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Ai-Driven Marketing Experiences And Their Impact On The Gen Z Consumer Preferences: The Mediating Role Of Perceived Trust

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ABSTRACT
The fast growth of artificial intelligence (AI) has completely changed the digital marketing environment by allowing marketers to develop highly customised campaigns based on each customer's unique interests and behaviours. Understanding how it influences Gen Z consumer preferences is also vital. This study assesses how AI-driven marketing experiences impact Gen Z consumer choices, with the emphasis on the mediating roles of perceived trust. A quantitative research approach was used to collect data from 526 frequent users of digital platforms in urban areas of India. The study was evaluated, and the correlations between significant variables were explored by applying structural equation modelling (SEM). The result showed that customers' perceived trust has a beneficial effect on accessibility, interaction, accuracy, and customisation experiences. Gen Z consumers show a strong preference for AI-based marketing services because they trust these services, according to their trust evaluation. And also, this investigation showed that while trust is the primary factor influencing customer behaviour, perceived trust serves as a critical mediator between all experience aspects and consumer preferences. By emphasizing behaviors that foster usefulness, relevance, and trust, the findings provide firms looking to improve personalization tactics with important suggestions
Keywords: Artificial Intelligence, Marketing Experience, Consumer Behavior, Generation Z, AI- Marketing
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INTRODUCTION:

AI technology currently operates through two main functions that deliver advanced capabilities to create new value. It has progressed from its initial experimental phase to become a standard tool used in modern marketing techniques. The marketing cycle experiences fundamental transformation through AI, which enables businesses to make data-driven choices and establish flexible pricing systems while creating personalised consumer experiences and delivering effective consumer support. The technological revolution introduced through digital transformation creates business opportunities that enhance operational efficiency and enable organisations to deliver personalised consumer experiences.

The growing acceptance of AI marketing campaigns as tactical tools shows their ability to enhance consumer loyalty through increased purchase rates and higher brand trust. Few studies have examined the psychological mechanisms that link AI marketing initiatives to branding results. According to earlier studies, brand loyalty ties with Generation Z consumers are strongly correlated with AI-based technologies. Previous research investigated AI's impact on brand experiences and brand image development, but researchers have not yet created a comprehensive framework that combines these factors. This research applies the S-O-R theory to AI marketing campaigns, which act as the stimulus, while perceived trust serves as the organism that leads to consumers developing repurchase intention and their preferences.

1.1 Problem Statement

Artificial intelligence (AI) is used in digital marketing in four ways: chatbots, predictive analysis, automated content delivery and recommendations tailored to individuals. Researchers have found that using AI has improved the personalisation and engagement between marketers and consumers, but have not examined how different AI marketing experiences impact the preferences of Generation Z. Concerns regarding data privacy, transparency, and algorithmic decision-making that affect consumers' confidence while interacting with various technology platforms are also extremely common. Though being a fast-growing segment of the digital marketplace, there is not enough empirical study to understand how perceived trust mediates the relationship between AI marketing experiences and the preferences of Generation Z consumers. By examining how AI-powered marketing experiences have impacted Generation Z consumers' preferences through their perceived trust, this study aims to close that gap.

1.2 Research Objectives

To investigate how Gen Z consumers' buying preferences are affected by AI-driven marketing experiences (accuracy, accessibility, interactivity, and accessibility).

To explore how Gen Z consumers' purchase choices and AI-driven marketing experiences are mediated by perceived trust.

1.3 Research Questions

The aims function as the foundation for the research questions provided below:

RQ1: How do Gen Z consumers' purchase preferences become influenced by AI-driven marketing experiences?

RQ2: Does the relationship between Gen Z consumers' purchase preferences and AI-driven marketing experiences get mediated by perceived trust?

