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AI-DRIVEN MARKETING STRATEGIES IN SMES: THE MODERATING ROLE OF TECHNOLOGICAL READINESS ON MARKET PERFORMANCE

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Abstract
Aim: *This study examines the effect of AI-Driven Marketing Strategies (AI-DMS) on Market Performance among SMEs, while Customer Engagement (CE) serves as the mediating variable and Technological Readiness serves as the moderating variable.*
Research Methodology: *The study employs a quantitative, descriptive, and cross-sectional research design using data collected from 390 SME managers, marketing specialists, and owners in Jaipur, Rajasthan, through a structured Likert-scale questionnaire measuring AI-DMS, CE, Technological Readiness, and Market Performance. This target group includes SME owners, managers, and marketing specialists who are directly involved in marketing and operational decision-making processes. Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) are used to evaluate reliability and validity. To evaluate construct validity, factor analysis is conducted using SPSS, while Structural Equation Modeling (SEM) is implemented in SmartPLS for assessing direct, mediating, and moderating relationships.*
Findings: *The results confirm that AI-Driven Marketing Strategies have a significant positive effect on CE and Market Performance. CE partially mediates the AI-DMS–Market Performance relationship, whereas Technological Readiness serves as a significant moderator, amplifying the positive influence of AI-DMS on Market Performance in technologically prepared SMEs*
Conclusion: *The study concludes that SMEs can enhance market outcomes by integrating AI-driven marketing initiatives with CE practices supported by technological readiness. These findings provide both theoretical and managerial insights for leveraging AI to achieve superior business performance in SMEs.*

Keywords: *AI-Driven Marketing, Customer Engagement, Technological Readiness, Market Performance, Structural Equation Modeling*

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1. Introduction

Artificial Intelligence (AI) has revolutionized the modern marketing landscape with the rapid advancements of technology, allowing businesses to leverage data-driven insights, automation, and personalized customer interactions (Huang & Rust, 2020). AI-driven marketing combines machine learning, predictive analytics, and intelligent customer relationship management (CRM) tools to sift through massive amounts of data and provide insights that help businesses act (Khan et al., 2024). These features allow companies to boost their customer engagement (CE), make superior marketing choices, and enhance company performance. Prior research has proved that CE positively impacts market performance (De Bruyn et al., 2020). The mechanisms through which CE is possible between AI-based marketing strategies and market performance are only briefly explained in empirical evidence, and technological readiness as a moderating effect is still hardly explored. There is still a lack of a comprehensive understanding of how AI-powered marketing strategies boost market performance. In today's dynamic markets, businesses are increasingly seeing AI as a strategic asset that offers a competitive advantage and improves business performance (Enholm et al., 2021).

The role of Small and Medium Enterprises (SMEs) in economic growth is very important as they are the main source of employment, innovation, industrial growth, and regional development. SMEs in Jaipur, Rajasthan, are a significant part of India's flourishing digital economy. While these businesses are more and more embracing AI-powered solutions to enhance their competitiveness, technological infrastructure, digital competences, and organizational readiness remain challenges. All these factors make Jaipur a wonderful study area for "examining the role of AI in marketing strategies. Through the use of AI-driven technologies, SMEs have been able to enhance the efficiency" of their operations, boost relationships with customers, and create better decision-making processes, leading to improved market performance (Akpan et al., 2020; Yesuf & Fields, 2025; Drydakis, 2022). In an era where traditional marketing strategies are failing to satisfy customers' expectations, AI-driven marketing provides the opportunity to make timely decisions, personalize customer interactions, and differentiate with competitive insights based on data (Saura et al., 2021; Vlačić et al., 2021).

AI's integration into marketing has revolutionized how businesses make decisions and engage with customers, making it a powerful tool for personalized marketing and data-driven decision making. However, even with the advent of AI, many SMEs are still facing challenges in achieving the maximum potential of AI due to, amongst others, limited financial resources, poor digital skills, lack of clear implementation plans, and technology infrastructure (Chatterjee et al., 2021; Lemos et al., 2022). Such restrictions hinder the beneficial application of AI technologies for enhancing customer interaction and, consequently, market performance. While CE is well understood to be a key variable in organizational performance, "there is a lack of empirical studies that address the mediating role of CE between AI-driven marketing strategies and market performance. Likewise, the role of technological readiness in enhancing this relationship has been poorly researched on an empirical basis, especially in the SME sector. In addition, previous research has shown that there are challenges in realising the added value of AI in companies due to low readiness of infrastructure, organisation and human resources (Jöhnk et al., 2020; Melo et al., 2023). To fill these research gaps, the present study examines direct, mediating, and moderating links between AI-powered marketing strategies, CE," technological readiness, and market performance and offers practical recommendations for SMEs.

