POSITIVE EFFECTS OF NEGATIVE DISCLOSURE: THE PERSUASIVE POWER OF NEGATIVE AI-GENERATED CONTENT IN SHAPING CONSUMER PRODUCT ATTITUDE

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ABSTRACT

Artificial intelligence-generated content (AIGC) holds significant potential and diverse applications in e-commerce. Although existing research has largely focused on AI's role in personalized recommendations and product advertising, few studies have examined AI-generated reviews. Drawing on source credibility theory (SCT), this study develops a research model to explore how displaying AI-generated negative reviews influences consumers' product attitudes. Using data from a Chinese e-commerce platform that employs AI to generate product reviews, we test our hypotheses through ordinary least squares (OLS) analysis. Our results indicate that displaying AI-generated negative reviews can enhance perceived review credibility and reduce perceived risk, ultimately improving consumers' product attitudes. Moreover, the impact of such reviews varies depending on product and influencer-related factors. By investigating the effects of AI-generated negative reviews on product attitudes, this study contributes to the AIGC and online review literature while offering practical governance insights. For platforms and retailers, these findings underscore the strategic value of negative reviews in fostering consumer trust and engagement.

Keywords: AI-generated content; Negative reviews; Source credibility theory; Influencer credibility

1. Introduction

The rapid advancement of generative artificial intelligence (GAI) has accelerated the integration of AI-generated content (AIGC) into platform operations, particularly in e-commerce (Xu et al., 2024; Zhou & Li, 2024; Zhou et al., 2023). Major platforms such as Amazon (amazon.com) and Meituan (meituan.com) now employ AI-generated product

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reviews to assist consumers' decision-making (Ovide, 2024). However, the predominance of positive AI-generated reviews has led to a scarcity of negative ones (Kastrenakes, 2023), likely due to business' concerns about potential adverse effects (Hennig-Thurau et al., 2015; Wu et al., 2015). This raises a critical question: Does the display of AI-generated negative reviews indeed produce the feared adverse effects, or could it lead to unforeseen positive outcomes?

In today's data-driven landscape, artificial intelligence (AI) systems have demonstrated remarkable capabilities in extracting insights efficiently from vast datasets (Longoni & Cian, 2022; Marwala & Hurwitz, 2015). While concerns persist about AIGC's reliability—particularly regarding training data quality and algorithmic biases (Li et al., 2023; Longoni et al., 2019)—extensive research confirms AI's superior analytical performance, enhancing decision-making efficiency and process optimization (Davenport et al., 2020; Huang & Rust, 2021; Ma et al., 2025).

E-commerce, as a sector deeply intertwined with consumer interactions, has been an early adopter of AIGC. Yet, existing research has primarily focused on personalized recommendations (Bawack et al., 2022; Wang et al., 2023), product marketing (Arango et al., 2023; Du et al., 2023; Zou et al., 2023), and customer service enhancements (Chung et al., 2020; Zhu et al., 2022). Despite the recognized influence of AI-generated reviews on purchasing decisions, there remains a notable gap in research regarding their effects, particularly regarding negative reviews. While some studies have examined the impact of AI-generated summaries on consumer behavior (Li et al., 2024), the potential effects of negative AIGC have been understudied.

The literature extensively documents the detrimental effects of human-generated negative reviews across industries, including dining (Wu et al., 2015), entertainment (Basuroy et al., 2003; Hennig-Thurau et al., 2015), hospitality (Lopes et al., 2022), and e-commerce (Lee et al., 2008; Liu et al., 2019; Pan et al., 2011; Weisstein et al., 2017). However, scholarly attention has largely centered on user-generated content (UGC), overlooking platform-based AIGC (Azimi & Ansari, 2023; Cao et al., 2011; Schlosser, 2011; Yin et al., 2023)—particularly the role of AI-generated negative reviews. This gap is notable given AI's growing content-creation role and its perceived impartiality compared to human reviewers (Lee, 2018).

Emerging evidence suggests significant differences in how consumers process AI-generated information. Unlike emotionally charged human reviews, AI employs standardized algorithmic processes (Sundar & Nass, 2001), producing outputs perceived as more objective and data-driven (Lee, 2018). This objectivity may enhance credibility, particularly when presenting balanced positive and negative perspectives (Jensen et al., 2014). Supporting this view, Garvey et al. (2023) found that consumers respond more positively to AI agents in negative contexts, attributing this to the perceived lack of selfish motives in AI. Similarly, Yalcin et al. (2022) demonstrated an asymmetric effect: algorithmic (vs. human) decision-makers negatively affect consumer responses when outcomes are favorable, but not when outcomes are unfavorable. These findings align with source credibility theory (SCT), suggesting the objective presentation by AI of negative information may enhance credibility by leveraging trustworthiness and expertise, thereby offering new mechanisms for shaping consumer perceptions in e-commerce.

Grounded in SCT, we propose that displaying AI-generated negative reviews enhances their perceived credibility, which in turn improves consumers' product attitudes. To test this, we collected data on 4,967 mobile phones from a major Chinese e-commerce platform using a web crawler. The platform employs AI algorithms trained on real consumer reviews to generate product reviews—presented in a dedicated "AI Purchasing Suggestions" module (Appendix A)—that include both positive feedback and certain negative insights for specific products. Our analysis, combining ordinary least squares (OLS) regression and text mining, reveals two key findings: Displaying AI-generated negative reviews can foster more favorable consumer attitudes toward the products. Furthermore, this effect is moderated by contextual factors; it weakens for high-priced or subsidized products but strengthens when promoted by influencers with large followings.

This study makes several key contributions. First, we extend AIGC research into the underexplored domain of AI-generated reviews in e-commerce, complementing existing work on product descriptions and advertisements (Arango et al., 2023; Zou et al., 2023). Paradoxically, our findings demonstrate that presenting AI-generated negative reviews alongside positive ones can enhance product attitudes, contributing to the understanding of AIGC. Second, our study expands the research within the domain of reviews. While prior research consistently shows human-generated negative reviews harm product evaluations and firm performance (Hennig-Thurau et al., 2015; Wu et al., 2015), we reveal AI's unique capacity to mitigate this effect through perceived objectivity (Aggarwal et al., 2012; Cao et al., 2011). This source-dependent effect advances SCT by showing how source credibility cues alter information processing. Finally, for platform managers, our results suggest a new approach in AIGC deployment. Rather than suppressing negative AI reviews, platforms should leverage AI's credibility advantage through transparent sourcing labels and implement balanced review presentation algorithms that largely enhance consumers' product attitudes.

