



## **Determinants of Customer Experience in Artificial Intelligence-based Social Media Content Creation Tools: An Empirical Study**

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### **Abstract**

The practice of digital marketing is being transformed as Artificial Intelligence (AI) grows increasingly dependent on itself for the creation of content on social media. This empirical study investigates the factors that affect customer experience while using AI-based tools for writing content in social media platforms. This specific study is based on purposive sampling methodology. Out of 310 responses obtained, 287 were utilised for the data analysis (removing incomplete responses, detecting and excluding outliers, and conducting reliability checks). The target population considered for this study is Digital marketers, social media influencers, content creators, and those business owners using AI-generated content. The Questionnaire was prepared using Google form and Likert scale questions were prepared. The data was collected and transferred to IBM SPSS & PLS-SEM for analysis. The Samples received from the respondents are transferred to IBM SPSS software for further analysis followed by Demographic Analysis, Factor Analysis, Reliability Test, SEM Analysis. The findings noted that user's perceptions depend on the quality of the content, as the well-structured, engaging, and grammatically accurate content leads to satisfaction. Another determinant is relevance as users associate interest in AI-generated content, which becomes a lot more relevant with current trends on social media. Customer trust in the AI-based writing instruments depends on the authenticity they put across to users, ethical queries, and handling human-like writing quality. Finally, Brand Visibility is significantly influenced by



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the effectiveness of AI-generated content in increasing user engagement and organic reach. The study outlines challenges faced by users in terms of originality, personalization, and dependency on AI-generated content. However, despite these challenges, most respondents show a positive attitude towards these AI-powered content writing tools if they remain high in quality, relevance, and credibility.

### Introduction

The tremendous acceptance of social media marketing (SMM) and its application in digital marketing enables marketers to reach the customers, create brand awareness, and sell products via the social networking platforms (Kaplan & Haenlein, 2010). In 2023, after a very rapid growth to about 4.9 billion users across the globe, social media platform provides unique opportunities for businesses to promote their services and products among targeted audiences via content marketing, influencers, and paid ads (Statista, 2023). In the academic literature, the social presence has been emphasized to guide consumer behavior development, brand loyalty cultivation, and purchase decision influence (Mangold & Faulds, 2009). The SMM represents a transformational approach to traditional marketing. As opposed to traditional marketing media that depend on one-sided communication, social media enable two-way relationships with customers through business engagement (Tuten & Solomon, 2017). Marketers use platforms like Facebook, Instagram, Twitter, LinkedIn, and TikTok to create personalized and interactive campaigns that have proven highly engaging (Dwivedi *et al.*, 2020). Studies state that social media marketing increases brand awareness, with 90% of marketers affirming it has significantly boosted their profiles (Stelzner, 2021). The costs of advertising on social media are also cheaper than with conventional media. Felix *et al.* (2017) mentioned that businesses can enhance their advertising efficiency by resorting to social media strategies, able to select specific types of demographic, interest, and behavior. These paid placements such as Facebook Ads and Instagram Sponsored Posts also show how social media uses its relevant algorithms to actively show the right content to the right audience (Ashley & Tuten, 2015). Targeting with precision has thus fundamentally changed the way social media marketing can be classified as a necessity for businesses in contemporary times.

At the very center of social media marketing lies content, as brands successfully adopted quality, engaging, and captivating information to gain control over their audiences (Pulizzi, 2012). As Holliman and Rowley (2014) established from research, content marketing is a vehicle for enhancing customer trust and relationships while putting companies at the forefront of their industries. Each one of these forms of content involves social media: blogs, videos, infographics, podcasts, and live streams (Baltes, 2015).

Storytelling has an essential part in content marketing because it can help these brands relate with consumers at an emotional level. Research indicates that storytelling humanizes brands and improves audience retention as well (Lundqvist *et al.*, 2013). A story well-written, alongside visuals and real experiences, magnifies brand authenticity and creates higher engagement (Gensler *et al.*, 2013). For instance, Nike social media campaigns highlight stories of inspiring athletes whose aspirations strike a chord with the audience and match Nike's brand beat.