Obj1. To examine the impact of "AI-driven marketing strategies on market performance."

Obj2. To analyze the effect of "AI-driven marketing strategies on customer engagement."

Obj3. To evaluate the impact of "customer engagement on market performance."

Obj4. To investigate the mediating role of customer engagement in the relationship between AI-driven marketing strategies and market performance.

Obj5. To assess the moderating role of technological readiness in the relationship between AI-driven marketing strategies and market performance.

Obj6. To provide suggestions and recommendations for SMEs on effectively using "AI-driven marketing strategies" to enhance market performance.

This study builds on the current literature in the SME context regarding the adoption of AI for marketing and performance outcomes as it introduces novel mediating concepts (CE) and moderating concepts (technological readiness) in this context, thereby enriching existing research on technology implementation and performance results (Vlačić et al., 2021; Enholm et al., 2021). The study reveals the impact of AI on business performance in terms of CE. The study provides critical insights for SMEs on the need to integrate their technological capabilities into the interactions with customers to maximize business outcomes of their

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AI systems (Akpan et al., 2020; Jöhnk et al., 2020).
Beyond the introduction, "the paper is organized as follows: Section 2 reviews contributions from various authors concerning past studies on AI-DMS in SMEs, the moderating role of technological readiness, and the mediating role of CE. Section 3 summarizes the research methods employed in the study. Section 4 discusses the results and findings, while Section 5 presents the discussion. Finally, Section 6 outlines the conclusions, implications, limitations, and recommendations for further studies." At last, the references are provided.

2.Literature Review

2.1Theoretical Framework

- Technology–Organization–Environment (TOE) Framework

The "TOE framework, developed by Louis G. Tornatzky and Mitchell Fleischer in 1990, helps understand how organizations adopt and implement technological innovations." This theory indicates that three aspects influence the success of innovation adoption based on technological aspects that examine the availability and appropriateness of technology, organizational aspects that examine resources and competencies, and structural and environmental aspects that examine industry forces and competitive landscape. Adopting technologies involves implementing them, which depends on two crucial aspects: organizational readiness and the organization's environment (Satyro et al., 2024). TOE is relevant in this study for analysing the moderating influence of the SMEs' infrastructure, the employees' skills, and the SMEs ' adaptability on the effectiveness of the AI-DMS. It aims to evaluate the impact of technological readiness on the linkage between AI strategies and market performance. In this research, the focus is on technological and organisational aspects, while TOE includes environmental aspects. The regulatory/competitive environment for SMEs in Jaipur, Rajasthan is relatively similar, and hence, the significance of the environmental aspect is not highlighted. Therefore, there is a greater emphasis on technological readiness.

- Resource-Based View (RBV)

Created by Jay Barney in 1991, the RBV provides a framework for analyzing the sources of competitive advantage for firms stemming from their internal resources and capabilities. The theory states that companies can beat out other companies due to their resources, which possess the "four key attributes – value, rarity, inimitability and non-substitutability." According to the RBV, companies need to use their technology resources, knowledge resources, and relationship resources to ensure high-performance results (Mailani et al., 2024). In this research, AI in marketing and engagement is regarded as a strategic resource for enhancing market performance. RBV aligns with the goals of studying the direct effect of performing an AI strategy on performance and the indirect effect of CE through proper resource management, demonstrating how companies can optimize their performance through CE.

