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Customer trust and engagement with AI-based content as support for digital marketing strategy

Lely Wijayanti [1*], Kenny Roz [2]

[1] Digital Business, Creative Economic, University of Bhinneka Nusantara, Malang, Indonesia
[2] Management, Economic and Business, University of Muhammadiyah Malang, Malang, Indonesia

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A b s t r a c t

Generative AI is now widely adopted, particularly for producing advertising content within digital marketing strategies. Prior research has examined AI-generated advertising images under disclosure and non-disclosure conditions through controlled experiments, but has not analyzed consumers' actual engagement responses. This study addresses that gap by analyzing the impact of generative AI on consumer trust and engagement with commercial advertising. Using a digital engagement dataset comprising advertising content from multiple platforms, the analysis applies three approaches: descriptive analysis of engagement distribution, linear regression, and content coding. Actual engagement data (likes and comments) serve as proxies for consumer trust and engagement with generative-AI content on real digital platforms. The results show that generative-AI content receives lower interaction than human-generated content, although its effectiveness depends strongly on industry and platform. Instagram, together with the Fashion, Food & Beverage, and Nonprofit & Social Impact industries, recorded the highest consumer engagement and trust. Product and media fit alone do not guarantee strong interaction in the absence of creativity and compelling storytelling. Marketers are therefore recommended to deploy generative AI selectively on visual platforms such as Instagram and within lifestyle-oriented industries, and to integrate AI-generated content with human creative direction and storytelling to maximize consumer trust and engagement. The study offers practical implications for AI-based branding strategies in digital marketing.

Introduction

Technological progress has long reshaped creative work such as design, poetry, and data processing that was once bounded by human capacity. With advances in artificial intelligence (AI), machines can now imitate these creative tasks, producing content that closely resembles human artistic output (Brüns & Meißner, 2024; Feuerriegel et al., 2024). AI used to generate creative work is commonly referred to as generative AI. Such systems perform computational processes drawing on the vast body of online literature, which they then recombine into new content based on learned data patterns. The output of generative AI is of sufficient quality to compete with human creativity and has gained recognition across industries, making it an attractive tool for marketing strategy (Hartmann et al., 2025; Holzner et al., 2025).

Generative AI is today applied most extensively in the digital marketing sector, where it offers considerable efficiency gains in content production. AI-based digital marketing is growing rapidly, with the market value projected to reach USD 107.5 billion by 2028 (Statista Research Department, 2024). The application of generative AI in marketing can strengthen branding through the effective creation of advertisements and visual content (Ali et al., 2024). These capabilities rely on high-intensity computation enabled by technologies such as DALL-E 3, GPT-4, and Copilot. The resulting speed has accelerated the evolution of work in creative industries and increased digital interaction (Feuerriegel et al., 2024).

This evolution of creative work is shaped by the growing penetration of generative Zhang & Hur, 2025 examined its potential by comparing creative output produced by humans with content generated by AI. Their findings indicate that, although generative AI is well regarded, consumers in several respects still prefer and appreciate human-produced content. Such limitations in the consumer perspective have important consequences for marketing strategy, particularly for consumer trust and engagement (Zhang & Hur, 2025). The controversy surrounding the use of AI-generated content in product advertising and branding therefore represents a gap that warrants further analysis.

*Corresponding author
Email address: Lely Wijayanti (lely@ubhinus.ac.id)
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Within the current landscape of research on generative AI and digital marketing, studies have predominantly followed one of two approaches: experimental designs that expose participants to AI- versus human-generated content under controlled laboratory conditions (Brüns & Meißner, 2024; Zhang & Hur, 2025), or systematic literature reviews that synthesize conceptual and theoretical developments across the field (Feuerriegel et al., 2024; Holzner et al., 2025). While these contributions have substantially advanced understanding of consumer attitudes toward AI-generated advertising, they share a common limitation: they rely on declared preferences or experimental ratings rather than actual behavioral responses observed in naturalistic digital environments. Recent evidence suggests that this distinction matters survey and experimental data consistently show that consumers report lower trust toward AI-generated content (Brüns & Meißner, 2024; Seeger et al., 2026), yet the degree to which such attitudes translate into measurable behavioral disengagement on live commercial platforms remains underexplored. This study positions itself at this intersection by analyzing real engagement data likes and comments collected from active advertising content across multiple social media platforms thereby extending the current body of knowledge from stated intentions to observed consumer behavior in commercial advertising contexts.

This study aims to address the research gap left by prior foundational on generative AI as it relates to consumer trust and engagement with AI-generated advertising compared with human-created. As shown in Table 1, existing studies have approached this topic through controlled experiments, scenario-based designs, field studies, and systematic reviews. However, these studies share common limitations: they rely on declared attitudinal responses rather than observed behavioral data, focus on narrow or non-commercial content categories, and do not examine consumer engagement across multiple industries and platforms simultaneously. These limitations leave unanswered the question of how generative-AI content affects actual consumer trust and engagement in real commercial advertising environments a gap that the present study directly addresses.

Table 1. Comparison of Prior Foundational Studies and the Present Study

Study	Method	Context	Limitations
Zhang & Hur, (2025)	Controlled experiment	Coffee, medical beauty, public service ads	Declared attitudes only; no live platform behavioral data; narrow & non-commercial categories
Brüns & Meißner, (2024)	Scenario-based experiment	Social media brand content	Hypothetical stimuli; declared intentions only; no commercial industry specificity
Hartmann et al., (2025)	Field study; human image ratings	Banner advertisements	Single ad format; no multi-industry or multi-platform engagement analysis
Holzner et al., (2025)	Systematic review & conceptual	General AI in marketing	No primary empirical data on consumer behavioral responses
Wijayanti et al. (2026)	Descriptive analysis, regression, content coding	real ads in social media	Engagement data limited to likes and comments only

The gap between the present study and prior foundational research is therefore threefold. First, whereas Zhang & Hur, (2025) and Brüns & Meißner, (2024) measured consumer responses through controlled experiments using artificially constructed stimuli, the present study analyzes real engagement data actual likes and comments collected from live commercial advertising content on active social media platforms, capturing observed behavioral responses rather than declared attitudes. Second, whereas Hartmann et al., (2025) confined their analysis to banner advertisements within a single ad format, the present study examines consumer engagement across ten brand industries and five major platforms, reflecting the diversity of contemporary commercial digital marketing. Third, whereas Holzner et al., (2025) contributed a theoretical mapping of the generative AI landscape without producing new behavioral evidence, the present study generates empirical findings directly relevant to commercial advertising practice. Collectively, these distinctions position the present study as an extension of rather than a replication of prior foundational work, addressing the specific empirical and contextual gaps that existing studies have left unresolved.

