patterns or lack the symbolic nuance found in human-crafted communication [24]. Such disruptions can weaken perceived coherence, threatening the stability of brand meaning over time. As such, the concept of cultural consistency offered a valuable framework to understand how divergences in message origin or style may shape collective brand perceptions and cultural outcomes.

Drawing on these theories, we made several inferences: brand authenticity positively influences brand culture, such that messages perceived as more genuine foster stronger cultural coherence; brand credibility positively influences brand culture, with higher trustworthiness strengthening collective brand meaning; consumers' EWOM intentions positively influence brand culture, as greater willingness to share content amplifies cultural diffusion; brand attitudes positively influence brand culture, given that favorable evaluations catalyze communal identification. Text origin moderates the relationships in the first four viewpoints, such that the positive effects of authenticity, credibility, EWOM intentions, and attitudes on brand culture are stronger for human-generated texts than for AI-generated texts. In order to more clearly illustrate how text origin and four perceptual dimensions work together on brand culture, we defined text sources as binary moderators (0=human, 1=AI) in the conceptual model. The text source is regulated through two paths. First, when the text is identified as “human”, consumers are more likely to regard the text content as having the author's intention and higher source originality, thereby amplifying the cognitive processing intensity of information and enhancing the positive impact of authenticity and credibility on brand culture. Second, when the text is marked as “AI”, the label becomes a negative peripheral cue, weakening emotional resonance and group identity, thus weakening the role of EWOM and attitude in promoting cultural resonance.

3. Study 1

3.1. Hypotheses

Despite the proliferation of generative AI tools in marketing, the influence of the AI platform itself on consumer perceptions of advertising messages remains an area of uncertainty. Drawing upon the Elaboration Likelihood Model (ELM) and brand signal theory, Study 1 makes a unique comparison between two widely used AI copy-generation platforms – DeepSeek and ChatGPT. The study's objective is to examine their differential impacts on consumers' perceptions of authenticity, credibility, EWOM intentions and brand attitudes. The present study proposes a methodology for the isolation of platform effects, with a view to facilitating a more comprehensive understanding of the influence of AI origin on brand culture.

Hypotheses:

H1a: Advertising copies generated by DeepSeek will be perceived as more authentic than those produced by ChatGPT.

H1b: Advertising copies generated by DeepSeek will be perceived as more credible than those produced by ChatGPT.

H1c: Advertising copies generated from DeepSeek will

evoke lower EWOM intentions than those from ChatGPT.

H1d: Advertising copies generated from DeepSeek will elicit less favorable brand attitudes than those from ChatGPT.

H1a is based on localized cultural nuance, as DeepSeek's training on Chinese corpora aligns better with 'Oriental' aesthetics. H1b was proposed because DeepSeek is expected to be more credible due to its higher accuracy in literary tasks and its tendency to provide structured, factually consistent outputs. H1c posits ChatGPT's edge in conversational fluency, facilitating higher social engagement (EWOM). H1d based that ChatGPT is predicted to generate more favorable brand attitudes because of its greater creative flair, emotional storytelling capabilities, and global conversational fluency.

3.2. Method

3.2.1. Participants

We conducted an offline experiment in Zhejiang University of Technology, which has been supported by ethics approval. We recruited 63 volunteers to participate in the experiment by publicizing online announcement in WeChat groups. Upon completion, the participants received a small financial compensation for their participation.

According to Biswas et al., we employed a random online invitation procedure to recruit participants, which helps reduce selection bias and broadens the participant pool beyond immediate social networks [29]. Compared with "pre-screening groups" or "targeted recruitment", random sampling can minimize the sample bias caused by the subjective judgment of researchers. Besides, it can improve external validity. Researchers hope that the conclusions have a certain degree of generalizability in daily scenarios, and improve the applicability of experimental results in real consumption scenarios through different types of consumers.

The study recruited 63 participants (82.5% female, 17.5% male). The age range of all participants is centered on from 18 to 25 years old (83.3%). The two groups did not differ in gender and age, with 35 participants in high-scoring group ($M_{\text{gender}} = 1.83$, $M_{\text{age}} = 2.09$), and 28 participants in low-scoring group ($M_{\text{gender}} = 1.82$, $M_{\text{age}} = 2.29$).