2. Literature Review and Hypotheses

2.1. AI Application in E-commerce

AI encompasses more than just advanced technologies. It utilizes powerful computational capabilities and extensive datasets to perform well in various tasks, including learning, imitation, summarization, and analysis (Benbya et al., 2020; Berente et al., 2021). This ability enables the simultaneous processing of large volumes of information, thus enhancing organizational efficiency and supporting informed decision-making (Davenport et al., 2020; Huang & Rust, 2021). As cyberspace governance evolves, the importance of AI grows, particularly within the e-commerce sector (Alt, 2022). While much of the research has concentrated on AI applications in personalized recommendations and product advertising (Arango et al., 2023; Bawack et al., 2022; Chung et al., 2020; Yoon & Lee, 2021; Zhu et al., 2022; Zou et al., 2023), it is also crucial to recognize the inherent impartiality of AI (Lee, 2018), which are essential for ethical applications across different domains.

In e-commerce, online reviews strongly affect consumer purchasing decisions. However, the overwhelming volume of reviews can lead to information overload (Jones et al., 2004; Scholz & Dorner, 2013; Zhang et al., 2021). Additionally, individual differences among consumers can contribute to disparate reviews for the same product and complicate the decision-making process (Cao et al., 2011). AI-generated product reviews (both positive and negative) are derived from consistent algorithmic processes (Sundar & Nass, 2001), resulting in recommendations that lack personal bias and rooted in the analysis of genuine consumer feedback. Research indicates that consumers trust AI-generated recommendations for utilitarian attributes more than human-source recommendations (Longoni & Cian, 2022). This suggests that AI-generated reviews, with their perceived objectivity and consistency, may provide a more reliable and efficient means for consumers to navigate the complexities of online product evaluations.

As GAI continues to play a pivotal role in content generation, there is an urgent need for research addressing the contribution of AI to creating fair and transparent online environments (Birkstedt et al., 2023). With AI reshaping electronic markets, it is vital for e-commerce platforms to prioritize the ethical and transparent use of AIGC. By presenting both positive and negative product reviews, platforms can offer consumers balanced and comprehensive information, empowering them to make informed decisions. This approach helps cultivate a transparent, authentic, and reliable image for the platform, thereby establishing a strong foundation for long-term growth.

2.2. Source Credibility Theory

Source credibility theory (SCT) offers a theoretical framework for examining how information source credibility shapes message acceptance and persuasion (Hovland & Weiss, 1951). At its core, SCT posits that an information source's credibility is primarily constructed through two dimensions: expertise and trustworthiness (Alam et al., 2024; Applbaum & Anatol, 1972; Flanagin & Metzger, 2007). Expertise refers to the specialized knowledge or experience that an information source possesses, which can enhance its reliability (Alam et al., 2024; Ayeh, 2015; Teng et al., 2014). Trustworthiness refers to the reliability of the information, often evaluated based on the source's objectivity and lack of self-serving bias (Luo et al., 2013; Wellman, 2024).

The advent of AIGC in e-commerce requires re-examining these dimensions. Unlike human sources, AIGC exhibits unique credibility characteristics: algorithmic objectivity (Lee, 2018), emotional neutrality (Sundar & Nass, 2001), and data-driven analysis (Longoni & Cian, 2022). This presents a theoretical paradox; although AI lacks human qualities traditionally associated with credibility, its programmed nature creates novel pathways for establishing trust.

On the one hand, AI demonstrates expertise through data-driven analysis. By processing vast amounts of product-related data, AI can identify patterns, trends, and potential issues that might elude human reviewers. This ability to synthesize complex information in a systematic manner positions AI as a highly knowledgeable source, fulfilling the expertise dimension of SCT. On the other hand, AI achieves trustworthiness through programmed vulnerability. The intentional inclusion of negative reviews creates counterintuitive transparency, signaling resistance to commercial bias (Sundar & Nass, 2001). Moreover, the systematic presentation of both positive and negative reviews reflects structured evaluation rigor (Marwala & Hurwitz, 2015), differing fundamentally from organic review diversity.

This theoretical framework provides critical insights into how AI-generated negative reviews shape consumer attitudes. When such reviews are systematically presented alongside positive ones, their algorithmic objectivity enhances the perceived credibility of the review ecosystem; this mechanism aligned with SCT's emphasis on information source trustworthiness as a key persuasive driver (Jensen et al., 2014). By bridging this conceptual interplay, SCT establishes itself as an essential lens for investigating the impact of AIGC in e-commerce contexts.

2.3. Review and Product Attitude

User reviews play a pivotal role in shaping consumer decision-making, significantly influencing their perceptions of products and subsequent purchasing choices (Bae & Lee, 2011; Berger et al., 2010; Steur et al., 2022). Consumers often rely on these reviews to assess product quality and minimize potential risks associated with their purchases (Azimi & Ansari, 2023; Thomas et al., 2019). However, in practice, businesses frequently incentivize users to post positive reviews through financial rewards (Ai et al., 2022). This practice extends to platforms that use AIGC, such as Amazon and Meituan, where AI-generated positive reviews are commonly featured. Nonetheless, whether the reviews originate from consumers or AI, their uniformity and potential for manipulation may evoke consumer skepticism (Hu et al., 2012). In contrast, presenting AI-generated negative reviews alongside positive ones yields markedly different effects due to unique credibility dynamics introduced by AI as an information source.

According to SCT, credibility is jointly determined by trustworthiness and expertise (Alam et al., 2024; Ayeh, 2015). Unlike human-generated reviews where negative comments may be perceived as emotionally charged (Lee, 2018), AI-generated negative reviews are seen as systematic outputs based on predefined parameters (Marwala & Hurwitz, 2015). This satisfies SCT's trustworthiness criterion through perceived algorithmic objectivity (Sundar & Nass, 2001), even when consumers know the content is AI-generated. Moreover, when consumers encounter only AI-generated positive reviews, they may question the information's credibility because this unbalanced presentation fails to provide a complete product picture (Cheung et al., 2012). In contrast, including both AI-generated positive and negative reviews not only fosters a more comprehensive and objective product representation (Jensen et al., 2014) but also elevates consumers' perception of the source's credibility to a level comparable to professional evaluations (Marwala & Hurwitz, 2015). Within SCT's framework, expertise also serves as a significant factor influencing credibility (Ayeh, 2015; Teng et al., 2014). When information is presented objectively, consumers are more likely to associate it with specialized knowledge, which enhances their credibility assessment of the source and fosters a positive attitude (Roy et al., 2024). Accordingly, we propose the following hypothesis:

H1: The display of AI-generated negative reviews has a positive effect on the product attitude.