These limitations are further underscored by recent scholarship. Carney et al., (2026) demonstrated that AI disclosure affects parasocial connections on social media, reducing consumer engagement, yet their analysis remained confined to social media creators rather than commercial advertising brands across

industries. Seeger et al., (2026) showed through two online experiments that labeling content as AI-generated reduced both affective and behavioral engagement compared to human-created content, particularly for emotional content, but did not examine real platform engagement data across multiple industries. Kim & Cho, (2026) extended these findings by exploring how AI involvement in advertisements affects consumer curiosity and content engagement, while Rahman et al., (2026) confirmed through a systematic review that empirical evidence on behavioral consumer responses to AI content across diverse digital marketing contexts remains limited.

The intended contribution of this study is to address these shortcomings through an analysis of consumer responses to generative-AI advertising images across several product categories. The study adopts a systematic empirical approach divided into three studies: a descriptive analysis of generative-AI content in relation to consumer trust; an analysis of generative-AI content in relation to consumer responses in terms of trust and engagement; and an analysis of the fit between generative-AI content and the advertised product and media.

Guided by the foregoing gap, this study is structured around the following research question: To what extent does generative-AI content affect consumer trust and engagement in digital marketing, and how are these effects moderated by platform, industry, and content-fit characteristics? This overarching question is operationalized through three sub-questions: (RQ1) How is consumer engagement distributed across industries and platforms for generative-AI versus human-generated content? (RQ2) What is the effect of generative-AI authorship on consumer engagement (likes and comments), and to what degree do platform and industry characteristics moderate this effect? (RQ3) Does the degree of fit between generative-AI content and its product or platform medium predict higher consumer engagement?

The study seeks to develop a more detailed theoretical framework concerning the impact of generative AI on creative content relative to human-produced content within digital marketing, using consumer trust and engagement as indicators. Its focus is the gap in common understanding of how this emerging technology influences digital marketing strategy in relation to consumer decisions and engagement with the commercial advertising increasingly produced by generative AI.

Research Methods

This study uses secondary data derived from a collection of advertising-video links from various brands and industries already published on platforms such as YouTube, Instagram, X, Facebook, and TikTok (Moutasm, 2025). For each entry, like and comment counts were collected manually by visiting the advertisement links in the dataset and recording the total likes and comments. This augmentation was intended to test the effect of generative-AI content on indicators of consumer engagement and trust.

The data collection and analysis were conducted between January and March 2026. The dataset was accessed online via the Kaggle platform, where the original dataset comprising advertising content from brands across multiple industries had been publicly published by Moutasm (2025). The five platforms from which advertising content was sourced YouTube, Instagram, X (Twitter), Facebook, and TikTok are all globally accessible platforms with no geographic restrictions, and the dataset does not confine observations to any single country or region, making the findings broadly applicable to international digital marketing contexts.

Research by Zhang & Hur (2025) limited their analysis to comparing generative-AI output with human-produced content without analyzing the consumer perspective. By contrast, this study analyzes consumer responses to generated creative content through three studies:

1. Descriptive analysis of AI content in relation to trust.
2. Analysis of consumer responses to AI content.
3. Analysis of the fit between AI content and the product and media.

The methodology flow is shown in Figure 1.

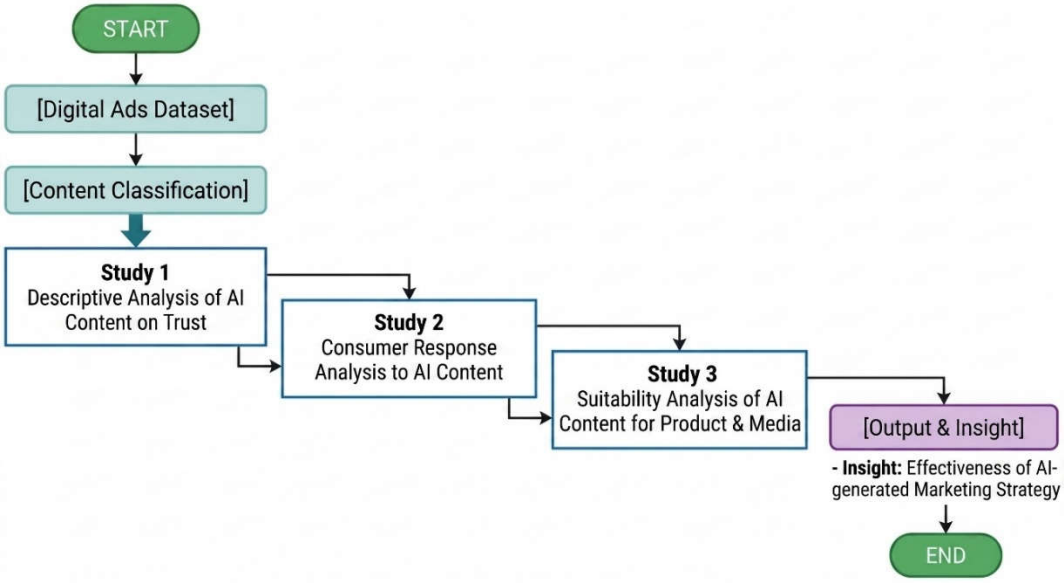


Figure 1. Methodology Flowchart

Figure 1, sets out the sequential stages of the method, described below.