2. REVIEW OF LITERATURE

In 2025, Markou et al. examined how the acceptability of AI-based tailored promotions is impacted by notions on ethics and trust, knowledge with and exposure to AI, digital consumer behavior, and identity concerns. Overall, their results implied that the adoption of AI in marketing involves a social and psychological process in addition to a technological one.In 2025, Stanikzai and Mittal investigated how UE is impacted by AIGC and HGC through the inventiveness and originality of contentpreneurs. Their work used a CB-SEM approach with data from telephone and web-based surveys of 324 contentpreneurs on Facebook, Instagram, X, and YouTube. Their results showed that UE is greatly impacted by AIGC and HGC. Because of its capacity to promote emotional connection, authenticity, and customised user experiences, the HGC effect is more persuasive than AIGC. The link between the predictors and the result variable is influenced by innovation and creativity, which act as partial mediators. In 2025, Hu et al. investigated the consequences of selecting chatbot avatars during an online buying process. They found in our experiment that a higher sense of psychological ownership was reported by individuals who actively chose their chatbot avatars. Each of the 119 participants recruited from a metropolitan university in the southern United States received course credits for their involvement. Their sense of trust and independence was greatly increased by this increased ownership, which in turn had an impact on a number of e-commerce outcomes. These results highlighted how consumers actively influence the efficacy of e-commerce. In 2025, Peter et al. investigated how Gen Z participants in India react to hyper-personalised ads powered by generative artificial intelligence. Forty members of Generation Z participated in semi-structured interviews using qualitative research techniques. To identify fundamental trends about brand interactions and emotional reactions to this kind of Next Gen AI-driven advertising, a thematic evaluation of the data was undertaken. AI-powered, highly customised ads that arouse deep emotions in viewers, increasing consumer loyalty and fostering closer, more intimate ties with them. According to their findings, companies can use Gen AI-powered, highly customised ads to arouse deep emotions in their target demographic, increasing consumer loyalty and fostering closer, more intimate relationships. In 2024, Guerra-Tamez et al. focused on how AI is influencing Generation Z's purchasing habits in the fields of fashion, technology, beauty, and education. Their results showed that brand trust is much increased by perception of AI accuracy¸ exposure to AI, and attitude toward AI, all of which have a beneficial effect on purchasing decisions. Notably, brand trust and purchase decisions are mediated by flow experience. In 2024, Bunea et al. investigated how Generation Z members' inclinations to shop online were affected by artificial intelligence (AI) strategies. Their project showed that exposure, use, and comprehension had substantial direct effects on PUAI and PEUAI, which in turn changed consumers' intentions to make purchases.

2.1 Research Gap

The literatures of Guerra-Tamez et al.¸Peter et al., and Bunea et al.,has explored the use of AI tools to affect consumer purchasing behaviour (i.e. intention to purchase/buy) for Generation Z (consenting adults age 18 through 29), consumer brand loyalty, and technological acceptance. However, although all of the researchers referenced above have provided significant and meaningful contributions to the growing knowledge base regarding purchasing behaviours within the marketplace, no one has conducted research that includes AI-related marketing experiences as a multi-dimensional (such as accuracy, interactivity, accessibility and customisation) and as direct influences on Generation Z's preferences through the mediating effect of trust as a unified construct.

2.2 Research Hypothesis

In order to investigate the underlying interactions and effects in the state of the study, research hypotheses have been established and evaluated in this section.

2.2.1 Accuracy Experience of AI marketing, and perceived trust among Gen Z consumers

According to Nadarzynski et al. a person's belief is that AI's recommendations and findings are precise when it comes to the accuracy of artificial intelligence (AI). This belief has an important impact on both brand loyalty and consumer behaviour. As AI technologies become more accurate and sophisticated, they are transforming the way consumers interact with companies and decide what to purchase. The perception of AI accuracy is particularly significant in the context of online commerce and e-commerce. According to Kim et al. the way in which consumers perceive AI to be accurate will also affect their overall level of trust in an organisation, and how therefore, the company presents AI technology to consumers can impact their perceptions of AI's accuracy and their overall level of trust in that organisation. An individual's perception of AI correctness, which is gauged by their confidence in the precision of AI's guidelines or findings, has a substantial impact on brand trust.

H_1: Accuracy experience of AI marketing has a significant positive effect on perceived trust among Gen Z consumers.

2.2.2 Interactive experience of AI Marketing and Perceived trust among Gen Z consumers

According to Gao and Liang, Gen Z's experience with AI interactions may have particular effects on their purchasing habits and brand trust. The research article investigates whether more Generation Z customers who are exposed to AI have higher levels of brand trust. This method not only advances comprehension. The way that Generation Z interacts with AI also offers insightful information for digital-age brand management tactics. These days, consumers use desktop computers and smartphones to browse the web for extended periods of time. Micheletto et al. Many industries have been using

AI-powered personalisation strategies more and more to enhance customer experiences. Through virtual try-on experiences made possible by artificial intelligence (AI) technologies, customers can view how cosmetic items would seem on their skin, hair, or nails. These virtual simulations are shown to positively influence consumers' intentions to purchase products because they reduce uncertainty and provide greater assurance in choosing a product. Consequently, the following theory was proposed by this research:

H_2: Interactive experience of AI marketing has a positive effect on perceived trust among Gen Z consumers.