### Literature Review

Since the pandemic's impacts have subsided, content marketing has been and will continue to be a driving force behind new kinds of digital advertising, especially in today's AI-based economy. According to recent scholarly studies, content marketing encompasses more than just blog posts and articles; it also includes webinars, interactive tools, and micro content created by artificial intelligence (Ahmad *et al.*, 2023). Considering that analytics and insights from behavioural science are now primarily used to personalise content experiences, the emphasis has shifted to creating value for customers. More recent research findings centre on the importance of personalisation, especially when applied on a large scale. Kumar and Sharma (2024) state that tailored content has a multiplicative effect on

engagement, conversion rates, and client retention. According to their e-commerce platform longitudinal research, personalising content marketing workflows increases customer lifetime value (CLV) by about 35%. Since personalised content is seen as a way to establish trust, this aligns with the original theories of relationship marketing.

The use of artificial intelligence and other forms of automation in content creation, curation, and dissemination is another development. Marketers can now create content practically immediately thanks to advancements in generative AI technologies like GPT models. But this hasn't alleviated marketers' concerns regarding authenticity and brand voice. Recent research by Müller & Grant (2023) demonstrated that AI content might increase content volume by 40%; but, in order to maintain emotional resonance and ethical compliance with brand principles, "human eyes" are necessary. Data analytics and performance metrics are becoming increasingly integral to content marketing efficacy. For example, Feldman *et al.* (2024) suggest using real-time data from user engagement, scroll depth, social sharing, and lead generation in dynamic analytics dashboards. In addition to facilitating A/B testing settings for content improvement, these will also make it easier for marketers to change tactics. There has never been a more efficient feedback loop between content strategy and performance.

Storytelling may be fundamental as a traditionally past form, but narrative has matured in itself. The products are often the centerpiece of these stories: they have turned into tales about community, sustainability, and identity. Kotler & Ingram (2023) state that these are "narrative-driven brand ecosystems," where companies use various means to create an interconnected tale to enhance user immersion. This type of transmedia storytelling adds value to brands by making them distinguishable in saturated markets while appealing to emotional processes of decision making. A similar trend is the increased focus on ethical content marketing. Consumers are very much inclined to be transparent now, since misinformation and algorithmic manipulation are the biggest issues facing market consumers. Li & Bukhari's (2023) research focuses on content credibility, particularly on social platforms where user-generated content and branded content often blur, adding to the debates over authenticity and reliability. From their

research, they found out that brands that endorse disclosure and promise true content are preferable and trust them while they consume content.

Content quality is a major consideration to prove credibility in this fast-paced digital marketing setting. First-class information representing various hypotheses needs to be provided to build trust and cultivate loyal customers. In their research, Schellong *et al.* (2022) have highlighted the dual function of credible content, namely, that it provides the necessary information to the target audience and shows brand competence and integrity. Consumers are increasingly interested in discovering content that is aligned with their values and factual, going beyond mere appeal and persuasion. According to Zhang *et al.* (2021), cognitive trust is facilitated when consumers deem content to be informative, unbiased, and relevant to their needs.

Moreover, the content quality actively shapes the perceived authenticity and transparency of social media marketing, as noted by Kim and Ko (2023). This is when information favors the customer rather than sounding too commercial, which increases trust. Moreover, Kang & Namkung (2020) argue that congruity of content with brand identity is crucial, as any message deemed discordant with brand values is likely to see customers losing faith and switching allegiance. Hassan *et al.* (2022) further proved that regulated industries, including healthcare and banking, are likely to enjoy institutional trust in return for continuously adding quality content.

Interactive content is a trust booster in its best application. Polls, comments, and UGC- user generated content mechanisms foster user engagement and confidence, Alalwan (2021) remarks. These, however, can also be sabotaged by civility and accuracy control. Pulling together findings in the e-commerce field, Chae *et al.* (2022) proved that a combination of honest, detailed product descriptions with consumer reviews promotes trust massively since it diminishes perceived risks and garners transactional confidence.

The recent advent of AI generative content throws open an entirely new dimension to these discussions. Gupta and Kumar (2024) caution that while generative AI can scale up the production of content, the absence of fact-grounding or the lack

of emotional resonance can result in loss of user trust if it is not judiciously curated. Hence, the role of human intervention in quality assurance still holds. Besides, according to the research by Lee *et al.* (2023), it was established that perceived ethical

content handling such as transparency about data and no manipulation relates closely with consumer trust among Gen Z audiences; thus today, trust in content also depends on data ethics.