3.2.2. Materials

We design the instruction with text topics (product features and brand story). The topic of this advertisement is "Collect a corner of time in the East, brew the poetry of breathing at this moment", which is thought over by researchers. The same instruction of To summer' advertising copy with subjective and creative requirements was inputted into DeepSeek and ChatGPT. The instruction is "Now I want to use the slogan 'Collect a corner of time in the East, brewing the poetry of breathing at this moment' to promote To Summer, a perfume brand. In order to let consumers better understand the brand culture of the brand, how can I expand this text to make it more story-telling and reflect the product function (please add some words with Chinese connotations in the text), and explain why you think so". Then, DeepSeek and ChatGPT generated an advertising copy respectively. Two advertising copies are shown in Appendix 1.

All the words and sentences in this experiment are Chinese. After the advertising copies and explanations are generated, the original Chinese version was translated into English shown in this research. Two Business English postgraduate students, who were fluent in both English and Chinese, first translated all the instruction and two Chinese advertising copies into English. Then, the first author of this study assessed their version and modified the detailed to enhance

the accuracy of the translation. The final English version written for the study was formulated.

3.2.3. Procedure

A total of sixty-three participants were distributed questionnaires to test differences in consumers' perception of brands. Documents including information sheets and consent forms for participants were sent out and signed. Under the conduction of professional teacher, To Summer, a Chinese perfume brand, was selected as the case of this study. According to the research from Yoo et al., [30] the pre-test question was developed into "Do you know the brand - To Summer?". Then, we set an item of using GenAI preference. Participants with a total score (≥ 3) were assigned to classroom 1, while participants with a score < 3 were assigned to classroom 2. Then, this experiment was carried out at the same time. In each group, participants were told, "You will read two advertising copies of To Summer with text topic of product features and brand story, please read carefully and complete the questionnaires after reading two texts." Afterward, we measured brand authenticity, brand credibility, EWOM intentions, brand attitudes and brand loyalty. After integrating all questionnaires and coding for them, we analyzed the independent variable (the generation platform) and the examination of the moderating effect of brand familiarity on the dependent variables (brand authenticity, brand credibility, electronic word - of - mouth marketing willingness, and brand attitude).

The two groups also did not differ in total scores of experiment ($M_{\text{high-scoring group}} = 3.14$, $M_{\text{low-scoring group}} = 2.00$). Specially, this shows that there is no obvious bias in the sample to the familiarity of the brand and GenAI preference, with using preference of two platforms ($M_{\text{high-scoring group}} = 1.29$, $M_{\text{low-scoring group}} = 1.00$) and brand familiarity ($M_{\text{high-scoring group}} = 1.86$, $M_{\text{low-scoring group}} = 1.00$). We measured each of four scales on a seven-point agreement Likert scale (1 = strongly disagree, 7 = strongly agree). Perceived brand authenticity was assessed by the mean of three items ($\alpha = 0.68$, $M = 5.06$, $SD = 0.96$) from Moulard et al. [31] We measured brand credibility ($\alpha = 0.72$, $M = 5.12$, $SD = 0.96$) and favorable EWOM intentions ($\alpha = 0.67$, $M = 5.01$, $SD = 0.95$) by adapting scales from Boerman et al. [32]. Brand attitudes was measured by three items ($\alpha = 0.82$, $M = 4.98$, $SD = 1.00$) from Campbell [43]. A single reversed item ($M = 3.833$, $SD = 1.651$) from Brüns and Meißner indicated brand loyalty [33].

3.3. Results

According to Chung, the Cronbach's Alpha coefficients of 4 scales are all greater than 0.6, and the scale has a better internal consistency reliability [34]. When the four scales are summarized into one table, the coefficient is 0.87, and the measurement results are relatively reliable. Factor loading coefficients are 0.82, 0.85, 0.81 and 0.91 respectively, which all greater than 0.4, and $KMO = 0.75$. Therefore, the scale has good validity. In the two groups, the independent sample t-test results of brand familiarity showed no significant differences in brand authenticity ($F = 0.06$, $t = -1.46$, $p = 0.15$), brand credibility ($F = 0.82$, $t = -0.34$, $p = 0.73$), EWOM intentions ($F = 0.62$, $t = 0.17$, $p = 0.86$) and brand attitudes ($F = 0.53$, $t = 0.30$, $p = 0.77$). The independent sample t-test results of using GenAI preference also showed no differ in brand authenticity ($F = 0.02$, $t = -0.04$, $p = 0.97$), brand credibility ($F = 0.06$, $t = 0.16$, $p = 0.87$), EWOM intentions ($F = 0.44$, $t = -0.59$, $p = 0.56$) and brand attitudes ($F = 0.11$, $t = 1.00$, $p = 0.32$). Therefore, H1a, H1b, H1c and H1d were not

supported.