2.4. The Moderating Role of Product Information

Source credibility theory (SCT) posits that consumers' acceptance of information is determined by the source's expertise and trustworthiness, along with contextual factors arising from the heterogeneity and uncertainty of both the information source and the receiver's environment (Alam et al., 2024; Roy et al., 2024). In this study, information from both the product and influencer dimensions constitutes key contextual factors. *At the product level*, price and subsidy claims are the most salient attributes in consumers' purchasing decisions, significantly influencing their initial attitudes, perceived risks, and involvement (Cakici & Tekeli, 2022).

When the perceived risk of a purchase is high, consumers tend to seek out more comprehensive and credible information sources. High-priced products inherently entail greater financial risk (Holttinen, 2014; Majumder et al., 2023), leading consumers to scrutinize information sources more carefully. In this scenario, the expertise dimension of SCT becomes particularly salient. Consumers expect information sources to demonstrate in-depth knowledge about the product's features, performance, and value for money.

In addition, although AI-generated negative reviews are inherently objective, they may face heightened scrutiny for high-priced items. Since high prices are often associated with superior quality (Sun et al., 2024), consumers may doubt the AI's expertise when encountering negative feedback (Kučinskas, 2024). Consequently, the positive impact of displaying AI-generated negative reviews on product attitude may diminish, as consumers may distrust the negative information's credibility. Thus, we propose the following hypothesis:

H2: The positive effect of displaying AI-generated negative reviews on product attitude will be weaker for products that have a higher sale price.

A subsidy claim on a product can significantly influence consumers' perception of its trustworthiness. Subsidized products typically feature price reductions, and subsidy claims can significantly shape consumers' expectations of product value and quality (Lee & Chen-Yu, 2018). Subsidies signal that the platform is willing to invest resources to make the product more affordable, which may lead consumers to perceive the product as having higher value or quality (Hong et al., 2019). This pre-existing positive perception biases consumers toward accepting positive information while dismissing negative information (Abbey et al., 2017).

For AI-generated negative reviews, the subsidy context may undermine the AI source's trustworthiness. Although AI-generated reviews provide objective assessments (Castelo, 2019; Lee, 2018), subsidy contexts inherently skew persuasion dynamics. Negative feedback becomes less impactful than positive assertions (Zhang et al., 2010), as pre-existing value perceptions heighten skepticism toward critical content. This suggests that even the professionalism and credibility of AI reviews may be diminished when subsidy information is prominently featured on product pages (Zheng et al., 2022). Collectively, we posit the following hypothesis:

H3: The positive effect of displaying AI-generated negative reviews on product attitude will be weaker for products that have subsidy claim.

2.5. The Moderating Role of Influencer Information

The e-commerce platform examined in this study distinguishes itself by integrating influencer insights with AI-generated reviews and product data. Influencers play a pivotal role on this platform by disseminating product information. Therefore, we consider influencers' specific characteristics as critical factors in our analysis. *At the influencer level*, metrics such as influencers' social ties (follower count) and rating level serve as essential indicators for evaluating influencer credibility and influence, as they directly reflect the authority and social validation of influencers within the platform.

In the current landscape of digital marketing and social media, influencers significantly shape discussions and trends, ultimately affecting consumers' purchasing decisions (Chung et al., 2023; Ki & Kim, 2019). From the perspective of SCT, social validation serves as an important cue for evaluating source trustworthiness (Flanagin & Metzger, 2007). Influencers with a large follower base are perceived as having higher social validation, signaling that their recommendations are widely accepted and trusted by the public (Tafesse & Wood, 2021). This perception of trustworthiness extends to the information they disseminate (Janssen et al., 2022; Nafees et al., 2021).

When AI-generated positive and negative reviews are presented simultaneously, influencers with a substantial follower count can enhance the perceived credibility of these reviews through their own trusted status (Margom & Amar, 2024). This phenomenon stems from consumers' conformity tendencies and trust in influencers, which collectively enhance product perceptions (Ki & Kim, 2019). Moreover, in a trust-rich environment marked by strong social connections, consumers are more likely to accept negative information (Racherla et al., 2012). We formally hypothesize:

H4: The positive effect of displaying AI-generated negative reviews on product attitude will be strengthened when the influencer has a strong social tie.

SCT highlights the significance of the expertise of information sources in shaping their perceived credibility (Ayeh, 2015). Within the framework of this study, influencer's rating level serves as an indicator of professionalism and reliability (Sadiq et al., 2023). High-level influencers' perceived product evaluation expertise aligns with SCT's expert source concept (Martínez-López et al., 2020).

When high-level influencers promote products accompanied by AI-generated positive and negative reviews, their endorsement serves as a signal of the reviews' credibility (Alfarraj et al., 2021). Consumers are more likely to believe that high-level influencers have the expertise to present objective information (Kuksov & Liao, 2019). This perceived expertise significantly boosts the likelihood of consumers accepting AI-generated negative reviews as valuable insights, instead of simply dismissing them. In contrast, low-level influencers' limited expertise and credibility reduce their ability to enhance comprehensive reviews' positive impact. As a result, the positive impact of AI-generated negative reviews on product attitude is more pronounced when associated with high-level influencers. Accordingly, we propose:

H5: The positive effect of displaying AI-generated negative reviews on product attitude will be strengthened when the influencer has a high rating level.

Drawing on SCT, this paper argues that displaying AI-generated negative content can positively influence consumers' product attitudes. Additionally, the study identifies two types of product-related factors—product price and subsidy claims—that can mitigate this impact. Conversely, two influencer-related factors—the strength of the influencer's social tie and influencer's rating level—can enhance this effect. The primary research framework is illustrated in Figure1.

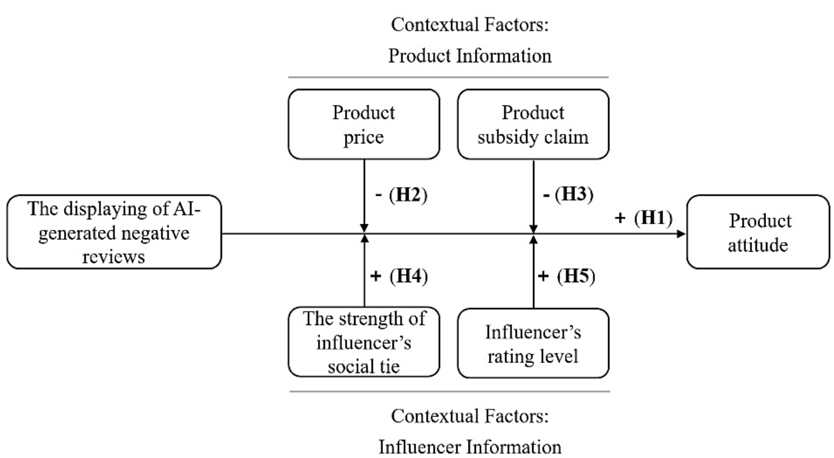

Figure 1: Research Model

3. Method

3.1. Data and Variables

This study examines an innovative Chinese e-commerce platform that utilizes AI technology to generate product reviews (as shown in Figure 2). Unlike traditional e-commerce platforms, this platform does not directly sell products. Its core business model features influencers disclosing promotional information for products from various e-commerce sites (as shown in Figure 3). Consumers use redirect links to shop on other e-commerce platforms, and the platform earns a commission from these transactions. Notably, influencers have the freedom to choose which product promotions to disclose, provided the subsidies are sufficiently attractive.