**Research Gap**

Category	Research Gap	Description
Behavioural Insights	Lack of thorough behavioural research	Few researches look at psychological and emotional aspects influencing CX using artificial intelligence techniques on social media.
Personalization Effect	Limited investigation of tailored content influences.	Little research on how user pleasure and engagement are affected by artificial intelligence personalising.

**Research Objective**

The research aims to investigate key factors affecting the customer experience while using AI-based content writing tools in social media marketing at an empirical level.

**Materials and Methods**

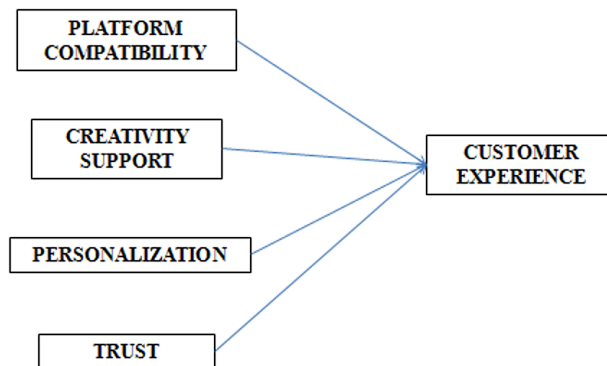
This research is a descriptive research design aimed at systematically describing and interpreting factors that affect the experience of the users of content writing tools that are powered by AI and niched-in social media. Descriptive research is the most appropriate to use in this case because it provides avenues for understanding what, how, and to what extent different factors are affecting user experience without manipulation of variables. This specific study is based on purposive sampling methodology. Out of 310 responses obtained,

287 were utilised for the data analysis (removing incomplete responses, detecting and excluding outliers, and conducting reliability checks). The target population considered for this study is Digital marketers, social media influencers, content creators, and those business owners using AI-generated content. The Questionnaire was prepared using Google form and Likert scale questions were prepared. The data was collected and transferred to IBM SPSS & PLS SEM for analysis.

**Proposed Research Model**

**Results**

The procedure for analysis of the data is aimed at converting raw data from survey responses into insightful meaning, testing one's hypotheses, and establishing the validity of the suggested model of research.



**Fig.1: Factors influencing customer experience of AI Based tool**

**Demography Analysis**

Demographic analysis describes population characteristics. It usually is addressed to understand the composition, trends, and patterns of a particular group of people. The areas studied in demographic analyses include age, gender, income, education level, occupation, marital status, and geographical

location. This evaluation provides knowledge of different peoples' behavioural patterns, needs, and preferences. Demographics are applied in many professions; for example, marketing deals with sociology, public policy, and economics to make decisions, adapt strategies, and build future forecasts.

**Table 1: Demography Details**

SI. No.	Factor	Specific highlighting criteria	% of response
1	Age	Between 25 and 30 years	90 %
2	Marital status	Married	58%
3	Occupation	Private Employee	65 %
4	Industrial Sector	Software	77 %

The demographic analysis of the respondents shows that the vast majority, at 90%, are aged between 25 and 30 years, indicating a young adult population. Most respondents are married, making up 58% of the total and thus demonstrating a reasonably balanced ratio for singles and married. The percentage of 65% private employees depicts a workforce primarily in the private sector. The representation of 77% of respondents from the software industry highlights a dominating presence from the IT sector.

to see if the results are consistent. An important test of internal consistency of a scale or questionnaire, it is commonly used in SPSS to calculate the Cronbach's alpha coefficient, which is a measure of reliability. Items with a high score (often  $\alpha \geq 0.7$ ) indicate a high level of reliability and trustworthiness. Researchers run the danger of basing their findings on inconsistent or even erroneous data if this step is skipped, casting doubt on the study's veracity.