3.4. Discussion

This study aims to make a comparison between consumer perceptions of advertising copy generated by two leading AI platforms – DeepSeek and ChatGPT – across four different dimensions: brand authenticity, brand credibility, EWOM intentions, and overall brand attitudes. In contrast to our initial hypotheses (H1a–H1d), no statistically significant differences were observed between the two AI sources across any measure (all $p > 0.05$). The null findings may be attributable to several interrelated factors. Firstly, it is evident that both DeepSeek and ChatGPT employ analogous large-scale pretraining and fine-tuning processes, thus yielding analogous linguistic style and coherence. In other words, xxxConsequently, consumers are unable to differentiate between the two. Secondly, the participants' baseline familiarity and neutral attitudes toward AI tools did not form a clear stratification (as measured), which reduces the possibility of interplatform differences becoming identifiable clues. Thirdly, the degree of fit between cultural familiarity and narrative style may not differ significantly among different platform outputs, thus not triggering consumers' differential judgments on authenticity/trustworthiness. Finally, the theme of the experimental materials (with a strong "Oriental poetic" narrative) may trigger central route elaboration in the subjects, thereby relatively "drowning" the influence of peripheral cues such as source labels (from different AI platforms).

4. Study 2

Study 1 shows that consumers' perceptions have no significant changes on reading different advertising copies produced by different Gen-AI platforms. To measure the associating factors of consumers' perceptions on brand culture with utilizing AIGC platforms, Study 2 explored whether customers will perceive different brand cultures based on the different advertising copies generated by AI and human. Therefore, we added the variable of perceived brand culture on the basis of Study 1's independent variables (brand authenticity, brand credibility, EWOM intentions, and brand attitudes).

4.1. Hypotheses

Having established that brand familiarity and using GenAI preferences have no significant differences on impacting consumers' perceptions of the brand culture, Study 2 investigates whether human versus AI authorship further influences consumers' perceptions of brand culture, which is defined as a macro-level symbolic text and a shared ideological resource that mediates collective brand meaning beyond individual attitudes [35, 26]. We built on Study 1 by focusing on DeepSeek copy vs. human-crafted narratives, predicting human authorship will strengthen perceptions of brand culture and amplify the role of credibility as a driver of cultural resonance.

Hypotheses:

H2a: Brand authenticity positively influences brand culture.

H2b: Brand credibility positively influences brand culture.

H2c: Consumers' EWOM intentions positively influence brand culture.

H2d: Brand attitudes positively influence brand culture.

H2e: The relationship between each perception dimension (authenticity, credibility, EWOM intentions, attitudes), brand

culture is moderated by text origin.

H2f: Based on H2e, human-generated text has a stronger effect than AI-generated text.

4.2. Method

4.2.1. Participants

In the pre-test study, we concluded that consumers' perception of advertising copies showed no differ in gender, age, using preference of GenAI platforms and brand familiarity.

Therefore, the criteria and methods for recruiting participants are as Study 1. We recruited 66 participants (74.24% female, 25.76% male). Using the same procedure on Zhejiang University of Technology as in pre-test study. The age range of all participants is centered on from 18 to 25 years old (72.73%). By coding and running in Python 3.12.0 version and Spyder 5.5.1 version respectively (code shown in the Appendix 3), we divided these 66 participants into two groups: Group A read the human-generated advertising copy, and Group B read the copy generated by Deepseek. The two groups did not differ in gender ($M_{(\text{Group A})} = 1.709$, $SD_{(\text{Group A})} = 0.467$; $M_{(\text{Group B})} = 1.79$, $SD_{(\text{Group B})} = 0.415$) and age ($M_{(\text{Group A})} = 2.24$, $SD_{(\text{Group A})} = 0.936$; $M_{(\text{Group B})} = 2.03$, $SD_{(\text{Group B})} = 0.684$).

4.2.2. Design and Measures

All the words and sentences in this experiment are Chinese, and the criteria of the translations to write this research as the same as Study 1. Based on the criteria and methods for main test materials shown as those of Study 1's materials, we developed the original instruction "If you are an advertising planner and want to conceive a slogan for the brand, and require it to focus on the brand story, how would you design it? With the same requirements as above, expand the slogan 'Collect a corner of time in the East, and brew the poetry of breathing at this moment' to generate an advertising text?". There was no significant difference in perceived advertising using different AI platforms measured in the Study 1. Therefore, we chose DeepSeek AI to input the instruction in this research. Also, we invited the two graduate students from the Chinese Department who were fluent in both English and Chinese to create a piece of advertising copy for To Summer with the same criteria as DeepSeek. Then, the second author perfected this advertising copy. The two copies are shown in Appendix 2.