2.2.3 Accessibility experience of AI marketing and Perceived Trust with Gen Z Consumers

Zarouali et al., the term accessibility describes how AI technologies enable organisations to effortlessly gather and analyse consumer data, which results in customised and useful user responses. The digital marketing environment establishes accessibility through the ability of customers to use AI-powered technologies that include chatbots, recommendation engines and virtual assistants across different digital platforms. AI technologies need to access and process consumer information at high speeds to deliver timely and relevant customer responses, which defines accessibility in AI marketing. The feature enables AI-powered tools to deliver instant information, personalised suggestions and efficient customer support through all online platforms. Thus, the subsequent hypothesis has been developed in the present study:

H_3: Accessibility experience of AI marketing has an optimistic effect on perceived trust among Gen Z consumers.

2.2.4 Customisation experience of AI marketing and perceived trust among Gen Z consumers.

According to Martin et al., despite the apparent benefits of AI personalisation, consumers have concerns about the acquisition, processing, and usage of their personal data. Consumer acceptance or rejection of AI-driven interactions is largely dependent on trust. Customers become resistant to tailored marketing campaigns when data usage is opaque or seen as exploitative. For marketers, the conflict between the advantages of personalisation and privacy concerns, often referred to as the "personalization–privacy paradox" represents a significant obstacle. McKnight et al., stated that, by utilising AI for marketing, companies can now create customised experiences for customers based on their past behaviour, preferences and other interaction attributes to improve efficiency through the creation of more personalised content. If customers do not trust AI Marketing because they see a disconnect or ambiguity in data collection/usage, they will likely have reduced confidence in any AI-powered systems. As a result, the present investigation offered the assumption that follows:

H_4: Customization experience of AI marketing has a significant positive effect on perceived trust among Gen Z consumers.

3. Research Methods

The sample plan, data collection, data processing technologies, and data analysis tools and techniques are all covered in this part. It covers systematic, scientific methods for gathering data, conducting research, and solving problems in order to achieve a particular objective. To quantify the factors and understand any potential correlation, the study's findings and conclusions should be quantitative. The goal of the study, its methodology, its distribution, and the target demographic will all be covered in detail in this part. Furthermore, it aims to advance knowledge of how Consumer behavior and preferences are influenced by generative AI marketing technologies and strategies. Stratified sampling was used to deliver the questionnaires to the selected study participants. The questionnaires were developed through Google Forms, together with alternative online survey platforms to achieve both easy access and successful data collection. 526 valid replies were received after 124 faulty questionnaires were eliminated. The research study selected assessment instruments through the process of adapting established measurement tools, which researchers had previously confirmed through their work. Our study is primarily confirmatory, and CB-SEM enables us to extensively analyse a well-established conceptual framework. The study used IBM SPSS Statistics 25 to analyse the constructs' reliability . The study guarantees robustness and reliability in assessing the recommended investigation model and looking at the interactions between variables by applying these exacting analytical methods and tools.

4. Analysis and Interpretation

Data analysis was conducted in two stages. The initial stage evaluated the validity, reliability and fit of our model using confirmatory factor analysis (CFA). The second stage also tested the hypotheses via structural equation modelling (SEM).

4.1 Evaluation of Measurement Model

Common method variance (CMV) was assessed using the Harman single-factor test. According to the Total Variance Explained table, six factors with eigenvalues greater than 1 together account for 68.945% of the variance. Therefore, CMV is not of great concern in this study; thus, the measurement items generally represent different latent constructs rather than being influenced by one common method factor, providing further support for the validity of the data collection process used in this study.