**Reliability Analysis of All the factors**

In order to determine if the scale or questionnaire has a single internal-consistent latent construct, this test is conducted. For example, if a survey asks various questions to gauge customer happiness, it would be useful to check the reliability of each item

**Table 2: Reliability Test**

Reliability Statistics	
Cronbach's Alpha	N of Items
.816	31

**Table 3: Model Estimates**

Model Summary <sup>b</sup>					
Model	R <sup>a</sup>	'R Square	Adjusted R Square	Std. Error of estimate	Durbin-Watson
1	.826a	.703	.648	1.52975	1.925

a. 'Predictors: (Constant), PC,CS,PS,TR  
b. Dependent Variable: CE

Reliability study was conducted on all variables utilising SPSS, yielding a Cronbach's Alpha value of 0.816 for the 31 scale items. This indicates that the internal consistency is elevated, implying that

the items are strongly associated and dependable in assessing the same construct. A result exceeding 0.8 is deemed satisfactory, indicating that the scale is reliable and suitable for further statistical studies.

The exceptionally high dependability indicates that the data gathered from respondents is consistent and credible, allowing for meaningful findings in the study.

**Model Fit Summary**

It is the aggregate of the goodness-of-fit estimates that detail quantitatively, how well the fitted model replicates the data observed.

There is a strong positive relationship between the dependent variable CE (Customer Experience) and the predictors PC (Platform Compatibility), CS (Creativity Support), PS (Personalization), and TR (Trust), as shown in the Model Summary, which indicates a multiple correlation coefficient of 0.826 in the regression model. With a R Squared value of 0.703, we can see that the four independent variables we looked at explain 70.3% of the variation in customer experience. After accounting for the sample size and number of predictors, the Adjusted R Squared value drops to

0.648, this is still indicative of a well-fitting model. A number of 1.52975 is the standard error of the estimate, which is the average distance between the observed value and the regression line. With a Durbin-Watson statistic of 1.925, which is near to 2, we may conclude that the residuals do not exhibit any substantial autocorrelation and that the independence assumption is correct.

**Sampling Adequacy Test**

Kaiser-Meyer-Olkin (KMO) and Bartlett's Test of Sphericity are two important statistical tests that determine if the data are sufficient for factor analysis. To determine how suitable the data is for structure detection, a KMO test calculates the proportion of variation among variables that might be common variance. Factor analysis is typically helpful when KMO values are near to 1 (about >0.6), but inadequacy of sample is indicated by values below 0.5. A similar test, the Bartlett Sphericity Test, looks for signs of discordance between the variables by comparing the correlation matrix to an identity matrix.

**Table 4: Test for Sampling Adequacy**

<b>'KMO and Bartlett's Test'</b>		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.807
Bartlett's Test of Sphericity	Approx. Chi-Square	5184.412
	df	976
	Sig.	.000

The data is adequate for factor analysis, according to the KMO and Bartlett's Test results, which show that the KMO Measure of Sampling Adequacy is 0.807. Conversely, there are sufficient correlations among the variables, as confirmed by Bartlett's Test of Sphericity, which is extremely significant (Chi-Square=5184.412, df=976, p<0.001). Thus, it is reasonable to conduct exploratory factor analysis on this dataset, given the combined results of the two tests support this.

**Factor Analysis**

When it comes to study in the social sciences and behavioural arts, factor analysis is among the most essential validations for the structure and reliability of measurement instruments. To do this, we must first find the latent structures, or factors, that explain the intercorrelation of the observed data. Factors with high loadings (often greater than

0.5) imply substantial correlations, according to this analysis. By comparing the amount of variation attributable to measurement error to the amount of variance by which an item correlates positively with the construct, we can find the Average variation Extracted (AVE). A value of 0.5 or more is deemed acceptable, suggesting satisfactory convergent validity. In contrast to Cronbach's alpha, which is more applicable when factor loadings are modified, Composite Reliability (CR) is defined as the measure of internal consistency of the construct; a CR value more than 0.7 would suggest a construct with good reliability. Typically, values above 0.7 are considered acceptable for Cronbach's alpha, a standard measure of internal consistency that examines the interrelatedness of items to determine the reliability of the scale. When taken as a whole, these measurement features provide a valid and trustworthy model, which boosts faith in the results.