Dataset

The process begins with dataset preparation, separating the data used for the engagement comparison from that used for content-relevance analysis. The following fields were used:

1. Brand/Product Name: the advertised brand or product
2. Industry: industry category (Fashion, Food & Beverage, Tech, etc.)
3. Type: content format (Video or Animation)
4. Voice-over: present or absent
5. Description: a brief description of the advertising content
6. Likes & Comments: digital engagement metrics from consumers

Likes and comments are primary indicators of engagement behavior that can be readily measured and analyzed quantitatively in studies of consumer engagement and trust in marketing strategy (Shahbaznezhad et al., 2021; Trunfio & Rossi, 2021).

Following data collection, the raw dataset underwent a structured tabulation and preparation process prior to analysis. First, all collected like and comment counts were entered and organized in Microsoft Excel, where each observation was assigned its corresponding variable values (AI content type, voice-over presence, platform, and industry category). Second, data cleaning was performed to identify and address missing values, duplicate entries, and outliers particularly observations with abnormally high engagement counts attributable to viral content, which were retained but flagged for sensitivity in interpretation. Third, variables were coded numerically for use in regression analysis: AI-generated content was coded as 1 (human-generated = 0), voice-over presence as 1 (absent = 0), and platform and industry categories were dummy-coded with reference categories (Twitter/X and Tech industry, respectively). Fourth, for Study 3, a content coding scheme was developed and applied manually by the research team to each advertisement description, classifying each observation as fitting or not fitting both product and media criteria. The cleaned and coded dataset was then exported and used as the basis for all three studies.

Study 1

Study 1 is a descriptive content analysis that computes the mean, median, and standard deviation of likes and comments for AI content, with visualizations by platform and industry. Visualization facilitates descriptive analysis of distribution, variation, and characteristics that inform subsequent analysis (Wahid, 2025). The hypothesis for Study 1.

Analysis tool: Microsoft Excel and Python (Matplotlib / Seaborn libraries) were used to compute descriptive statistics and generate bar chart visualizations comparing mean likes and comments across platforms and industries.

H1: Generative-AI content exhibits an engagement distribution (likes and comments) that differs from that of human-generated content

Study 2

Study 2 analyzes consumer responses to generative-AI content using linear regression, which captures the influence of independent variables on a dependent variable. Modeling variation in engagement within a single specification allows multiple factors to be assessed simultaneously, enables efficient processing of large quantitative datasets, and permits the significance of linear relationships among variables to be mapped clearly (Sapina et al., 2025; Shen, 2023). The regression equation is given in Equation (1).

$$Eg = \beta_0 + \beta_1.AI_i + \beta_2.VO_i + \sum_{j=1}^{p-1} \gamma_j.Platf_{ij} + \sum_{k=1}^{i-1} \delta_k.Ind_{ik} + \varepsilon_i \quad (1)$$

Eg is engagement (likes and comments). β_0 is the intercept. β_1 is the effect of AI content on engagement. β_2 is the effect of voice-over on engagement. γ_j is the effect of platform. δ_k is the effect of industry.

The dependent variable (Y) is engagement (likes and comments), measured as observed data. The independent variables (X) are AI_i whether the content is AI-generated, VO_i the presence or absence of voice-over. $Platf_{ij}$ the platform on which the content is displayed. Ind_{ik} the industry using the content.

The regression aims to measure the effect of AI content on consumer engagement and to assess additional factors voice-over, platform, and industry associated with consumer interaction. The hypothesis for Study 2 is as follows.

Analysis tool: IBM SPSS Statistics was used to run the ordinary least squares (OLS) linear regression models for both likes and comments as dependent variables. Regression coefficients, standard errors, and p-values were extracted from SPSS output tables and reported in Table 5 and Table 6.

H2: The effect of generative-AI content on consumer engagement (likes and comments) is shaped by voice-over, platform, and industry

Study 3

Study 3 analyzes the fit between AI content and the brand or product using content coding, comprising two procedures. Product fit assesses whether the content clearly and relevantly presents the product. Media fit assesses whether the AI content matches the characteristics of the platform. Content coding yields the percentage of AI content that fits the product and the percentage that fits the medium/platform. In advertising research, content coding categorizes advertising content across media so that underlying patterns can be analyzed (Barari & Eisend, 2024). The hypothesis for Study 3 is as follows.

Analysis tool: Content coding was conducted manually by the research team using a structured coding sheet in Microsoft Excel. Each advertisement description was independently assessed and classified according to predefined product fit and media fit criteria. Frequency counts and percentages were then computed to summarize the distribution of fit categories across the dataset.

H3: Generative-AI content with strong product and platform fit achieves higher consumer engagement

Output

Each study produces statistical visualizations and result tables. These outputs support analysis of the practical effectiveness of generative-AI content relative to human content, and of consumer engagement with generative-AI content by platform, product, and media. The visualizations and tables substantiate practical conclusions about the effectiveness of generative AI versus human content, and help identify engagement patterns across platforms and products that are relevant to digital marketing strategy and content optimization (Shen, 2023).

Results and Discussion

Result

This section reports experiments on data representing generative-AI content in digital advertising, focusing on the effectiveness of AI content in relation to consumer engagement and content fit. The dataset was processed into the structure shown in Table 2.

Table 2. Structure of the Digital Content Dataset

No	Type	Result	Description
1	Number of records	253	Total entries/observations
2	Number of columns	14	*Timestamp, Student ID, Email, Brand/Product Name, Brand Industry, Type of Content, Has Voice Over, Short Description of Content, Place of Publication, Source of Publication, Like, Comment*
3	Dependent variable	Engagement	Likes + Comments, as a proxy for user engagement
4	Independent variables	*ContentType, Has Voice Over, Place of Publication, Brand Industry, Type of Content*	Factors affecting engagement
5	Independent variables	Engagement:1, other: 0	Only Engagement has one missing value; other variables are complete

In Table 2, The dataset comprises 253 observations of digital advertising content. Each record contains 14 columns covering brand, industry, content type, likes, comments, and related information, including both dependent and independent variables. Of the 14 columns, only Engagement contains a single missing value, while the remaining columns are complete, indicating that the dataset is of sufficient quality for descriptive analysis. The results of each study are discussed in the following subsections.