With the vision of "leveraging AI technology to efficiently extract product information from across the internet and help consumers make informed decisions," the platform employs AI to generate positive and negative reviews of products. These reviews are generated based on algorithms that have analyzed authentic consumer feedback, rather than simply summarizing pre-existing reviews. It is important to note that not every product has AI-generated reviews. The platform's algorithm determines which products receive such reviews. Furthermore, not every product that has AI-generated reviews includes negative ones. The AI-generated reviews are displayed below the basic product information (as shown in Figure 2).

We specifically collected data on all mobile phone brands listed on the platform. As a result, we obtained a dataset of 4,967 mobile phones. We chose this type of product due to its high demand, extensive user base, and abundant reviews. These factors provide robust data support for AI-generated reviews and enhance the stability of our analysis. Furthermore, as search goods (Nelson, 1970; Roy & Naidoo, 2017), mobile phones allow consumers to assess objective attributes like performance and battery life via online reviews. This facilitates decision-making (Dong et al., 2022; Mudambi & Schuff, 2010).

Figure 2: An Example of Product Price and Subsidy Claim on the Page

Figure 3: An Example of Influencer Social Tie and Rating Level on the Page

Dependent variable. In this study, product attitude serves as the dependent variable and is measured by the "worth-buying rate." This rate is derived from data collected on the platform from consumers when they click the "worth" button. As the platform does not directly provide product sales information, it lacks features such as shopping carts or consumer behavior data commonly found on other platforms. Consequently, our analysis is limited to product attitude in this context, and we posit that the worth-buying rate can reasonably reflect consumers' attitudes toward the products. The data itself is expressed as a percentage, ranging from 0 to 100%. In the course of our analysis, we scaled this data by multiplying it by 100, and in order to mitigate skewness, we applied a logarithmic transformation (*logWorth*).

Independent variable. The independent variable is a binary variable, coded as 1 if a product has both positive and negative AI-generated reviews, and 0 if it only has positive reviews (*AIGC-N*). **Moderating variables**. We consider two categories of moderating variables: those related to the product and those associated with influencers. Product price (*logPrice*) refers to the current selling price of the product, while the product subsidy claim (*Subsidy*) is a binary variable coded as 1 if a subsidy statement is present and 0 if not. Within our research context, influencers play a pivotal role in disseminating product information, making their characteristics essential for our analysis. Specifically, we account for two key moderating factors concerning influencers: the strength of the influencer's social tie and the influencer's rating level. These factors are represented by the number of followers (*logSocial tie*) and the influencer's rating level on the platform (*Level*), respectively.

Additionally, we controlled for several potential confounding factors that could influence the dependent variable. At the product level, we accounted for both the discount amount (*logDiscount*) and the positive review rate (*logPositive rate*), defined as the proportion of positive reviews displayed for each product on the platform. Given that the platform does not facilitate direct purchasing, consumers must complete transactions through external e-commerce platforms, making the purchase channel (*Channel*) a significant control variable. At the influencer level, as previously mentioned, all product purchase links on the platform are generated by influencers. Therefore, we operationalized the number of product links published by each influencer as a proxy for their influence capability (*logAbility*) and included this as a control variable. Furthermore, we accounted for the duration of product information disclosure (*Days*), as an extended disclosure period may increase user engagement with the "worth" button, potentially elevating the worth-buying rate.

Table 1: Variable Operationalization and Summary Statistics (N = 4,967).

Variables	Operationalization	Mean	SD	Min	Max
Main variables					
AIGC-N	Equals 1 if there has negative product review generated by AI, and 0 otherwise.	0.267	0.443	0	1
Worth	The worth-buying rate which clicked by users.	20.238	34.268	0	100
Price	The current selling price of the product.	3791.682	2743.139	0.010	22999
Subsidy	Equals 1 if there has subsidy claim, and 0 otherwise.	0.043	0.203	0	1
Social tie	The number of influencer's followers.	3705.103	9905.815	0	58206
Level	The rating level of the influencer on the platform ranges from 1 to 8, with higher levels enjoying more benefits.	7.395	1.094	2	8
Controls					
Channel	The product purchase channel is coded as 1 if it is a mainstream channel, otherwise it is coded as 0.	0.631	0.483	0	1
Discount	The discount amount of the product.	230.352	660.049	0	17601
Ability	The number of articles about products published by the influencer.	13620.340	14978.380	1	81894
Positive rate	The product's own positive review rate.	97.327	1.154	95	100
Days	The number of days since the influencer posted the product information by the time of data collection.	8.587	2.273	5	13

3.2. Model Specification

As previously mentioned, we propose that the presence of negative AI-generated reviews (AIGC-N) positively influences product attitudes (*logWorth*). It is crucial to consider the potential moderating effects of product and influencer characteristics, as these may significantly impact the relationship. Accordingly, we have incorporated these factors into our research model. The primary effects and the corresponding moderating effects are presented in Equation 1:

$$logWorth = \alpha_0 + \alpha_1 AIGC\text{-}N + \alpha_2 logPrice + \alpha_3 Subsidy + \alpha_4 logSocial\ tie + \alpha_5 Level + \alpha_6 AIGC\text{-}N * logPrice + \alpha_7 AIGC\text{-}N * Subsidy + \alpha_8 AIGC\text{-}N * logSocial\ tie + \alpha_9 AIGC\text{-}N * Level + \alpha_{controls}\text{controls} + \varepsilon. \quad (1)$$

Before conducting the formal analysis, we examined the interrelationships among the variables to ascertain correlations and determine the directionality of these relationships. The results of the Pearson Correlation analysis, presented in Table 2, indicate significant correlations between the independent variable and the dependent variable. These findings establish a foundation for further investigation.