**Table 5: Factor loadings, AVE, CR and Cronbach's alpha**

Constructs	Factor loading	CR	AVE	Cronbach's $\alpha$
<b>Platform Compatibility</b>		0.820	0.690	0.763
PC1	0.699			
PC2	0.765			
PC3	0.823			
PC4	0.888			
PC5	0.821			
<b>Creativity Support</b>		0.786	0.675	0.854
CS1	0.711			
CS2	0.710			
CS3	0.734			
CS4	0.680			
CS5	0.720			
CS6	0.760			
<b>Personalization</b>		0.864	0.656	0.765
PS1	0.803			
PS2	0.782			
PS3	0.875			
PS4	0.866			
PS5	0.623			
PS6	0.814			
<b>Trust</b>		0.713	0.637	0.819
TR1	0.610			
TR2	0.794			
TR3	0.663			
TR4	0.487			
TR5	0.765			
TR6	0.889			
TR7	0.844			
<b>Customer Experience</b>		0.833	0.564	0.825
CE1	0.797			
CE2	0.843			
CE3	0.617			
CE4	0.788			
CE5	0.777			
CE6	0.870			
CE7	0.844			

Determining the Reliability and Validity of Measurement Constructs was accomplished through factor analysis alongside computations for Composite Reliability (CR), Average Variance Extracted (AVE), and Cronbach's alpha. Strong indicators of correlation among the items and their respective constructs were found, since all the item's factor loadings were greater than the lower limit of 0.5, with the bulk scoring greater than 0.7.

The values of CR were found to be greater than the cut-off of 0.7 for the following constructs: Platform Compatibility (0.820), Creativity Support (0.786), Personalization (0.864), Trust (0.713) and Customer Experience (0.833), thereby confirming internal consistency. Values for Cronbach's alpha went from 0.763 till 0.854, also indicating supported reliability for these constructs. The AVE values were above the accepted range of 0.5 for all constructs ranging from

0.564 (Customer Experience) to 0.690 (Platform Compatibility), thus proving scales for convergent validity. This underpins that the measurement model is reliable and valid and is suitable for the following SEM and hypothesis testing.

**Discriminant Validity Analysis**

Discriminant validity is a measure used in research to assess how far apart a concept or construct really is from other concepts or constructs. It says that a variable or scale is not simply reflecting something else, and that it is an independent

measure of the variable it was supposed to measure without overlapping appreciably with any unrelated variables. In other words, discriminant validity states that the two constructs in question are different. The more types of constructs one considers, the stronger the empirical results become. This form of validity is especially important in research that comprises studies with several constructs and it becomes necessary when using tools like surveys or questionnaires to ensure that each construct truly captures different aspects of the overall idea being looked at.

**Table 6: Discriminant Validity**

	PC	CS	PS	TR	CE
PC	0.830				
CS	0.493	0.821			
PS	0.437	0.608	0.809		
TR	0.385	0.543	0.597	0.798	
CE	0.294	0.424	0.481	0.524	0.750

On the diagonal is displayed the matrix values for whom the square roots of AVE average variance extracted for each construct are calculated, while the off-diagonal values display their correlations between constructs. As for the criteria provided by Fornell-Larcker, discriminant validity is met if for each construct, the square root of the average variance extracted (which is shown in diagonal elements) has to be bigger than the correlation values (off-diagonal elements) with respect to other constructs in the model.

**Construct-by-Construct Analysis**

**Platform Compatibility (PC)**

- Square root of AVE = 0.830
- Correlations with other constructs range from 0.294 (with CE) to 0.493 (with CS)
- Since 0.830 > all its correlations, discriminant validity is established for PC.

**Creativity Support (CS)**

- Square root of AVE = 0.821
- Correlations with other constructs range from 0.424 (with CE) to 0.608 (with PS)
- 0.821 > all its correlations, indicating discriminant validity is established.

**Personalization (PS)**

- Square root of AVE = 0.809
- Highest correlation is with CS (0.608), followed by TR (0.597)
- As 0.809 > all these values, discriminant validity holds for PS.

**Trust (TR)**

- Square root of AVE = 0.798
- Highest correlation is with PS (0.597), then CS (0.543)
- With 0.798 > all correlations, discriminant validity is confirmed.

**Customer Experience (CE)**

- Square root of AVE = 0.750
- Highest correlation is with TR (0.524), followed by PS (0.481)
- Since 0.750 is greater than all correlation values, CE also demonstrates discriminant validity.