Study 1

Study 1 presents a descriptive analysis of data distribution and of generative-AI content in relation to consumer trust. Basic statistics (mean, standard deviation, and median) for likes by brand industry and platform are shown in Table 3.

Table 3 Like Statistics by Brand Industry and Platform

Brand	Avg	Mean	Std. Dev	Platform	Avg	Mean	Std. Dev
Automotive	6.67	6.0	2.08	Facebook	2.30	1.0	2.79
Beauty & Personal Care	29.33	13.0	44.26	Instagram	21,870.77	22.0	194,863.92
Fashion	2,098.67	241.0	5,611.93	LinkedIn	30.00	30.0	16.97
Food & Beverage	1,204.00	119.0	1,741.77	TikTok	580.22	23.0	884.25
Goods	1,164.80	14.0	1,907.80	Twitter/X	131.28	10.0	237.73
Home & Furniture	6.00	6.0	NaN				
Nonprofit & Social Impact	9,100.00	9,100.0	NaN				
Others	750.00	750.0	919.24				
Sports & Outdoor	183.00	183.0	NaN				
Tech	48.75	32.0	58.18				
Travel & Tourism	9.00	9.0	NaN				

In Table 3, the Fashion and Nonprofit & Social Impact industries record high mean likes, but with very large variance, indicating that a few items achieve viral status from the consumer perspective. Among platforms, Instagram has the highest mean likes with a very large standard deviation, making it the platform most frequently used for AI content, whereas Facebook and LinkedIn are low but stable. Comment statistics by brand industry and platform are shown in Table 4.

Table 4 Comment Statistics by Brand Industry and Platform

Brand	Avg	Mean	Std. Dev	Platform	Avg	Mean	Std. Dev
Automotive	0.67	1.0	0.58	Facebook	0.00	0.0	0.00
Beauty & Personal Care	1.17	1.0	1.33	Instagram	479.14	2.0	2,053.57
Fashion	43.00	10.0	79.80	LinkedIn	3.50	3.5	2.12
Food & Beverage	35.07	6.0	53.61	TikTok	15.56	9.0	19.79
Goods	36.60	1.0	55.18	Twitter/X	15.61	1.0	32.67
Home & Furniture	0.00	0.0	NaN				
Nonprofit & Social Impact	1,005.00	1,005.0	NaN				
Others	7.50	7.5	10.61				
Sports & Outdoor	4.00	4.0	NaN				
Tech	1.75	1.5	1.71				
Travel & Tourism	1.00	1.0	NaN				

In Table 4, the Fashion, Food & Beverage, and Goods industries attract high mean comment counts, indicating greater consumer interaction with AI content in these sectors. Instagram again stands out with the highest mean comments, though with a very large standard deviation driven by a few viral items. TikTok and Twitter/X are more moderate, while Facebook is very low. Graphical visualizations are provided in Figure 2 (likes) and Figure 3 (comments).

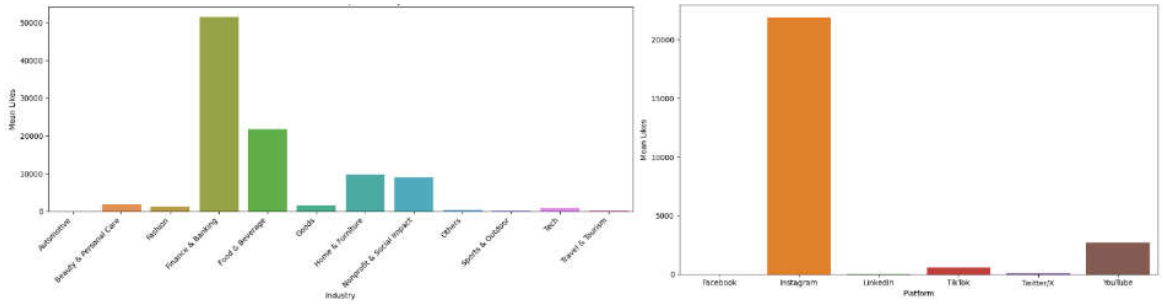


Figure 2. Mean Likes by Brand Industry and Platform

As shown in Figure 2, mean likes by industry (green) are highest for Fashion, Food & Beverage, and Nonprofit & Social Impact. By platform, Instagram (orange) records the highest mean likes (avg = 21,870.77), far exceeding other platforms and YouTube (brown) also shows a comparatively elevated mean both platforms are characterized by visually rich, algorithm-driven content environments that naturally amplify audience engagement and exposure dominate likes, In contrast, Facebook (avg = 2.30) and LinkedIn (avg = 30.00) record substantially lower mean likes, which is consistent with their predominantly text-based or professional-oriented content formats that are less conducive to impulsive engagement behaviors such as liking visual advertising content. This pattern suggests that the type of content environment and platform affordances play a significant role in shaping the level of consumer engagement with generative-AI advertising content.