Table 2: Pearson Correlation Matrix

	Variables	1	2	3	4	5	6	7	8	9	10
1	*logWorth*	1.00									
2	*AIGC-N*	0.080***	1.00								
3	*logPrice*	0.064***	0.161***	1.00							
4	*Subsidy*	0.127***	0.067***	0.011	1.00						
5	*logSocial tie*	0.177***	0.042***	0.053***	0.170***	1.00					
6	*Level*	0.140***	0.040***	0.029**	0.064***	0.552***	1.00				
7	*Channel*	-0.044***	0.175***	-0.017	-0.201***	0.012	0.086***	1.00			
8	*logDiscount*	0.119***	0.119***	0.091***	-0.024*	0.035**	0.068***	0.071***	1.00		
9	*logAbility*	0.025*	0.061***	0.026*	0.073***	0.735***	0.626***	0.100***	0.021	1.00	
10	*logPositive rate*	0.055***	-0.080***	0.090***	-0.054***	0.047***	0.018	0.214***	-0.017	0.038***	1.00
11	*Days*	0.034**	0.013	0.027*	0.033**	-0.048***	-0.020	-0.047***	-0.050***	-0.019	0.018

Notes: *** p<0.01, ** p<0.05, * p<0.1.

4. Empirical Results

4.1. Main Hypothesis Tests

Table 3 presents the results of the primary hypothesis tests conducted in this research. Initially, we estimated Model 1, which included only the control variables. Subsequently, Model 2 demonstrated that displaying AI-generated negative reviews of products positively influences product attitude (α_1 = 0.307, p < 0.01). This finding is further corroborated by the results of Model 3 (α_1 = 2.465, p < 0.01), collectively supporting H1.

The moderating effects of product and influencer are explored in Model 3. The analysis reveals a negative moderating effect of product price on the relationship between the display of AI-generated negative reviews and product attitude (α_6 = -0.172, p < 0.05), thus supporting H2. Additionally, the findings indicate that claims of product subsidies also exert a negative moderating influence on product attitude (α_7 = -0.632, p < 0.05), thus lending support to H3.

Regarding the strength of the influencer's social tie, our findings indicate that it positively moderates the relationship between the display of AI-generated negative product reviews and product attitude (α_8 = 0.049, p < 0.1), thereby supporting H4. Conversely, the results fail to support our initial hypothesis that the influencer's rating level positively moderates the relationship between the display of AI-generated negative reviews and consumers' product attitudes (α_9 = -0.053, p > 0.1). The negative moderating effect of influencer rating level may stem from consumers' attribution processes—specifically, higher-level influencers are more likely to be perceived as acting out of self-interest (e.g., pursuing platform privileges) rather than providing genuine product recommendations. Such skepticism may foster negative perceptions of both the influencer and the promoted product, ultimately undermining the credibility of the reviews. We further discuss this finding in Section 5.

Table 3: Main Effect and Moderating Effects

Variables	Model1	Model2	Model3
AIGC-N* logPrice			-0.172**
			(0.076)
AIGC-N* Subsidy			-0.632**
			(0.264)
AIGC-N* logSocial tie			0.049*
			(0.028)
AIGC-N* Level			-0.053
			(0.067)
AIGC-N		0.307***	2.465***
		(0.061)	(0.795)
logPrice	0.079**	0.052	0.091**
	(0.032)	(0.032)	(0.036)
Subsidy	0.824***	0.756***	1.009***
	(0.132)	(0.132)	(0.168)
logSocial tie	0.199***	0.200***	0.188***
	(0.015)	(0.015)	(0.016)
Level	0.262***	0.265***	0.273***
	(0.031)	(0.031)	(0.034)
Channel	-0.126**	-0.188***	-0.182***
	(0.057)	(0.058)	(0.058)
logDiscount	0.075***	0.071***	0.071***
	(0.009)	(0.009)	(0.009)
logAbility	-0.267***	-0.270***	-0.268***
	(0.020)	(0.020)	(0.020)
logPositive rate	0.099***	0.115***	0.119***
	(0.023)	(0.023)	(0.023)
Days	0.037***	0.036***	0.037***
	(0.011)	(0.011)	(0.011)
Constant	-11.180***	-12.456***	-13.436***
	(2.244)	(2.253)	(2.274)
Observations	4,967	4,967	4,967
R-squared	0.096	0.101	0.103

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

To enhance understanding of the moderating effects exerted by product and influencer dynamics, we have developed schematic representations illustrating the influence of four distinct moderating variables across various levels. Specifically, the moderating roles of product price and product subsidy claims are elucidated in Figure 4 and 5, respectively, while the influencer's social ties' moderating role is depicted in Figure 6.

When a product is priced higher, the positive impact of displaying AI-generated negative reviews on consumer attitude towards the product is less pronounced compared to scenarios involving lower prices, as illustrated in Figure 4. As shown in Figure 5, the positive effect of displaying AI-generated negative reviews on product attitude weakens when the product is associated with a subsidy claim. These findings suggest that product-related information, particularly its price and subsidy claim, serves as a critical boundary condition that negatively moderates the relationship between the display of AI-generated negative reviews and consumer attitude.

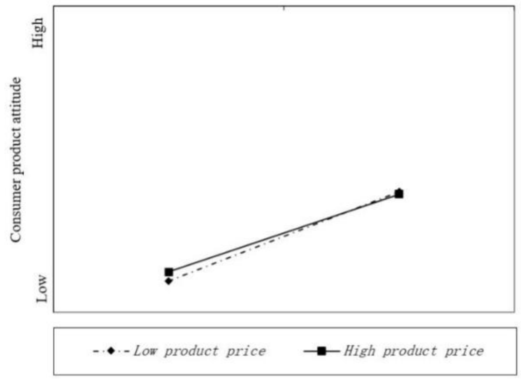

Figure 4: The Moderating Effect of Product Price

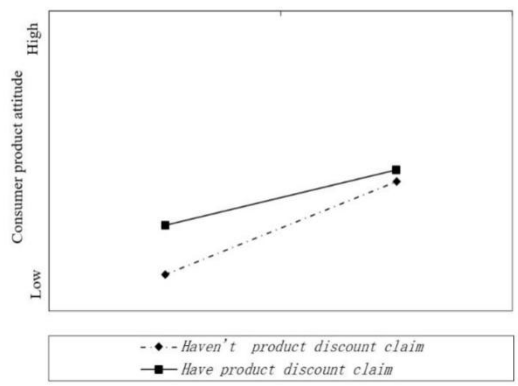

Figure 5: The Moderating Effect of Product Subsidy Claim

The main effect of displaying AI-generated negative reviews on product attitude is strengthened when the influencer has a larger fan base, see details in Figure 6. This finding implies that stronger social ties among influencers are likely to enhance their influence, suggesting that the influencer's content is perceived as higher quality and more credible. Such trust in the influencer further reinforces consumer trust in the products and in AIGC, thereby exerting a positive moderating effect that amplifies the beneficial outcomes associated with disclosing AI-generated negative reviews.