**SEM Algorithm Analysis**

The SEM (Structural Equation Modeling) algorithm is defined as a statistical tool through which one can analyze the structural relationships between

observed and latent variables within a model. The SEM algorithm can be understood as a combination of factor analysis and multiple regressions, checking at once a series of dependence relationships. SEM models usually consist of two sub-models: the

measurement model, which specifies how latent constructs are measured by observed variables, and the structural model, which describes the relationship between the latent constructs.

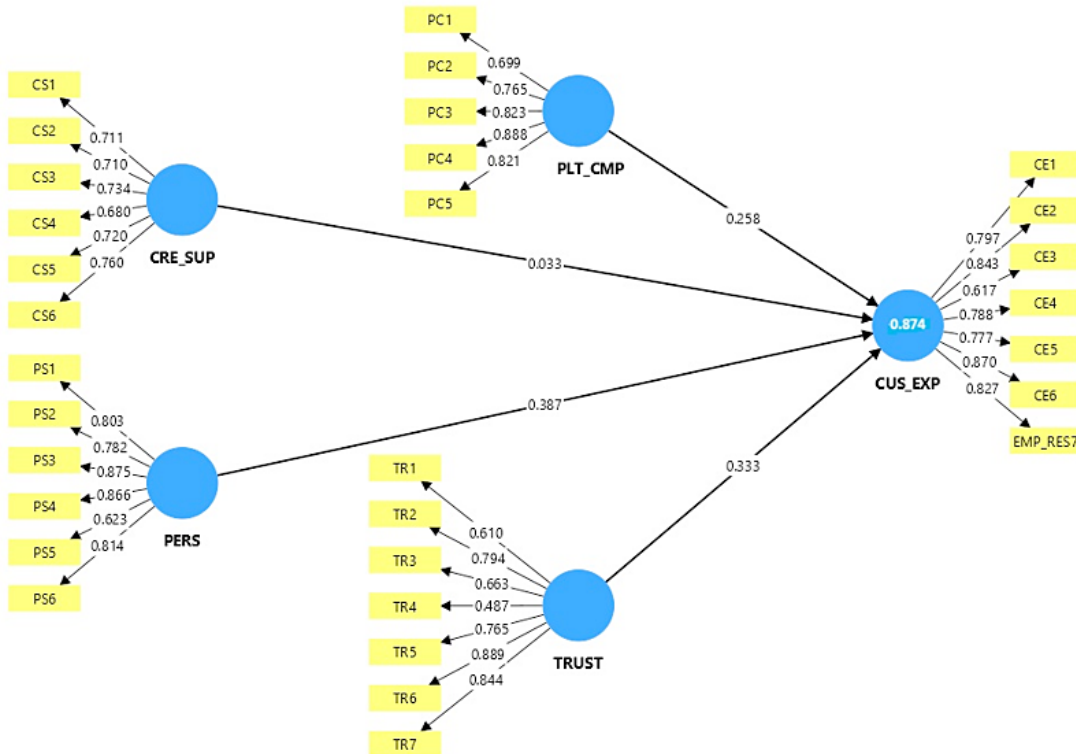


Fig. 2: PLS SEM Algorithm

Table 7: Statistical Analysis (Direct Effect)

Structural Path	Effects	Beta	t-values	p-values	Result
PC→CE	Direct	0.258	17.82	0.002	Accepted
CS→CE	Direct	0.033	19.36	0.000	Accepted
PS→CE	Direct	0.387	1.437	0.001	Accepted
TR→CE	Direct	0.333	4.235	0.000	Accepted

The verification of direct effects for the structural model estimation generated using the PLS-SEM algorithm indicates that all the hypothesized direct effects are statistically significant and thus accepted. The path coefficient PC→CE indicates a beta value of 0.258 along with a t-value of 17.82 and a p-value of 0.002; thus, the direct effect is moderate and significantly positive. CS→CE has a rather small beta of 0.033 due to a high t-value of 19.36 and

a p-value of 0.000. Therefore, CS→CE indicates a very small but statistically significant effect. On the other hand, PS→CE indicates a very high association, with a beta of 0.387, a t-value of 1.437, and a p-value of 0.001. Lastly, TR→CE presents a very strong effect with a beta of 0.333, a t-value of 4.235, and a very highly significant p-value of 0.000. Thus, these results firmly attest to the validity of the proposed structural paths and indicate that each

construct contributes significantly to the explanatory power of the model.