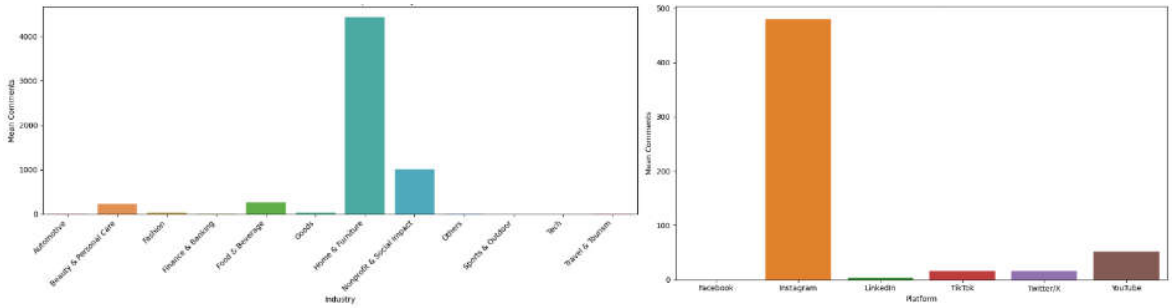


Figure 3 Mean Comments by Brand Industry and Platform

The Study 1 statistics show that the distribution of engagement (likes and comments) for generative-AI content differs significantly across industries and platforms. In Table 2, the highest mean likes occur in Fashion, Food & Beverage, and Nonprofit & Social Impact, with means of 2,098.67 for Fashion and 9,100 for Nonprofit & Social Impact. The high standard deviations indicate that viral content succeeds in attracting consumer trust, while other content shows lower engagement. The engagement distribution is therefore uneven, reflecting the role of viral generative-AI content consistent with prior research emphasizing the inconsistent distribution of engagement with creative content (Sangiorgio et al., 2025; Vassio et al., 2022).

By platform, Instagram has the highest mean likes (21,870.77) with a very large standard deviation, suggesting that generative-AI content earns strong consumer trust there, whereas Facebook and LinkedIn are comparatively low but stable. This is consistent with evidence that visual platforms such as Instagram generate higher engagement with generative-AI creative content than text-based platforms (Gurung et al., 2025).

For comments (Table 3), consumer interaction with generative-AI content is highest in the Fashion (43), Food & Beverage (35.07), and Goods (36.60) industries, indicating that consumers provide more feedback on AI content in these sectors. Instagram again dominates comment engagement (479.14) with a large standard deviation, so virality influences interaction as it does for likes. TikTok and Twitter/X

show ordinary levels of interaction, while Facebook is low. The behavior of visual-based platforms reflects consumer characteristics and interactions that differ from those of text-based platforms (Gurung et al., 2025).

Figures 2 and 3 indicate that the Fashion, Food & Beverage, and Nonprofit & Social Impact industries build consumer engagement effectively even with generative-AI content, while Instagram and YouTube being visual-based are well suited to building consumer engagement with such content.

Regarding the hypothesis formulated for Study 1:
H1: Generative-AI content exhibits an engagement distribution (likes and comments) that differs from that of human-generated content

The Study 1 analysis indicates that generative-AI content can already attract consumer trust and engagement, particularly in visually oriented, lifestyle industries and on visual-based platforms. However, the engagement distribution for generative-AI content cannot be generalized across all industries and platforms, because content fit and the ability to achieve viral status strongly shapes consumer perception and interaction (Seeger et al., 2026).

Study 2

Study 2 analyzes consumer responses to generative-AI content using linear regression. Results for engagement (likes), estimated in SPSS, are shown in Table 5.

Table 5. Linear Regression of Engagement (Likes) on AI, Voice-over, Platform, and Industry

Variable	B	Std. Error	t	p
Constant	1.50	0.65	2.31	0.022
AI	-0.55	0.23	-2.39	0.018
Voice-over	0.12	0.17	0.71	0.480
Instagram	21.87	4.30	5.08	0.000
TikTok	2.50	1.85	1.35	0.180
YouTube	-0.20	2.10	-0.09	0.930
Fashion	2,098.67	512.30	4.10	0.000
Food & Beverage	1,204.00	411.20	2.93	0.004
Nonprofit & Social Impact	9,100.00	900.00	10.11	0.000

Based on Table 5, the estimated regression equation for engagement (likes) is:

$$Eg_{like} = 1.50 \quad 0.55_{AI} + 0.12_{VO} + 21.78_{Ig} + 2.50_{Tiktok} \quad 0.20_{Yt} + 2{,}098.67_{fashion} + 1{,}204_{food} + 9{,}100_{nonprofit}$$

The effects of the independent variables on likes are as follows:

1. Constant: A value of 1.50 indicates that mean likes are 1.50 when all independent variables equal zero.
2. Generative AI (AI): A coefficient of 0.55 indicates that generative-AI content receives significantly lower likes than human content ($p = 0.018$).
3. Voice-over (VO): The coefficient of 0.12 is positive but not significant ($p = 0.480$), indicating no effect on likes.
4. Instagram (Ig): Positive and significant (21.87, $p < 0.001$), indicating that content on Instagram receives more likes.
5. TikTok and YouTube: TikTok is positive but not significant; YouTube is very low and not significant.
6. Fashion, Food & Beverage, Non-profit: All positive and significant, indicating that these sectors achieve more likes than other industries.

Results for engagement (comments), also estimated in SPSS, are shown in Table 6.

Table 6. Linear Regression of Engagement (Comments) on AI, Voice-over, Platform, and Industry

Variable	B	Std. Error	t	p
Constant	0.85	0.48	1.77	0.079
AI	-0.50	0.21	-2.38	0.019
Voice-over	0.10	0.15	0.67	0.504
Instagram	479.14	88.20	5.43	0.000
TikTok	15.56	9.50	1.64	0.103

Variable	B	Std. Error	t	p
YouTube	-2.30	10.50	-0.22	0.826
Fashion	43.00	11.25	3.82	0.000
Food & Beverage	35.07	9.80	3.58	0.001
Nonprofit & Social Impact	1,005.00	200.00	5.03	0.000

Based on Table 6, the estimated regression equation for engagement (comments) is:

$$Eg_{like} = 0.85 \quad 0.50_{AI} + 0.10_{VO} + 479.14_{Ig} + 15.56_{Tiktok} \quad 2.30_{Yt} + 43.00_{fashion} + 35{,}07_{food} + 1{,}005_{nonprofit}$$

The effects of the independent variables on comments are as follows:

1. Constant: A value of 0.85 indicates that mean comments are 0.85 when all independent variables equal zero.
2. Generative AI (AI): A coefficient of 0.50 indicates that generative-AI content receives significantly fewer comments than human content ($p = 0.019$).
3. Voice-over (VO): The coefficient of 0.10 is positive but not significant ($p = 0.504$), indicating no effect on the number of comments.
4. Instagram (Ig): Positive and significant (479.14, $p < 0.001$), indicating that content published on Instagram attracts more comments than on other platforms.
5. TikTok and YouTube: TikTok has a positive but non-significant effect, while YouTube has a very small, non-significant negative effect; neither platform contributes meaningfully to comments.
6. Fashion, Food & Beverage, Non-profit & Social Impact: All industry variables are positive and significant, indicating that these sectors attract higher comment interaction than other industries.