Prior to undertaking the estimation analysis of the model, it was necessary to assess whether or not the normality assumptions of the data were applicable. To do this, the Skewness (Skew.) and Kurtosis (Kurt) statistics were used to evaluate whether or not the data is normally distributed. According to the aforementioned authors, the Skew and Kurt values must be; -3 to +3 and -10 to +10 respectively. Having satisfied the above criteria, convergent validity and reliability of constructs were examined for their respective measurement models using the maximum likelihood method incorporating standardised factor loadings (Std.β), Cronbach's Alpha (α), and Construct Reliability (CR). Initially, the Std.β were analysed, and the results revealed that they ranged from 0.664 to 0.950

and are, therefore, all above the recommended cut-off of 0.50 [62].

The values of KMO show appropriate sample adequacy, with KMO values ranging between 0.676 and 0.815, confirming that the data sample exceeds the threshold standards of factor analysis. To assess the reliability of the constructs, two commonly used reliability indices, α and CR, were utilised. All of these reliability indicators of all study constructs, as shown in Table 1, were found to be above the threshold reliability standard of 0.70, which meets the criteria established by [62] and [63]. Therefore, all of the study's constructs can be considered as reliable due to the high levels of reliability for the study's items, and the convergent validity results confirm that items have consistent internal reliability when measuring the same construct.

Table 1: Data Normality and Statistics of Reliability

Measures	Model Items	*Skew.*	*Kurt.*	*Std.β*	*KMO*	*α*	*CR*
Accuracy Experience **(*ACC_EXP*)**	*ACC_EXP1*	-.732	-.042	.705	.701	.778	.779
	ACC_EXP2	-.769	-.088	.775			
	ACC_EXP3	-.726	-.182	.723			
Interactive Experience **(*INT_EXP*)**	*INT_EXP1*	-.742	-.065	.762	.691	.753	.753
	INT_EXP2	-.691	-.132	.680			
	INT_EXP3	-.783	-.127	.686			
Accessibility Experience **(*ASS_EXP*)**	*ASS_EXP1*	.333	-.800	.933	.676	.882	.892
	ASS_EXP2	.554	-.348	.660			
	ASS_EXP3	.817	-.522	.954			
Customisation Experience **(*CUS_EXP*)**	*CUS_EXP1*	-.736	-.113	.710	.692	.753	.753
	CUS_EXP2	-.736	.042	.695			
	CUS_EXP3	-.778	-.040	.725			
Perceived Trust **(*PER_TRT*)**	*PER_TRT1*	-.658	-.371	.744	.815	.832	.832
	PER_TRT2	-.752	-.063	.733			
	PER_TRT3	-.725	-.278	.778			
	PER_TRT4	-.684	-.272	.721			
Gen Z Consumer Preference **(*CON_PRE*)**	*CON_PRE 1*	-.630	-.320	.683	.795	.801	.801
	CON_PRE 2	-.802	-.019	.687			
	CON_PRE 3	-.683	-.198	.771			
	CON_PRE 4	-.651	-.159	.691			

The maximum variance extracted by each construct was calculated using Average Variance Extracted (AVE). AVE values for all 10 constructs exceeded 0.5, with AVEs ranging from 0.502 for CON_PRE to 0.739 for ASS_EXP. Thus, the study demonstrated evidential validity amongst all exogenous constructs, demonstrating that they were not highly correlated [66]. All results mentioned above indicated that the constructs of the measurement model had been measured correctly via the constructs used in research operationalisation

.Table 2: Assessment of Discriminant Validity

Measures	*ACC_EXP*	*INT_EXP*	*ASS_EXP*	*CUS_EXP*	*PER_TRT*	*CON_PRE*	*AVE*
ACC_EXP	**.735**						.540
INT_EXP	.280	**.710**					.505
ASS_EXP	-.022	.082	**.860**				.739
CUS_EXP	.418	.298	.056	**.710**			.504
PER_TRT	.392	.365	.124	.371	**.744**		.554
CON_PRE	.309	.311	.072	.293	.373	**.709**	.502

The suggested model shows a great fit with the observed data, according to the model fit indices shown in the table. Because it remains below the suggested threshold of 3, which must be exceeded for poor model fit, the CMIN/DF ratio of 1.182 represents adequate model fit. Strong model fit is shown by the Goodness of Fit Index testing at 0.967 and the Adjusted Goodness of Fit Index testing at 0.956, both of which surpass their respective thresholds of 0.95 and 0.90. With a value of 0.993, the Comparative Fit Index exhibits remarkable comparative fit, surpassing its recommended target of 0.95. With a value of 0.019, the Root Mean Square Error of Approximation demonstrates an extremely close model fit with actual data, substantially below the permitted maximum limit of 0.05. The Standardised Root Mean Square Residual shows a value of 0.033, which falls below the recommended threshold of 0.05 to show almost no residual differences. The measurement model satisfies all recommended threshold values because its fit indices confirm a very good model fit, which establishes the proposed model's adequacy and validity