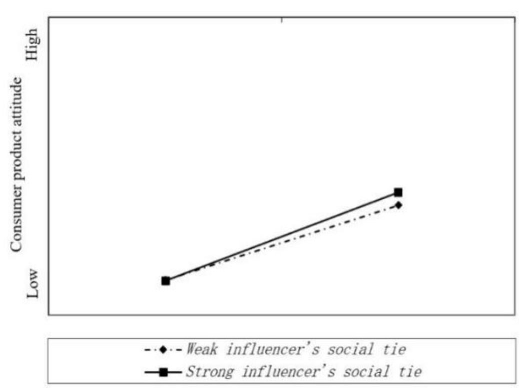

Figure 6: The Moderating Effect of the Strength of Influencer's Social Tie

4.2. Robust Check

To evaluate the robustness of our initially reported outcomes, we employed multiple alternative specifications and confirmed their consistency. Specifically, we conducted three types of robustness checks. First, we performed cross-validation of the results by utilizing a Tobit regression as an alternative model. Subsequently, we replaced the dependent variable with the number of save for the regression analysis. Finally, we incorporated additional control variables into the regression framework that may potentially influence the dependent variable.

Given that our measure of product attitude (the worth-buying rate) is considered censored data (ranging from 0 to 100), we employed a Tobit model for data analysis (Amemiya, 1984). The results displayed in Table 4 decisively support the positive impact of displaying AI-generated negative reviews on product attitude (α_1 = 0.998, p < 0.01). Furthermore, the results of the moderating effects are also generally consistent with previous analyses (α_6 = -0.500, p < 0.05; α_7 = -1.748, p < 0.05; α_8 = 0.123, p > 0.1; α_9 = -0.216, p > 0.1).

Table 4: Results of Tobit Regression

Variables	Model1	Model2	Model3
AIGC-N* logPrice			-0.500**
			(0.247)
AIGC-N* Subsidy			-1.748**
			(0.767)
AIGC-N* logSocial tie			0.123
			(0.090)
AIGC-N* Level			-0.216
			(0.231)
AIGC-N		0.998***	7.777***
		(0.198)	(2.627)
logPrice	0.300***	0.209*	0.333***
	(0.106)	(0.107)	(0.124)
Subsidy	2.082***	1.850***	2.563***
	(0.389)	(0.390)	(0.491)
logSocial tie	0.676***	0.677***	0.645***
	(0.051)	(0.051)	(0.055)
Level	0.953***	0.961***	1.004***
	(0.110)	(0.110)	(0.125)
Channel	-0.338*	-0.557***	-0.542***
	(0.190)	(0.195)	(0.196)
logDiscount	0.244***	0.229***	0.228***
	(0.031)	(0.031)	(0.031)
logAbility	-0.875***	-0.886***	-0.879***
	(0.067)	(0.067)	(0.067)
logPositive rate	0.347***	0.393***	0.408***
	(0.076)	(0.076)	(0.076)
Days	0.128***	0.121***	0.124***
	(0.037)	(0.037)	(0.037)
var(e.logworth)	23.242***	23.064***	22.983***
	(1.028)	(1.020)	(1.016)
Constant	-45.902***	-49.446***	-52.801***
	(7.405)	(7.426)	(7.517)
Observations	4,967	4,967	4,967

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Subsequently, we substituted the dependent variable with the "number of product favorites." Generally, consumers indicate their interest or preference for a product by favoriting it, which can be regarded as a reflection of their attitudes (Liu et al., 2017). Numerous empirical studies have employed the act of favoriting as a proxy for consumer attitudes, revealing significant correlations with variables such as purchase behavior and brand loyalty. Therefore, we utilized this variable in place of the worth-buying rate to conduct robustness checks. The results are shown in Table 5, and both the main effects and moderating effects align with the hypotheses of this study.

Table 5: Results of Substituting the Dependent Variable

Variables	Model1	Model2	Model3
AIGC-N* logPrice			-0.069**
			(0.033)
AIGC-N* Subsidy			-0.338***
			(0.113)
AIGC-N* logSocial tie			0.038***
			(0.012)
AIGC-N* Level			-0.046
			(0.029)
AIGC-N		0.142***	1.175***
		(0.026)	(0.341)
logPrice	-0.035**	-0.048***	-0.033**
	(0.014)	(0.014)	(0.016)
Subsidy	0.762***	0.731***	0.862***
	(0.057)	(0.057)	(0.072)
logSocial tie	0.104***	0.104***	0.095***
	(0.006)	(0.006)	(0.007)
Level	0.080***	0.081***	0.089***
	(0.013)	(0.013)	(0.015)
Channel	-0.022	-0.051**	-0.048*
	(0.024)	(0.025)	(0.025)
logDiscount	0.053***	0.051***	0.051***
	(0.004)	(0.004)	(0.004)
logAbility	-0.133***	-0.134***	-0.134***
	(0.009)	(0.009)	(0.009)
logPositive rate	0.025**	0.032***	0.034***
	(0.010)	(0.010)	(0.010)
Days	-0.004	-0.005	-0.004
	(0.005)	(0.005)	(0.005)
Constant	-2.655***	-3.247***	-3.689***
	(0.964)	(0.967)	(0.975)
Observations	4,967	4,967	4,967
R-squared	0.146	0.151	0.154

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Additionally, we incorporated numerous control variables that might influence product attitude, such as the count of hot reviews (*logHotreview*), original price (*logOriginal price*), word count of AI-generated negative reviews (*logNegative count*) and the ratio of negative reviews (*logNegative ratio*). As shown in Table 6, the results remain robust.

Table 6: Results of Adding Control Variables

Variables	Model1	Model2	Model3
AIGC-N* logPrice			-0.182**
			(0.076)
AIGC-N* Subsidy			-0.592**
			(0.263)
AIGC-N* logSocial tie			0.055**
			(0.028)
AIGC-N* Level			-0.054
			(0.066)
AIGC-N		0.209***	2.384***
		(0.075)	(0.794)
logPrice	-0.646***	-0.622**	-0.587**
	(0.249)	(0.249)	(0.249)
Subsidy	0.830***	0.796***	1.034***
	(0.132)	(0.132)	(0.167)
logSocial tie	0.193***	0.192***	0.180***