All constructs were assessed on a seven-point agreement Likert scale (1 = strongly disagree, 7 = strongly agree): The scales of brand authenticity ($\alpha = 0.85$, $M = 5.11$, $SD = 0.77$), brand credibility ($\alpha = 0.82$, $M = 5.08$, $SD = 0.76$), EWOM intentions ($\alpha = 0.89$, $M = 4.99$, $SD = 0.83$) and brand attitude ($\alpha = 0.89$, $M = 5.01$, $SD = 0.85$) from the Study 1 was still used in the formal experiment. In order to measure the differences in consumers' perception of brand culture in different advertisements (copies generated by human or AI), we added a scale with four items ($\alpha = 0.89$, $M = 5.18$, $SD = 0.81$) from Desai et al. [36], Douglas [37]. According to Chung, the Cronbaeh' Alpha coefficients of five scales are all greater than 0.8 [34], and the scale has a better internal consistency reliability. When the four scales are summarized into one table, the coefficient is 0.96, and the measurement results are excellent. Factor loading coefficients are 0.92, 0.93, 0.91, 0.92 and 0.94 respectively, which all greater than 0.9, and KMO = 0.909. Therefore, the scale has excellent validity. The results was shown in Table 1.

Table 1. Reliability Analysis

KMO	Approx. Chi-Square	df	p	Cronbaeh' Alpha
0.706	172.704	6	<0.01	0.909

4.3. Results

To test 6 hypothesis, correlation analyses was examined by

Table 2. Correlation analysis of variables

	M±SD	1	2	3	4	5
Brand culture	5.18±0.81	1	0.833**	0.842**	0.806**	0.840**
Authenticity	5.11±0.77		1	0.857**	0.761**	0.777**
Credibility	5.08±0.76			1	0.799**	0.802**
EWOM Intentions	4.99±0.83				1	0.845**
Brand Attitudes	5.01±0.85					1

Note: at the 0.01 level (double tailed), the correlation is significant.

Secondly, an independent-samples t-test (see Table 3) of the manipulation check confirmed that there were significant variances in the text authenticity (Group A: M = 5.66, SD = 0.72, Group B: M = 4.56, SD = 0.26, $t(33) = 8.274$, $p < 0.001$, Cohen's $d = 0.54$), text credibility (Group A: M = 5.57, SD = 0.77, Group B: M = 4.60, SD = 0.33, $t(33) = 6.676$, $p < 0.001$,

SPSS 27.0 version, whose results were shown in the Table 2. The square root of each construct's AVE was basically higher than its correlations with the other constructs, supporting good discriminant validity [38].

Cohen's $d = 0.59$), EWOM intentions (Group A: M = 5.56, SD = 0.78, Group B: M = 4.43, SD = 0.37, $t(33) = 7.467$, $p < 0.001$, Cohen's $d = 0.61$), brand attitudes (Group A: M = 5.63, SD = 0.74, Group B: M = 4.39, SD = 0.34, $t(33) = 8.661$, $p < 0.001$, Cohen's $d = 0.58$) and brand culture (Group A: M = 5.80, SD = 0.65, Group B: M = 4.55, SD = 0.30, $t(33) = 9.943$, $p < .001$, Cohen's $d = 0.51$).

Table 3. Results from independent-sample t test

Main variables			M	SD	t	p
Text source	Brand culture	Human Text	5.80	0.65	9.943	<0.001
		AI Text	4.55	0.30		
	Authenticity	Human Text	5.66	0.72	8.274	<0.001
		AI Text	4.56	0.26		
	Credibility	Human Text	5.57	0.77	6.676	<0.001
		AI Text	4.60	0.33		
	EWOM Intentions	Human Text	5.56	0.78	7.467	<0.001
		AI Text	4.43	0.37		
	Brand Attitudes	Human Text	5.63	0.74	8.661	<0.001
		AI Text	4.39	0.34		

Note: $p < 0.01$, At a significance level of 0.01, the difference in corresponding variables between human text and AI text is statistically significant, indicating that the two types of text exhibit different behaviors in brand culture, authenticity, and other aspects, and the differences are significant.

Thirdly, we tested main and interaction effects on brand culture using hierarchical regression (see Table 2). Hayes' PROCESS macro (Model 1) in SPSS 27 was used to assess H2a–H2f [39]

H2a predicted that brand authenticity would positively influence brand culture. This effect was positive but not significant ($\beta = 0.158$, $p = 0.169$). H2b predicted that brand credibility would positively influence brand culture. This was supported ($\beta = 0.297$, $p = 0.014$). H2c predicted that EWOM Intentions would positively influence brand culture, whose effect was non-significant ($\beta = 0.098$, $p = 0.367$). H2d predicted that brand attitudes would positively influence brand culture. This effect was marginally positive but did not reach significance, ($\beta = 0.209$, $p = 0.074$).