### Discussions

Optimizing the accompanying content generation tools and AI services, among others, must focus on multiple social media platforms including Instagram, Facebook, LinkedIn, and Twitter. It may be helpful to consider investing in platforms where seamless integration of the AI tool is paramount and outputs produced in a format and style that are consistent with the unique algorithmic and aesthetic expectations of each platform. Scheduling and publishing content capabilities should also address platform-dependent nuances so that they work more efficiently and smoothly.

Secondly creativity support has implications for managerial practice with relatively less direct impact. Managers must ensure that AI tools assume a wide array of language tones, story structures, and multimodal characteristics (e.g., image and video prompts) as helpful to content users who need refreshing and creative ideas. Training modules or examples that show very creative possibilities for the tool will help build user confidence and contribution. Managers should also consider periodically updating the tool's generative models to align the creative outputs with the latest trends and viral digital formats. Third, the study found Personalization to be the most significant and positive cause of customer experience ( $\beta = 0.387$ ). This suggests that AI content tools must provide a high level of personalization—from content tone and styling preferences to user behavioral data for improved targeting. Managers should commit to creating smart user profiles and corresponding preference-learning mechanisms so that the AI would grow alongside the user. The major priorities in their product development roadmap should center on brand voice cloning, adaptation to audience sentiment, and capabilities for niche targeting.

Trust in AI emerged as another primary dimension affecting the customer experience. Managers must be transparent about AI regarding its data sources, how content is generated, and ethical boundaries for its usage. Being transparent about when and how AI is involved in content generation will help gain user trust and counter skepticism. Besides this, human agency aspects must be integrated—for example,

editing of content, review history, and plagiarism checks—to ensure the output remains accurate, humane, and legally publishable.

In addition, it was found that brand awareness and user engagement were affected by the quality and authenticity of AI-generated content; thus, managers should evaluate AI on an analytics dashboard that tracks user engagement with metrics such as engagement, conversion rates, and feedback loops that apply to content strategy. Organizations should embrace AI-generated content as a co-creative partner rather than the replacement of human creativity so that it retains ethicality, originality, and brand alignment.

### Conclusion

The results of the present study reveal that four factors affect customer experience with AI-based content-writing tools accessed on social media: platform compatibility, creativity support, personalization, and trust in AI. Perceived personalization was the strongest determinant, signifying the necessity of developing preferred content with respect to customer behavior for greater satisfaction and engagement. This is consistent with earlier research findings supporting more personalized content leads to a deeper bond with users and broader customer lifetime value (Kumar & Sharma, 2024). Second, platform compatibility emerged as a positive influence on user experience; thus, maximizing AI tools' integration with several social media platforms makes them more usable and efficient. When content creation tools match platform-specific formats and interactions, users become likely to co-create content using these tools. Creativity support was of lesser influence but still very relevant. Users appreciate AI tools that help generate original and interesting content ideas, especially when they help tell stories that touch an emotional chord—a statement reconfirming the emphasis laid by existing literature in narrative-driven brand communication (Lundqvist *et al.*, 2013; Kotler & Ingram, 2023). Trust in AI may also be a game-changer. The findings suggest that user trust in AI-generated content with regard to its ethical, transparent, and human-like nature is crucial to engendering that trust and ensuring continued use. Prior literature found that using content perceived to be genuinely authentic and ethically sound increases user trust and brand credibility (Lee *et al.*, 2023;

Li & Bukhari, 2023). The content quality—defined as the degree to which the content is accurate, structured, relevant, and original—was observed to be largely contributory to customer experiences. Users tend to be satisfied when the content is not only grammatically accurate but also trendy, relevant to their audience, and personalized with respect to their specifications. However, the originality of the content still remains questionable, alongside over-dependence on AI. These factors suggest the necessity of human moderation and post-processing of AI-generated material prior to publication, and thus support the position of Müller and Grant (2023), calling attention to the fact that human involvement is paramount in creating content that is consistent with a brand's voice and ethical standards.

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#### Author Contributions

- **Surjadeep Dutta:** Conceptualization, Methodology, Writing – Original Draft.
- **Paul Arun Kumar James:** Data Collection, Analysis.
- **Prabhavathy Raja Ebenezer:** Project Review, Editing.
- **Sarthak Sengupta:** Project Editing and Inrerpretation.

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