Table 3: Assessment of Model Fitness

Model Fit Index	Threshold Level	Model Fit Value	References
CMIN/DF	< 3	1.182	[58]
CFI	>0.95	.993	[69]
GFI	>0.95	.967	[67]
AGFI	>0.90	.956	[68]
RMSEA	<0.05	.019	[70]
SRMR	<0.05	.033	[71]

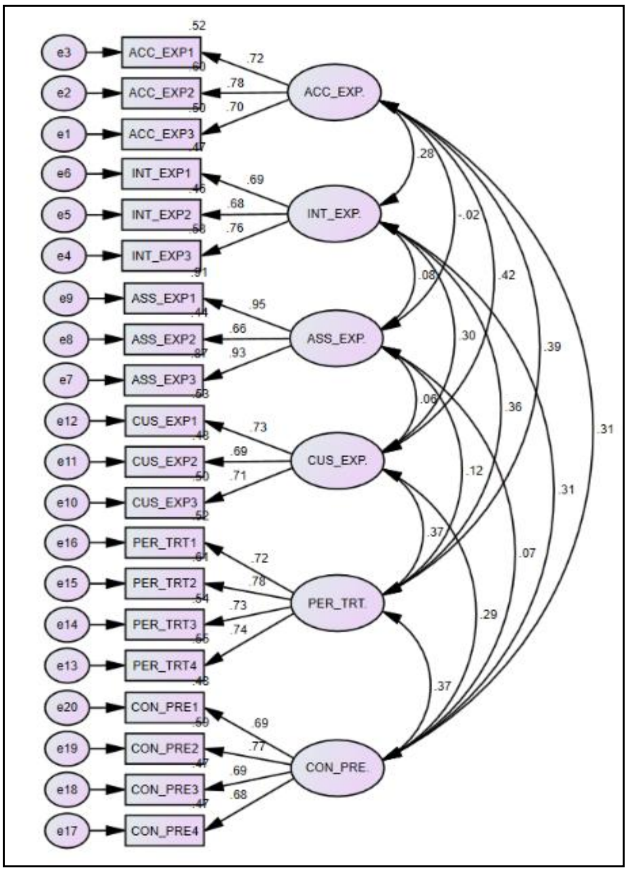

Figure 1: Structure of Measurement Model

4.2 Structural Model Evaluation

In order in assessing their scientific ideas and examine the connections between their research variables, the researchers implemented structural modelling. Before beginning their regression analysis, the researchers measured the Variance Inflation Factor (VIF) and Tolerance for measuring multicollinearity amongst their independent variables. The VIF values were between 1,000 and 1.150, and the values of tolerance were between 0.870 and 1.000. The values remained within acceptable boundaries because tolerance values exceeded 0.10 and *VIF* values stayed beneath the 5 threshold which proved that multicollinearity did not affect the model

.Table 4: Assessment of Multicollinearity

Measures	*Tolerance*	*VIF*
PER_TRT	.878	1.138
	.920	1.086
	.990	1.010
	.870	1.150
CON_PRE	1.000	1.000

The results of the regression analysis for Hypotheses H1 through H4 show that Perceived Trust (PER_TRT) has been beneficially influenced by multiple elements of experience. The Accessibility Experience (*ACC_EXP*) positive trust impact between B = 0.225 and β = 0.225 achieved t = 5.332 and p = 0.000, which shows high statistical significance. The Interaction Experience (*INT_EXP*) positive trust impact between B = 0.196 and β = 0.184 achieved t = 4.470 and p = 0.000. The Assistance Experience (*ASS_EXP*) demonstrates a trust relationship that is statistically significant but produces a smaller impact than other factors (B = 0.084, β = 0.101, t = 2.536, p = 0.011). Customisation Experience (*CUS_EXP*) has a trust relationship that reaches statistical significance with B = 0.182 and β = 0.171, which produced t = 4.026 and p = 0.000. The four experiential factors that respondents experience in your study establish a direct relationship to their development of perceived trust, according to your research findings