Table 4. Hierarchical Regression Analyses

	β	t	p	R ²	
Authenticity	0.158	1.393	0.169		
Credibility	0.297	2.533	0.014	0.834	
EWOM Intentions	0.098	0.909	0.367		Sig <0.01
Brand Attitudes	0.209	1.819	0.074		
Text source	-0.255	-3.052	0.003		

Note: (1) Dependent variable: Brand culture (2) Model checking: $F = 60.497$; $p < 0.01$

Thirdly, we introduced Text origin (coded 0 = Human-generated text, 1 = AI-generated text) to test for both its main effect and its moderating role (H5a/H5b). Text Origin showed a significant negative main effect on brand culture ($\beta = -0.255$, $t = -3.052$, $p = 0.003$), indicating that, holding perceptions constant, AI-generated texts (Origin = 1) are associated with lower brand culture scores compared to human-generated texts (Origin = 0), holding perception dimensions constant. Because no interaction terms were included in this step, hypotheses H2e and H2f regarding moderation remain untested in this model.

4.4. Discussion

While H2e-f moderation interaction terms were not statistically robust, a powerful main effect of text origin was observed, where human authorship consistently outperformed AI across all dimensions ($p < 0.001$).

Study 2 demonstrated that advertising texts generated by human subjects significantly enhanced perceptions of brand culture in comparison to those generated by AI ($t(33) = 9.943$, $p < 0.001$). This finding corroborates the prediction made by the ELM that source cues influence peripheral processing [14]. Regression analysis isolated Brand Credibility ($\beta = 0.297$, $p = 0.014$) as the sole significant driver of brand culture formation, while authenticity and attitude failed to reach statistical significance. Although authenticity and attitudes showed positive relationships with brand culture, they did not reach statistical significance, implying that more elaborate or emotionally resonant storytelling may be required to activate central-route elaboration for these dimensions [12]. The non-significant effect of EWOM intentions ($\beta = 0.098$, $p = 0.367$) further indicates that willingness to share contents alone cannot offset the negative peripheral cue of AI authorship [2]. From a brand signal theory perspective [20], AI-generated texts appear to lack the human-centered signals of sincerity and craftsmanship, impairing cultural coherence [7]. Cultural consistency theory likewise predicts that algorithmically produced narratives may disrupt symbolic alignment with shared values, a disruption clearly observed in the lower culture scores for AI texts [40]. The findings, overall, highlight the significance of human in the creation of brand narratives, with the objective of safeguarding cultural depth and resonance.

5. General Discussion

With the advent of generative AI technologies, marketers now have the capability to craft content of significance for creative endeavors. This development signifies a substantial augmentation of the capabilities of assistant AI in the context of brand construction [33].

The present study examined the manner in which the provenance of brand communications—whether generated by disparate AI platforms (DeepSeek vs. ChatGPT) or authored by humans—shapes consumer perceptions and the co-creation of brand culture. The present study is grounded in the Elaboration Likelihood Model's peripheral-cue framework [14], alongside brand signal theory [20] and cultural consistency theory [41]. Two sets of hypotheses were formulated: first, that consumers would discern differences in persuasive impact between DeepSeek and ChatGPT outputs; second, that human-authored texts would outperform AI-generated texts in authenticity, credibility and cultural resonance.

In Study 1, no significant differences emerged between DeepSeek and ChatGPT on any measure—authenticity, credibility, EWOM intention or attitude (all $p > 0.05$). This suggests that when disclosure and content quality are standardized, the algorithmic origin alone does not constitute a salient peripheral cue, corroborating recent findings on the homogeneity of off-the-shelf AI texts [42].

Study 2, however, revealed that human-authored narratives significantly outperformed AI-generated ones in terms of authenticity ($t(33) = 8.274$, $p < .001$) and credibility ($t(33) = 9.943$, $p < .001$). Furthermore, human-authored narratives elicited higher cultural resonance scores. The findings lend

support to the hypothesis that “technological authorship” functions as a negative peripheral cue, with consumers inferring lower sincerity and craftsmanship when texts are labelled machine-generated [7]. This disruption to the symbolic alignment necessary for community identification has been further explored in the work of Park and Kim [40].