	(0.015)	(0.015)	(0.016)
Level	0.259***	0.260***	0.268***
	(0.031)	(0.031)	(0.034)
Channel	-0.162***	-0.184***	-0.176***
	(0.057)	(0.058)	(0.058)
logDiscount	0.052***	0.051***	0.051***
	(0.012)	(0.012)	(0.012)
logAbility	-0.255***	-0.257***	-0.255***
	(0.020)	(0.020)	(0.020)
logPositive rate	0.093***	0.100***	0.103***
	(0.023)	(0.023)	(0.023)
Days	0.037***	0.037***	0.038***
	(0.011)	(0.011)	(0.011)
logHotreview	-0.156***	-0.160***	-0.162***
	(0.026)	(0.026)	(0.026)
logOriginal price	0.758***	0.720***	0.727***
	(0.255)	(0.255)	(0.255)
logNegative count	0.046	-0.028	-0.009
	(0.093)	(0.097)	(0.097)
logNegative ratio	1.898	2.249	1.907
	(1.650)	(1.654)	(1.658)
Constant	-10.871***	-11.338***	-12.293***
	(2.248)	(2.252)	(2.273)
Observations	4,967	4,967	4,967
R-squared	0.109	0.111	0.113

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

4.3. Additional Analysis

While our previous analysis confirmed the significant impact of displaying AI-generated negative reviews on consumers' product attitudes, we conduct further thematic analysis of negative review texts to better understand the underlying mechanisms of this phenomenon. This extends research aims to (1) uncover the latent thematic structure of negative reviews to explain how they enhance product attitudes, and (2) extract quantifiable metrics through text analysis to establish a theoretical foundation for future research. The specific analytical procedure is as follows:

First, we systematically clean the collected negative review texts, including creating a domain-specific stopword list and performing word segmentation using Python's jieba library. Based on the segmentation results, we generate a visual word cloud (Figure 7) through word frequency statistics. The word cloud reveals that terms directly related to mobile device performance—such as "camera," "battery capacity," "satellite communication," and "transmission speed" — appeared most frequently, indicating that consumers' negative comments primarily focused on technical specifications and functional performance.

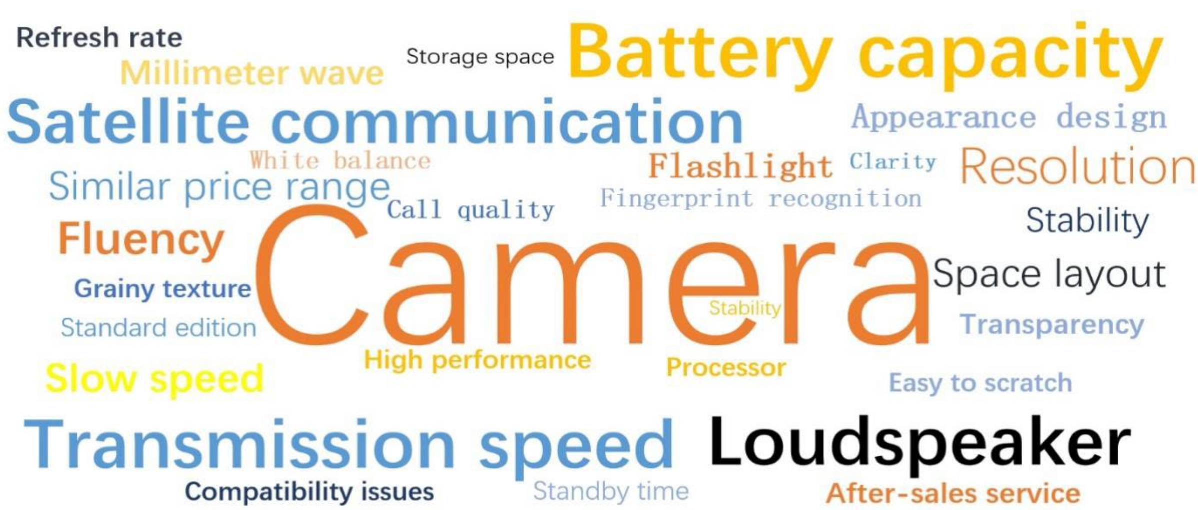

Figure 7: Analysis of Negative Review Keywords

We then employ Latent Dirichlet Allocation (LDA) topic modeling to identify core themes in the negative text dataset. Determining the optimal number of topics is a crucial step in LDA analysis. Following Hannigan et al. (2019), we evaluate this using perplexity and coherence scores (Maier et al., 2021). As shown in Figures 8 and 9, the coherence score peaked at 3 topics, while perplexity reached its lowest point at 11 topics. Balancing research needs with model interpretability, we ultimately determine that 3 topics best represented the semantic structure of our data.

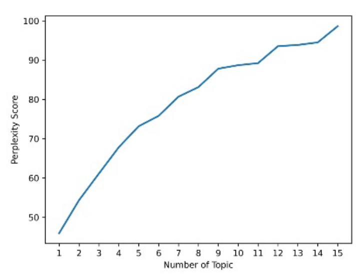

Figure 8: Perplexity Score

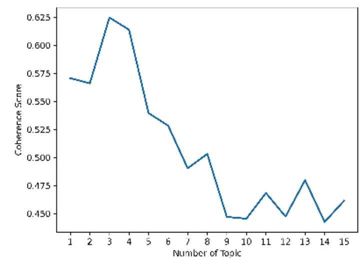

Figure 9: Coherence Score

In terms of model parameter settings, we fix the number of topics at three and extracted ten feature words for each topic. After 50 iterations of training, we obtained a "theme-vocabulary" matrix (Table 7). The three core themes identified were photographic performance, battery life and charging, and screen and design. From these results, we find that the intensity of the camera performance theme is the highest (0.371), indicating that users frequently criticize aspects related to photography and camera features. However, since ordinary users do not have high expectations for professional photography capabilities, these negative reviews have a limited impact on their attitudes toward the product. The second highest intensity is for the theme of battery life and charging (0.335). Generally speaking, battery issues are a common problem in the industry, and most smartphone manufacturers face similar complaints. As a result, consumer expectations are already low, and revealing battery problems may actually enhance credibility. The intensity of the screen and design theme is relatively low (0.294) but still occupies a significant portion. Design aspects, such as weight and speakers, are subjective and vary from person to person, meaning they are not seen as product defects. Consequently, users tend to be more tolerant of such issues, which does not lead to a negative attitude toward the product.

Table 7: Theme-vocabulary Matrix

No	Topic	High-frequency keywords	Theme intensity
Topic1	Photographic performance	Photography, Screen, Camera, Overheating, Performance, Battery capacity, Frame, Lens, Functionality, Quality	0.371
Topic2	Battery life and charging	Battery life, Charging, Screen, Battery, Refresh rate, Headphones, Signal, Functionality, Interface, Wireless	0.335
Topic3	Screen and design	Screen, System, Price, Weight, Camera, Texture, Photography, Storage, Tactile experience, Speaker	0.294

5. General Discussion

This study examines the impact of AI-generated negative product reviews on e-commerce platforms, demonstrating their potential to enhance product attitudes—especially when influencers have strong social ties. However, this positive effect weakens with higher product prices or the presence of subsidy claims.