2.2AI-Driven Marketing Strategies and Market Performance in SMEs

Strategies of AI-based marketing have been extensively studied in terms of their contribution to market success, especially in SMEs. AI-powered marketing significantly improves marketing efficiency, customer targeting, decision-making, and organizational performance via automation, predictive analytics, and personalization, as shown in previous studies (Bag et al., 2021; Huang & Rust, 2020; De Bruyn et al., 2020). While most studies agreed that AI can help improve the marketing effectiveness and performance of firms, they also highlighted the importance of other factors like organizational skills, availability of resources, and effective CE in the successful implementation of AI (Bag et al., 2021; De Bruyn et al., 2020; Huang & Rust, 2020). Overall, these studies suggest that AI-powered marketing is a strategic tool that can enhance customer targeting, streamline operations, and boost business performance.
In the same way, Research on SMEs also indicates that AI in marketing contributes to the improvement of SME growth, operational resilience, and competitive advantage. However, the benefits are not just related to "the use of AI, but also to the technological capacity of the companies and their readiness to adopt AI (Saura et al., 2021; Drydakis, 2022; Enholm et al., 2021). The results indicate that the use of AI does not necessarily lead to better market performance." Instead, the mechanisms by which and when AI-powered marketing tactics become more effective for organizational outcomes are likely to be CE and technological readiness. This sets the groundwork for this current study.

2.3Role of Customer Engagement in AI-Driven Marketing

AI has "revolutionized customer engagement by empowering businesses with the ability to provide personalized, interactive, and data-driven customer experiences through various technologies, including chatbots, recommendation systems, and predictive analytics. Previous research has consistently shown that

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AI-based marketing can improve customer engagement in various ways, such as through better communication, customer interaction, and service quality, ultimately boosting organizational performance (Ameen et al., 2020; Adam et al., 2020; Bag et al., 2021)." Likewise, AI-driven personalisation has been shown to enhance customer experiences and brand interactions, which in turn has a positive impact on CE and retention (Beyari & Hashem, 2025; Nguyen et al., 2022; Prentice & Nguyen, 2020).
Although there is common agreement on these points, previous studies have largely centered on the direct impacts of AI on customer experience and engagement, rather than examining the pathways connecting customer engagement with the successful execution of AI-based marketing strategies in enhancing market performance, especially in SMEs. Furthermore, limited research has looked at CE from a holistic perspective that also takes into account the organizational environment that affects the effectiveness of AI. To fill this void, the present study further investigates customer engagement as a mediator between the AI marketing strategies and market performance, thereby adding to previous research and empirical evidence in the context of SMEs.

2.4Technological Readiness and Its Influence on AI Effectiveness in SMEs
Technological readiness is becoming a key determinant of the capacity of SMEs to implement AI successfully. Previous studies indicate that leveraging AI is not just about having access to cutting-edge technology, but also about having the right organizational conditions such as sufficient resources, digital infrastructure, employee skills, and adaptability (Jöhnk et al., 2020; Holmström, 2021). Research shows that companies with strong technology readiness are more likely to successfully adopt AI and reap significant benefits in business processes and results.
In the SME realm, technological readiness increases the capacity of SMEs to embrace AI successfully by bolstering organizational resilience, operational efficiency, and competitive edge (Lemos et al., 2022; Dey et al., 2023). Likewise, companies that are better technologically at implementing AI projects generate more value from AI projects, while those that are less technologically prepared experience less value generation (Enholm et al., 2021; Rana et al., 2021). While there is a foundation of research that shows the significance of technological readiness for AI implementation, "there is still a lack of empirical evidence that explores the moderating effect of technological readiness on the link between AI-enabled marketing strategies and market performance in SMEs." The present study assumes technological readiness as a moderating factor to enrich the existing literature and understand the conditions under which AI-enabled marketing strategies work best to enhance market performance.

2.5Research gap
SME organizations have numerous unexplored areas in AI-based marketing research despite the existing body of research. Existing "studies have primarily focused on the direct impact of AI on firm performance, with limited empirical evidence examining this relationship specifically within SMEs (Bag et al., 2021; Enholm et al., 2021). The studies demonstrated that AI is an important component in increasing CE. However, they lack data on how AI-supported marketing strategies influence CE in SMEs and, as a result, contribute to market performance (Ameen et al., 2020; Nguyen et al., 2022)." Technological readiness is an important variable in the implementation of AI, but its role as a moderating or boundary variable to impact the effectiveness of AI marketing strategies on performance outcomes has not been examined (Jöhnk et al., 2020; Lemos et al., 2022). Finally, there are a limited number of integrated studies that explore AI-DMS, CE, and technological readiness together in a model to explain market performance in SMEs. To fulfil this gap, the study proposed these hypotheses:
H1:"There is a significant impact of AI-Driven Marketing Strategies on Market Performance."
H2:"There is a significant impact of AI-Driven Marketing Strategies on Customer Engagement."
H3:"There is a significant impact of Customer Engagement on Market Performance."
H4:"There is a significant mediating impact of customer engagement on AI-Driven Marketing Strategies and Market Performance."
"There is a significant moderating impact of Technological Readiness on AI-Driven Marketing Strategies and Market Performance."