In summary, the studies extend ELM by recognizing ‘AI authorship’ as a peripheral cue, refine brand signal theory by identifying algorithmic origin as a negative signal, and broaden cultural consistency theory by showing that source cues can disrupt symbolic alignment. While artificial intelligence (AI) can offer efficiency, human involvement remains essential to preserve depth and trust in brand storytelling. It is recommended that future research explore the potential of bespoke, fine-tuned AI models or multimedia formats to mitigate the identified authenticity deficits.

5.1. Theoretical Implications

Our findings make four substantial theoretical contributions. This study makes contribution on methodological advancement by conducting two-study comparative design. The juxtaposition of intra-AI platform comparisons (Study 1) and AI vs. human comparisons (Study 2) offers a methodological template for future AI communication research. By isolating platform effects before evaluating authorship effects, our approach mitigates confounding variables and clarifies the roots of consumer discrimination. This design can be adapted to investigate other peripheral cues—such as AI-driven personalization or avatar presence—thus advancing empirical rigor in the evolving field of human-AI interaction studies.

Our paper presents a pioneering extension of the Elaboration Likelihood Model (ELM) to technological authorship. Traditional ELM research emphasizes the role of source credibility and message quality in determining whether consumers process persuasive communications via central or peripheral routes [14]. Our findings expand this framework by introducing “technological authorship” as a boundary condition for peripheral cue processing. The null results obtained from the study for DeepSeek vs. ChatGPT demonstrate that consumers regard different Generative AI engines as being functionally equivalent peripheral sources when content and disclosure are controlled. Study 2, however, revealed that AI-authored texts elicit weaker attitudes and lower cultural resonance than human-authored texts, illustrating that the mere disclosure of AI generation serves as a negative peripheral cue. This extension suggests that technological authorship must be integrated into the ELM's source cue taxonomy, as it can override central-route arguments even when message arguments themselves are held constant.

Then, we contribute to refining brand signal theory in the AI context. Brand signal theory posits that consumers infer product or service quality from observable signals—such as craftsmanship or expert endorsement—when direct evaluation is difficult [20]. Our studies identify AI authorship as a novel negative signal: participants inferred lower sincerity, authenticity, and communal alignment when narratives were labeled as machine-generated. This nuance refines brand signal theory by demonstrating that consumers not only respond to the presence of expert or celebrity endorsements, but also react negatively to non-human sources. Consequently, the work makes a significant contribution to the field of signalling literature by highlighting the potential

drawbacks of algorithmic authorship with regard to perceived signal integrity, particularly in the context of symbolic domains such as brand culture.

The findings integrate with cultural consistency frameworks by comparing consumers' preferences on different advertising copies generated by Gen-AI and human thinking. Cultural consistency theories emphasize that brand narratives must resonate with shared values and symbolic meanings to foster group identity and loyalty [41]. Our data show that AI-authored texts disrupt this alignment: despite equivalent informational content, they generate lower cultural coherence scores. This finding integrates technological authorship into cultural consistency models, suggesting that narrative origin affects symbolic alignment beyond message semantics. It encourages scholars to consider authorship cues alongside narrative content when assessing cultural fit.

5.2. Managerial Implications

The findings of this study offer tangible strategies for brand managers and marketers to navigate the integration of generative AI in brand communication while preserving cultural coherence. Below are actionable implications derived from the research, structured to address key challenges in AI-mediated brand storytelling. Our paper offers actionable managerial guidance for GenAI assistant usage, emphasizing 1) the importance of adopting hybrid human-AI co-creation workflows as well as 2) the necessity of making strategic disclosure of AI involvement, 3) investing in brand-specific AI training, 4) monitoring consumer feedback on AI-authored content and 5) training marketing teams in AI literacy. Also, this study can inspire brands and marketers to segment communication strategies by audience.

First, the evident discrepancy in efficacy between human-generated and AI-generated texts indicates that marketers should employ AI tools for the initial drafting and ideation stages, while retaining human oversight for the final narrative refinement. In practice, AI can be deployed to generate standardised copy, such as feature descriptions or routine announcements, while human specialists refine tone, cultural references and emotional nuance. This hybrid workflow has been developed to balance efficiency gains with the need to preserve authenticity and credibility, thus ensuring that brand communications retain the human touch that is known to drive cultural resonance.