.Table 5: Regression Coefficient-(H_1 to H_4)

Hypothesis	Independent	Dependent	*B*	*β*	*t*	*Sig.*
H_1	*ACC_EXP*	*PER_TRT*	.225	.225	5.332	.000
H_2	*INT_EXP*		.196	.184	4.470	.000
H_3	*ASS_EXP*		.084	.101	2.536	.011
H_4	*CUS_EXP*		.182	.171	4.026	.000
Unstandardized Coefficients (B); Standardised Coefficients (β)						

The regression analysis conducted to test Hypothesis H5 looks into whether or not having a Perceived Trust (PER_TRT) has an impact upon the level of Consumer Preference (CON_PRE). The findings suggested that there was a very strong and statistically significant positive correlation between these variables because $B = 0.280$, $\beta = 0.304$, $t = 7.317$, and $p=0.000$. The standardized coefficient of $\beta = 0.304$ indicates that the level of trust perceived by consumers has a strong effect on their likelihood to continue using the service. As the p-value is less than 0.05, we conclude that this hypothesis has been confirmed.

5. DISCUSSION AND CONCLUSION

The outcomes of this work indicate that all four dimensions of consumer experience—Accessibility Experience (ACC_EXP), Interaction Experience (INT_EXP), Assistance Experience (ASS_EXP), and Customisation Experience (CUS_EXP)—significantly influence Perceived Trust (PER_TRT). Accessibility and Interaction Experience showed particularly strong effects, highlighting the importance of seamless access and quality interactions in fostering trust, line with prior literature by Nadarzynski et al.,and Winarto and Wisesa , who emphasised that positive experiential factors are critical in developing trust in online services. Assistance Experience, although smaller in magnitude, was still significant, reflecting that timely and effective support contributes to users' trust, echoing findings by Nadarzynski et al., on service quality and trust formation. In a similar vein, Perceived Trust was heavily influenced by Customisation Experience, illustrating that general satisfaction with the process of service is crucial in determining trust perceptions. Additionally, results demonstrate that Perceived Trust is an important predictor of Consumer Preference; thus, these results support the theory that when a consumer has confidence in a company or product, they will be more likely to want to maintain their relationship with the business.

5.1 IMPLICATIONS

From a very pragmatic perspective, this research adds to the marketer's and digital platform designers' repertoire of tools for understanding how to influence Consumer Preference and ultimately retain Gen Z as a customer through long-term engagement. The findings provide strong evidence that upgrading AI-driven experiences by making them more efficient and intuitive, enhancing the quality of human-machine interactions, offering instant help and a wide variety of Customisation Experience can effectively establish perceived trust in the user's mind. These factors will not only build trust but also lead to continuance intentions and loyalty. Additionally, making sure that AI interfacing with customers is something they can figure out easily, without a steep learning curve, and that they can also find out that it is really worth their while would be of help in getting them onboard with or maintain their brand Also, the revelations of the study point to the need for a mindset shift among businesses in which AI marketing is seen as a combination of technology acceptance principles and trust-building strategies. Such a way will make crafting marketing campaigns that are backed by data and yet touch the emotional side of the consumers be achieved. They will also be the resultant behaviour that would be expected from the target audience after exposure to the said marketing. Businesses that successfully gather and apply these marketing insights may be able to stand out in the marketplace, boost customer satisfaction, and create a customer loyalty program that continues to be successful and long-lasting even in an artificial intelligence-dominated digital environment.

5.2 LIMITATIONS AND FUTURE RESEARCH SCOPE

The findings of the presented research could be expanded upon in a variety of ways by future research. Firstly, follow-up studies may consider expanding the sample to include people from rural areas or different countries so as to look at cultural and regional differences in the way Gen Z reacts to AI-driven marketing. Second, working on longitudinal studies to analyse how shifts in consumer attitudes and behaviour develop over time would be one method of monitoring; this would put forward even more assurance of causality. Thirdly, this research on the variables influencing consumer choice could enhance studies on the impact of AI marketing. Examining mediating variables could help us better understand how AI marketing affects consumer choice. Lastly, research also could be directed to other generational cohorts apart from Gen Z so as to showcase differences in responses of age groups to AI-enabled marketing strategies, thus giving wider insights for marketers intending to customize campaigns for diverse consumer segments

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