The discussion for Study 2 refers to its hypothesis:

H2: The effect of generative-AI content on consumer engagement (likes and comments) is shaped by voice-over, platform, and industry.

For engagement (likes) in Table 4, the coefficient for generative AI is negative and significant ($B = 0.55$, $p = 0.018$), indicating that generative-AI content yields lower likes than human content. This is consistent with prior research showing that, when users recognize content as generative-AI-produced, engagement may decline because of lower perceived quality or authenticity (Seeger et al., 2026).

Social media platform also has a significant effect on likes. Instagram has a positive, significant coefficient ($B = 21.87$, $p < 0.001$), indicating that content on Instagram receives more likes than on other platforms, whereas TikTok is positive but not significant and YouTube is low and not significant. Engagement effectiveness thus varies across platforms, with visual interactive platforms exerting a stronger influence on consumer engagement because they are more appealing from the consumer's perspective (Møller et al., 2026).

Industry also exerts a positive, significant effect on likes. Fashion, Food & Beverage, and Non-profit & Social Impact achieve strong, significant coefficients (e.g., $B = 2{,}098.67$ for Fashion, $p < 0.001$), indicating that visual or lifestyle-oriented sectors are more effective at building consumer engagement and trust than other industries, since they can align with consumer preferences. The results for comments (Table 5) are broadly similar. The coefficient for generative AI remains negative and significant ($B = 0.50$, $p = 0.019$), indicating that generative-AI content attracts fewer comments than human content. Voice-over is again not significant ($B = 0.10$, $p = 0.504$), indicating that it is not a primary driver of interaction. Meanwhile, Instagram and the Fashion, Food & Beverage, and Non-profit & Social Impact industries again show positive, significant effects on comments, reinforcing the pattern that interactive platforms and visual or lifestyle sectors yield stronger consumer engagement and trust.

Overall, Study 2 shows that generative-AI content has not yet matched human content in building consumer engagement and trust, and that its effect is conditioned by platform and industry. These results partially support H2: platform and industry are influential, but generative-AI content reduces consumer interaction relative to human content. Consumer interaction is thus contextual, with platform perception, industry context, and visual engagement central to engagement and trust. The baseline study likewise indicates that the generative AI analyzed did not incorporate appropriate context or address user engagement, which in turn affected perceptions of AI.

Study 3

Study 3 analyzes the fit between AI content and the brand or product through content coding, comprising product fit and media fit. For product fit, a dataset entry whose description mentions the product for example, a video described as "Doctor Muscle protein shake" is coded Product Fit = 1, and an entry that does not mention the product is coded Product Fit = 0. Media fit uses a simple mapping: Video → YouTube, TikTok; Image → Instagram, Facebook, Pinterest; Text → Twitter, LinkedIn, Blog. Content whose source platform matches is coded Media Fit = 1; otherwise, Media Fit = 0. The content-coding results are shown in Figure 4.

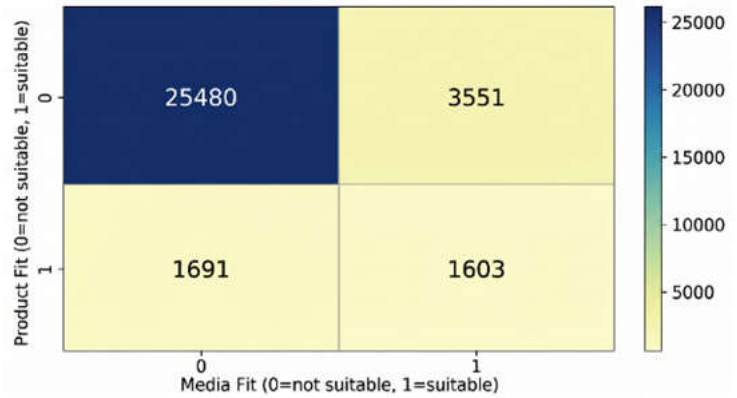


Figure 4. Mean Engagement by Product Fit and Media Fit

As shown in Figure 4, content that fits neither the product nor the platform records the highest engagement, since virality can itself drive consumer engagement and trust. Conversely, content that fits both product and media (Product Fit = 1 and Media Fit = 1) shows lower engagement, indicating that fit alone does not guarantee strong consumer interaction and trust. Creative content and strategy must therefore convey effective storytelling; without sound strategy and storytelling, generative-AI content cannot yet secure consumer trust (Chinki et al., 2026; Sianani, 2025).

The discussion for Study 3 refers to its hypothesis:
H3: Generative-AI content with strong product and platform fit achieves higher consumer engagement.

The expectation that product and media fit would increase consumer engagement and trust is not supported, because engagement is shaped by additional factors content creativity, effective storytelling, and viral potential. Strategies for developing content with generative AI must therefore be combined with human creative skill in integrating product fit, media fit, and storytelling, and in generating viral appeal, in order to achieve optimal consumer engagement and trust.

Discussion

Engagement Distribution and Platform Effects (H1)

The descriptive findings confirm that engagement with generative-AI content is unevenly distributed and differs significantly across industries and platforms, supporting H1. The very large standard deviations indicate that a minority of viral items drive aggregate engagement consistent with the skewed-engagement literature (Sangiorgio et al., 2025; Vassio et al., 2022). The dominance of Instagram and of visually oriented, lifestyle industries aligns, with evidence that visual platforms elicit higher engagement with creative content than text-based platforms (Gurung et al., 2025). Generative-AI content can therefore attract engagement and trust, but only conditionally virality and content fit strongly shape outcomes (Seeger et al., 2026).