Second, given that explicit AI attribution functions as a negative peripheral cue, it is vital for brands to carefully manage how they communicate AI usage to consumers. In order to circumvent the presentation of AI as the sole author, marketers may opt to position it as a "creative assistant" or "co-author". This strategic approach entails the framing of the technology as a supportive entity, as opposed to a substitutive one. For instance, the utilization of a label such as "Produced with AI assistance under editorial review" serves to communicate ongoing human involvement, thereby mitigating any potential negative inferences regarding authenticity. It is imperative for brands to assess a range of disclosure formats in order to ascertain the most effective method of framing information that will maintain the level of trust required.

Third, the present studies utilized off-the-shelf AI platforms; however, investing in proprietary, brand-trained AI models has the potential to reduce the authenticity gap. Our findings align with the 2025 'AI-authorship effect' literature, which demonstrates that emotional communications suffer

more from AI disclosure than factual ones. Specifically, luxury and heritage brands are most vulnerable to the authenticity deficit because AI authorship signals 'low effort', which clashes with the exclusive essence of luxury craftsmanship. Conversely, utilitarian brands may benefit from AI's efficiency without significant cultural dilution.

Besides, it is imperative for organizations to implement real-time monitoring of consumer responses through social listening, sentiment analysis, and EWOM tracking, in order to ensure the success of AI-generated campaigns. Key metrics include brand culture indicators (e.g., references to shared values in comments) and trust signals (e.g., mentions of "authentic" or "genuine"). The utilization of continuous feedback loops facilitates the expeditious iteration of disclosure strategies and workflow adjustments, thereby ensuring that the integration of AI does not inadvertently erode brand equity.

Furthermore, In order to ensure effective marketing outcomes, firms must equip their marketing professionals with a comprehensive understanding of both the capabilities and limitations of AI. It is crucial that training programs encompass prompt engineering, the ethics of disclosure, and techniques for blending human creativity with machine efficiency. By fostering AI literacy, organizations empower teams to harness generative tools strategically, thus avoiding the pitfalls of overautomation that have the potential to damage brand culture.

Finally, the degree of consumer sensitivity to AI authorship may vary across demographics and cultural contexts. In the context of premium or heritage-oriented segments, where authenticity is of the greatest importance, there is a possibility that a reaction to AI disclosure may be more negative than in digital-native or utility-focused segments, where efficiency is a priority. It is recommended that brands implement a strategy of campaign segmentation, utilizing artificial intelligence (AI) in transactional communications, such as billing reminders, while reserving human authorship for narrative touchpoints that have the potential to elicit a high degree of impact.

6. Limitations and Future Researches

Notwithstanding the contributions of the present study, there are several limitations that must be acknowledged. Firstly, the experimental stimuli focused exclusively on text-based brand narratives; findings may not generalize to multimedia formats such as video or audio content, where production values and sensory cues could modulate authorship effects. Secondly, the participants were drawn from a single cultural context, which may have resulted in a limitation of the cross-cultural applicability of the study. It is recommended that future studies incorporate diverse consumer populations in order to assess whether technological authorship carries uniform negative valence across regions. Thirdly, the AI manipulations employed generic, off-the-shelf models; bespoke, fine-tuned AI systems might yield different authenticity perceptions. Fourthly, the between-subjects design precludes examination of within-subject comparisons, which could illuminate individual thresholds for detecting AI authorship. In conclusion, the brief nature of the measures employed herein engenders immediate reactions; however, they do not take into account the long-term effects on brand equity or loyalty. It is imperative that longitudinal research is conducted in order to

ascertain whether initial authenticity deficits persist or attenuate over repeated exposures. By addressing these limitations, future work can deepen understanding of the dynamic interplay between AI authorship and consumer brand perceptions.

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Appendix 1:

Generated result from DeepSeek AI:

“Picking up a corner of the East, storing the aroma of the twenty-four solar terms;

Take the tender buds of Suzhou spring tea and rub them into the morning mist of Wuyi Mountain;

Distill Qiongzhou agarwood using ancient methods, condensing the fragrance for six hours;

When burning incense, you can see the cracks of Song Dynasty celadon, and in the mist, you can feel like you are in Fanlou, Bianjing;

Watching the summer, I use the century-old incense classics as a guide, taking the essence of plum, orchid, bamboo and chrysanthemum in four seasons;

Transform the thousand-year-old Eastern breathing method into a trace of poetry on the desk at this moment;

The sandalwood smoke lingers in the beams for twelve hours, just like the changing scenery of Suzhou gardens.”

Generated result from ChatGPT AI:

“Deep in the cloudy tea mountain, Guan Xia perfumer poured his heart into a plant of morning dew grass and trees, gently picking the corner of the quiet time;

by the ancient fermentation process, brewed into a bottle of condensed oriental flavor of the fragrance.