Contrary to expectations, the influencer's rating level exhibited a negative (albeit non-significant) moderating effect, rather than the hypothesized positive effect. One plausible explanation is that as influencers' status rises, they may gain more privileges (Leban et al., 2021), heightening consumers' skepticism toward their motives and the information they provide. In our context, AI-generated negative reviews may receive disproportionate attention, and consumers' trust in AIGC credibility may be undermined by their distrust of the influencer. Consequently, the overall impact of negative reviews on product attitudes may be weakened. This finding offers actionable insights for platform managers seeking to optimize influencer marketing strategies.

5.1. Theoretical Contributions

First, our research significantly advances the understanding of AIGC in marketing by examining an underexplored area in the literature. Prior studies have focused on AIGC in advertising and product recommendations

(Bawack et al., 2022; Wang et al., 2023) or consumer responses to AI-generated summaries (Li et al., 2024), but few examine the strategic disclosure of AI-generated negative content. Our findings show that negative reviews generated by AI serve as data-driven evidence of defects that enhance system credibility through their perceived objectivity (Lee, 2018). When displayed alongside positive reviews, these AI-generated negative reviews improve consumer product attitudes. This finding not only challenges the conventional wisdom that negative feedback is detrimental to brand image but also extends the SCT by positioning AI as a credible information source.

Second, our study advances the theoretical understanding of product reviews by introducing AI as novel review source. Prior research has focused on human-generated reviews (Cheung et al., 2012; Hsieh & Li, 2020), exploring their influence on consumer perceptions and firm performance (Hennig-Thurau et al., 2015; Wu et al., 2015). However, this study reveals unique psychological mechanisms associated with AI-generated reviews. By showing that AI-generated negative reviews enhance online review system credibility, we identify a new pathway for information sources to influence consumer decision-making (Aggarwal et al., 2012; Cao et al., 2011). This study highlights the need to reevaluate existing online review system models by incorporating AIGC's unique characteristics. By doing so, we contribute to the development of a more comprehensive theoretical framework that can better explain and predict consumer behavior in the digital age, especially in the context of rapidly evolving AI technologies.

Third, our research contributes to the theoretical understanding of boundary conditions in consumer decision-making by identifying and explicating the moderating effects of contextual factors. At the product level, we show that price and subsidy claim negatively moderate the impact of AI-generated negative reviews, suggesting that consumers' price sensitivity can override the credibility-enhancing effects of balanced AI-generated reviews. This finding extends the price-perceived value framework by demonstrating how price considerations interact with information credibility in shaping consumer attitudes.

At the influencer level, we advance influencer marketing literature by uncovering a paradox of influencer credibility in the context of AIGC. While prior research consistently posits that high-status influencers enhance message persuasiveness (Djafarova & Rushworth, 2017), we demonstrate that their platform privileges—often signaled by rating levels—may backfire when coupled with AI-generated negative reviews. Our discovery that influencers' rating level and social ties moderate the main effect enriches the understanding of social influence mechanisms in the digital marketplace, particularly in platforms where social proof is crucial for consumer decision-making. This finding extends influencer marketing research, which mainly focuses on the persuasive power of influencers' personal recommendations, by highlighting their significant role in shaping consumers' attitudes toward AIGC.

5.2. Managerial Implications

Our findings offer actionable insights for platform managers leveraging AIGC. First, unlike the industry norm of prioritizing positive AI reviews (e.g., Meituan's "AI-generated positive summaries"), we show that credible negative AI reviews—when perceived as professional and diagnostic—can improve product attitudes. Therefore, platforms should re-evaluate the role of negative AIGC. On the one hand, they can improve the fairness and credibility of reviews by systematically integrating negative yet credible feedback (for example, by training models on highly rated "helpful" negative human reviews). On the other hand, they should implement transparent labeling for AI-generated comments to enhance the credibility of the feedback source.

Second, platform managers need to consider the impact of product price and subsidy information when displaying AI-generated negative reviews. Platforms could develop a "dynamic balance system" that automatically adjusts the display ratio of positive to negative reviews based on product pricing and subsidies. For instance, this system could reduce the prominence of negative reviews for high-priced products that also offer subsidies. Regarding influencer management, since social ties have a positive moderating effect while rating levels show negative effects, platforms should prioritize products recommended by influencers with large followings but moderate ratings. For high-level influencers, platforms could mitigate skepticism by providing AI transparency label and avoiding prominently displaying negative reviews alongside privileged influencers.

Third, this study provides critical guidance for policymaking and regulatory practices. Our findings demonstrate that professional and trustworthy AIGC can establish a more comprehensive and unbiased product evaluation environment for consumers, thereby facilitating rational decision-making. Based on these insights, policymakers should prioritize the growing influence of AI in consumer markets, with policy design focusing on enhancing the professionalism, reliability, and transparency of AIGC. In regulatory implementation, we recommend establishing a "tiered AIGC disclosure system" with clearly defined information requirements at different levels. For instance, at the basic level, all AIGC content should be mandatorily labeled as "AI-generated" to ensure consumers are aware of its origin. At the intermediate level, additional explanations such as "AI-generated based on specific data dimensions" should be required. At the advanced level, platforms should present the generative logic flow for critical content (e.g., negative reviews) to reveal AI decision-making processes and improve interpretability. This tiered system regulates AIGC market practices while educating consumers about AIGC mechanisms, fostering greater trust and satisfaction with AI technologies.

5.3. Limitations and Future Research

This study provides valuable insights into how AI-generated reviews affect consumer product attitude, but several limitations—which simultaneously suggest future research directions—should be noted.

First, by focusing exclusively on smartphones, our study may have limited generalizability. Smartphones represent a high-involvement, functional product category, and consumer responses to AI-generated reviews may differ for other types of products, particularly experiential products such as cosmetics, travel services, or entertainment. Future research should examine a broader range of product categories to determine how product type moderates these effects.

Second, although product attitude is a theoretically significant measure, it cannot fully capture actual purchasing behavior. While attitudes often predict behavior, we lack understanding of how AI-generated reviews influence actual consumer actions. Future studies should combine experimental designs with behavioral data analysis to link AI-generated reviews to specific outcomes like purchases, returns, and ratings.

Third, although we identified several moderating factors that influence the impact of AI-generated reviews, the underlying mechanisms driving these effects warrant further exploration. For instance, future studies could investigate the psychological processes through which consumers perceive and evaluate AI-generated content, including the role of trust, perceived objectivity, and source credibility. Additionally, researchers should examine how AI-generated reviews interact with other platform features (e.g., user reviews, visual content) to better understand digital marketplace decision-making.

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Appendix A. An Example of Product Detail Page on the E-commerce Platform.