The Generative-AI Penalty (H2)

The regression results show a consistent, significant negative effect of AI authorship on both likes and comments, indicating that generative-AI content underperforms human content even after controlling for platform and industry. This is consistent with research showing that recognition of AI authorship lowers perceived authenticity and quality (Brüns & Meißner, 2024; Seeger et al., 2026). Because platform and industry effects are significant while AI remains negative, H2 is only partially supported: contextual factors matter, but they do not offset the AI penalty. The non-significance of voice-over suggests that

production features are secondary to platform fit and industry context in this dataset, echoing the contextual view of engagement (Møller et al., 2026).

Fit Versus Creativity (H3)

The content-coding results contradict the expectation that product–media fit raises engagement; instead, the highest engagement occurs for poorly fitting content, while well-fitting content underperforms. H3 is therefore not supported. This counterintuitive pattern is best explained by virality and storytelling: mechanical congruence does not substitute for creative narrative (Chinki et al., 2026; Sianani, 2025). The implication is that generative-AI content requires human creative direction to achieve strong engagement.

Theoretical and Practical Implications

Theoretically, the study extends the conditional view of AI-content reception by using real engagement data from commercial advertising rather than experimental ratings, addressing the gap left by Zhang & Hur (2025), whose findings were based on laboratory-controlled stimuli rather than observed behavioral engagement on live platforms. Practically, marketers should deploy generative AI selectively favoring visual platforms (Instagram, YouTube) and visual/lifestyle industries (Fashion, Food & Beverage, Nonprofit & Social Impact) and should pair AI production with human storytelling rather than relying on product–media fit alone.

Conclusion

This study examined the effect of generative-AI content on consumer trust and engagement in digital marketing strategy through three interrelated studies. In Study 1, descriptive analysis showed that the engagement distribution (likes and comments) for generative-AI content differs significantly across industries and platforms. The Fashion, Food & Beverage, and Nonprofit & Social Impact industries recorded the highest mean likes and comments, while Instagram emerged as the platform with the most dominant consumer engagement. This indicates that generative-AI content is more effective in visually oriented, lifestyle industries and on visual-based platforms, although the engagement distribution tends to be inconsistent and strongly influenced by viral content. H1 is therefore supported.

In Study 2, linear regression showed that generative-AI content yields significantly lower likes ($B = 0.55$, $p = 0.018$) and comments ($B = 0.50$, $p = 0.019$) than human content. Voice-over had no significant effect, whereas Instagram and the Fashion, Food & Beverage, and Nonprofit & Social Impact industries had positive, significant effects on engagement. Consumer engagement and trust are thus contextual and strongly shaped by platform fit and industry characteristics. H2 is partially supported: platform and industry are influential, but generative-AI content reduces consumer interaction relative to human content.

In Study 3, content coding of product fit and media fit showed that fit with product and platform does not automatically increase consumer engagement and trust. Content that fit neither product nor platform recorded higher interaction, owing to virality. H3 is therefore not supported, since content fit alone is insufficient without creativity, strong storytelling, and viral potential.

Overall, the study concludes that generative-AI content is not yet able to fully replace human content in building consumer trust and engagement. The effectiveness of AI-based branding in digital marketing depends heavily on industry context, platform selection, creative quality, and storytelling. Ideally, therefore, generative AI in digital marketing should be integrated with human creativity to produce content that is relevant, authentic, and capable of generating optimal consumer engagement.

Nevertheless, this study is subject to several limitations that should be acknowledged. First, the engagement metrics used likes and comments represent only a partial measure of consumer trust and engagement; other behavioral signals such as shares, saves, and watch time, which may provide a more comprehensive picture of audience interaction, were not captured. Second, the dataset is drawn from a single secondary source Moutasm, (2025) comprising 253 observations, which limits the generalizability of findings across broader commercial advertising contexts. Third, because the study relies on observational secondary data rather than an experimental design, causal inference cannot be established; the negative association between AI-generated content and engagement may be confounded by unobserved variables such as content quality, posting frequency, or audience demographics. Fourth, the influence of viral content introduces substantial variance in the engagement distribution, making it difficult to isolate the effect of AI authorship from the effect of virality. Fifth, the content coding in Study 3 was conducted based on textual descriptions of advertising content rather than direct visual inspection

of the advertisements themselves, which may introduce subjectivity in the classification of product fit and media fit.

These limitations point to several directions for future research. Future studies should employ broader and more diverse engagement metrics including shares, saves, reach, and conversion rates to develop a more complete understanding of how generative-AI content shapes consumer behavior across digital platforms. Longitudinal designs that track engagement over time would allow researchers to assess whether the negative effect of AI authorship on consumer trust is stable or diminishes as consumers become more accustomed to AI-generated content. Future research should also consider experimental or quasi-experimental designs that enable causal identification of the AI content effect, controlling for confounding variables such as content quality and audience characteristics. Additionally, cross-cultural comparisons across different national and regional markets would enrich understanding of how cultural context moderates consumer responses to AI-generated advertising. Finally, future studies could extend the scope of content categories and platforms examined including emerging platforms and industries not covered in this dataset to build a more generalizable empirical base for AI-based branding strategy in digital marketing.