The first note like the wind through the willow, leading you into the “rainy river” of the hazy mood;

middle note like the Zen words under the pine, the soul into the “half-curtained dream” of the moment of tranquility;

the last note is integrated into the sandalwood aftertaste,

like the “the end of the world” long aftertaste The last note is the aftertaste of sandalwood, like the long aftertaste of “the end of the world”.

Every breath, is a poetic travel in the skin bloom:

transparent water base, instant penetration of the pores, so that the texture of the skin is like the first rain moist;

silky extension of the texture, long-lasting scent, accompanied by you from the sunrise to the twilight, not stained with mundane dust;

micro-molecule micro-encapsulation locking technology, so that the scent in the temperature between the turn of the layers of the blossom, like the cycle of the seasons of the Zen Zen enlightenment.

To Summer, not only fragrance, is also a modern interpretation of oriental aesthetics;

in each wisp of dense, you perceive not only the fragrance, is more than a thousand years of poetry, “landscape have met, the wind and moon with this body” of the classic heritage.”

Appendix 2:

Generated result from DeepSeek AI:

“At the bottom of my grandmother's camphorwood box, there are osmanthus flowers from 1972. Every time I open the box, there is a wisp of old sweet fragrance escaping, wrapped in the unique spicy and cool medicinal smell of camphorwood, lingering in the dust;

The old inkstone in my father's study, every time I grind ink, the black ink spreads, and the ink fragrance is always mixed with a few bitter cypresses.

We say this is homesickness, Guanxia says it is a corner of time in the East.

They use the mud of Jingdezhen, the fungus of Yunnan, and the snow of Kunlun, and they use their almost pious craftsmanship to collect, store, and ferment the scattered old times. This is a long wait and transformation, until every drop of essential oil can replicate the weight of a breath in the glass.

Now, when I light the candle wick of [Yihe Golden Osmanthus],

I finally understand: The so-called hometown is just a damp fog in the genes.”

Generated result from human:

“In November, the winter wind swept across 35 degrees north latitude; Snowflakes fell on the Central Plains; The newly sown wheat tasted the first sweetness of winter;

Grandpa rolled a cigarette and said that there would be a good harvest next year.

At the beginning of the new year, the family sat together, The snow outside the window pressed down the branches, and the green of the pine and cypress trees was more verdant in the white; In a trance, the voice of grandpa saying that new firewood would be added in the new year came again; The snow wet my shoulders, and the pine and cypress wood crackled in the stove; Squatting by the stove, there was a deep fragrance that could not be contained.

In March, the sunshine in the north slanted from the branches of the trees; Morning and dusk turned to spring, and the ice and snow had not yet melted; After four years away

from home, grandpa's voice was far away in heaven. The cool spring breeze passed slowly, and the snowflakes on the pine and cypress branches fell. I wanted to reach out and grab a few snowflakes, just like grabbing a few unknown fragrances in my childhood memories.

Now, when I light the candle wick of [Kunlun Boiling Snow], I finally understand where the aroma comes from: Missing you is a heavy snow that never melts.

Appendix 3:

Code in Python 3.12.0 version and Spyder 5.5.1:

```
import pandas as pd
import numpy as np
import os

# 设置桌面路径（请根据用户名修改）
desktop_path = os.path.join(os.path.expanduser("~"),
"Desktop")

# 输入文件路径（假设 Excel 文件在桌面）
input_file = os.path.join(desktop_path, "Total.xlsx")

# 检查文件是否存在
if not os.path.exists(input_file):
    print(f"❌ 错误：未找到文件 {input_file}。请确保文件在桌面上。")
else:
    # 读取 Excel 第一个 sheet
    df = pd.read_excel(input_file, sheet_name=0)

    # 添加随机数列进行打乱
    df_shuffled = df.sample(frac=1,
random_state=42).reset_index(drop=True)

    # 创建一个新列用于分组（A组、B组）
    df_shuffled["Group"] = np.where(df_shuffled.index %
2 == 0, "A", "B")

    # 分组保存
    group_A = df_shuffled[df_shuffled["Group"] ==
"A"].reset_index(drop=True)
    group_B = df_shuffled[df_shuffled["Group"] ==
"B"].reset_index(drop=True)

    # 保存文件到桌面
    group_A.to_excel(os.path.join(desktop_path,
"group_A.xlsx"), index=False)
    group_B.to_excel(os.path.join(desktop_path,
"group_B.xlsx"), index=False)

    print(f"✅ 分组成功，文件已保存到桌面：
group_A.xlsx 和 group_B.xlsx")
```