References

Ali, M. S. M., Wasel, K. Z. A., & Abdelhamid, A. M. M. (2024). Generative AI and Media Content Creation: Investigating the Factors Shaping User Acceptance in the Arab Gulf States. *Journalism and Media*, *5*(4), 1624–1645. https://doi.org/10.3390/journalmedia5040101

Barari, M., & Eisend, M. (2024). Computational Content Analysis in Advertising Research. *Journal of Advertising*, *53*(5), 681–699. https://doi.org/10.1080/00913367.2024.2407642

Brüns, J. D., & Meißner, M. (2024). Do you create your content yourself? Using generative artificial intelligence for social media content creation diminishes perceived brand authenticity. *Journal of Retailing and Consumer Services*, *79*, 103790. https://doi.org/10.1016/j.jretconser.2024.103790

Carney, S., Riveros, I., & Tully, S. M. (2026). Made With AI: Consumer Engagement With Social Media Containing AI Disclosures. *Journal of Consumer Research*. https://doi.org/10.1093/jcr/ucag013

Chinki, Rana, S., Yadav, M. P., & Sinha, N. (2026). Crafting narratives to influence consumers: a systematic review of storytelling marketing. *Asia-Pacific Journal of Business Administration*, *18*(2), 289–313. https://doi.org/10.1108/APJBA-12-2024-0693

Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2024). Generative AI. *Business & Information Systems Engineering*, *66*(1), 111–126. https://doi.org/10.1007/s12599-023-00834-7

Gurung, M. I., Agarwal, N., Bhuiyan, M. M. I., & Poudel, D. (2025). Symbolic signals on Instagram: how visual media shapes engagement, emotion, trust, and diffusion. *Social Network Analysis and Mining*, *15*(1), 57. https://doi.org/10.1007/s13278-025-01469-0

Hartmann, J., Exner, Y., & Domdey, S. (2025). The power of generative marketing: Can generative AI create superhuman visual marketing content? *International Journal of Research in Marketing*, *42*(1), 13–31. https://doi.org/10.1016/j.ijresmar.2024.09.002

Holzner, N., Maier, S., & Feuerriegel, S. (2025). Generative AI and Creativity: A Systematic Literature Review and Meta-Analysis. *ArXiv Preprint ArXiv*. https://doi.org/https://doi.org/10.48550/arXiv.2505.17241

Kim, S., & Cho, E. (2026). How AI involvement affects curiosity and content engagement in AI-generated advertisements. *Journal of Retailing and Consumer Services*, *92*, 104756. https://doi.org/10.1016/j.jretconser.2026.104756

Møller, A. G., Romero, D. M., Jurgens, D., & Aiello, L. M. (2026). The impact of generative AI on social media: an experimental study. *Scientific Reports*, *16*(1), 9376. https://doi.org/10.1038/s41598-026-40110-8

Moutasm, T. (2025). *AI Video Generation for Branding Products Dataset*. Kaggle.Com. https://www.kaggle.com/datasets/moutasmtamimi/ai-video-generation-for-branding-products-dataset

Rahman, A., Khan, M. A., Mahmud, F. U., Bishnu, K. K., Rahman, A., Mridha, M. F., & Hossen, Md. J. (2026). A Systematic Literature Review on the Impact of Generative AI in Digital Marketing: Advancements, Opportunities, and Challenges. *Computers, Materials & Continua*, *87*(3), 1–10. https://doi.org/10.32604/cmc.2026.071029

Sangiorgio, E., Di Marco, N., Etta, G., Cinelli, M., Cerqueti, R., & Quattrociocchi, W. (2025). Evaluating the effect of viral posts on social media engagement. *Scientific Reports*, *15*(1), 639. https://doi.org/10.1038/s41598-024-84960-6

Sapina, N., Nanda, A., Arifin, M. A., Rahmaddeni, R., & Efrizoni, L. (2025). Analisis Faktor-Faktor yang Mempengaruhi Engagement Video di Platform TikTok Menggunakan Multiple Linear Regression. *MALCOM: Indonesian Journal of Machine Learning and Computer Science*, *5*(3), 875–885. https://doi.org/10.57152/malcom.v5i3.1987

Seeger, F., Wessel, M., & Lehrer, C. (2026). AI content labeling and user engagement on social media: The role of AI level, content type, and disclosure timing. *Electronic Markets*, *36*(1), 31. https://doi.org/10.1007/s12525-026-00883-2

Shahbaznezhad, H., Dolan, R., & Rashidirad, M. (2021). The Role of Social Media Content Format and Platform in Users' Engagement Behavior. *Journal of Interactive Marketing*, *53*(1), 47–65. https://doi.org/10.1016/j.intmar.2020.05.001

Shen, Z. (2023). Platform or Content Strategy? Exploring Engagement With Brand Posts on Different Social Media Platforms. *Sage Open*, *13*(4). https://doi.org/10.1177/21582440231219096

Sianani, M. A. D. (2025). Peran Brand Storytelling dalam Membangun Persepsi Konsumen: Kajian Systematic Literature Review dengan Kerangka Prisma. *Jurnal Riset Manajemen*, *3*(4), 109–126. https://doi.org/10.54066/jurma.v3i4.3647

Statista Research Department. (2024). *AI in marketing revenue worldwide 2020–2028*. Https://Www.Statista.Com/Statistics/1293758/Ai-Marketing-Revenue-Worldwide/#:~:Text=In%202021,%20the%20market%20for,Than%20107.5%20billion%20by%202028.

Trunfio, M., & Rossi, S. (2021). Conceptualising and measuring social media engagement: A systematic literature review. *Italian Journal of Marketing*, *2021*(3), 267–292. https://doi.org/10.1007/s43039-021-00035-8

Vassio, L., Garetto, M., Leonardi, E., & Chiasserini, C. F. (2022). Mining and modelling temporal dynamics of followers' engagement on online social networks. *Social Network Analysis and Mining*, *12*(1), 96. https://doi.org/10.1007/s13278-022-00928-2

Wahid, A. M. (2025). Empirical Analysis of Social Media Interaction Metrics and Their Impact on Startup Engagement. *IJIIS: International Journal of Informatics and Information Systems*, *8*(3), 161–174. https://doi.org/10.47738/ijiis.v8i3.272

Zhang, L., & Hur, C. (2025). The Impact of Generative AI Images on Consumer Attitudes in Advertising. *Administrative Sciences*, *15*(10), 395. https://doi.org/10.3390/admsci15100395