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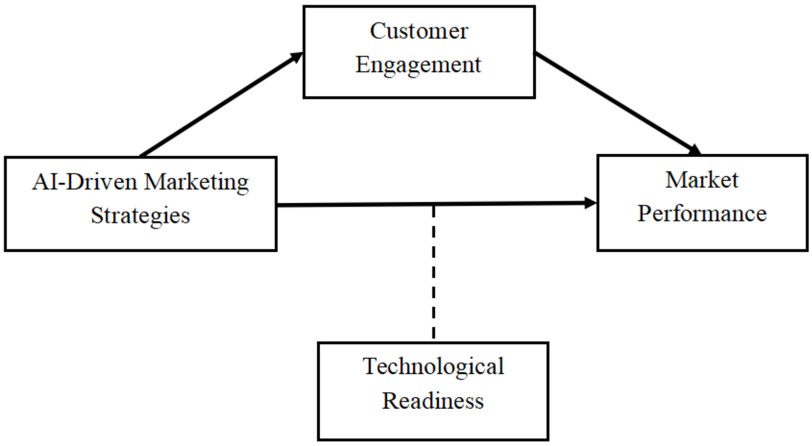

Figure 1: Conceptual Framework

(Source: Self-prepared by Author)

3.Research Methodology

3.1Research Design and Approach

The study uses a quantitative research method to examine the interrelationships and impacts of AI-DMS, CE, and Technology readiness on Market performance. The present study uses the explanatory research design for testing the hypotheses and determining the causal relationships between the different variables (Amoa-Gyarteng et al., 2024). Further, a descriptive research design is adopted to give information regarding respondents' attributes and aspects of the research. The synergy of this study allows researchers to gain a comprehensive picture of the way in which variables work and how they interact among small and medium-sized enterprises.

3.2Study Area

The study area focuses on Jaipur, Rajasthan, a rapidly developing metropolitan city characterized by diverse demographics, expanding urban infrastructure, and increasing adoption of digital technologies in business operations and customer practices (Choudhary et al., 2025).

3.3Sampling Technique and Sample

The sampling frame consists of the registered SMEs based on the updated MSME classification by the Government of India in the MSME Act (2020). The list of eligible firms is compiled from government records, industrial associations, and business directories. The study is the focus of "the SME owners, managers, and marketing specialists who are engaged in marketing and technology decisions. According to the researcher, the minimum sample size required based on the statistical requirement is 385 respondents using Cochran's formula (Hasan & Kumar, 2024). 500 questionnaires are sent out, and 402 questionnaires are returned. 12 questionnaires were not included in the analysis due to missing data, leaving 390 questionnaires for analysis, giving an effective response rate of 78.0%. Purposive sampling was used to ensure that the respondents possess the necessary knowledge and experience" about AI-driven marketing practices and technology adoption, resulting in the collection of meaningful and reliable data for the research.

3.4Data Collection Method

This study uses a "self-structured questionnaire as an instrument for obtaining primary data from SME respondents, which is filled out with Google Forms. This questionnaire aims to capture four research constructs: AI-Driven Marketing Strategies (AI-DMS), CE (CE), Technological Readiness, and Market Performance. The items for measurement are mostly based on scales previously validated and reported in the literature and adapted for the goals and SME context of the study, keeping their conceptual meaning. The items on all constructs are rated on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Using one measurement scale throughout the study makes it easier to assess the latent constructs. It helps in testing the reliability and validity of the study as well as in testing the proposed relationships between the study variables through Structural Equation Modeling (SEM)."

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3.5Statistical Tools & Techniques

The study employs Excel, SPSS, and SmartPLS as its main tools for processing and analyzing data. The researchers begin their data work through Excel, which they use for initial data cleaning and organization, before they conduct descriptive statistical analysis and preliminary research through SPSS. SmartPLS enables researchers to perform advanced research through its Structural Equation Modeling (SEM). The study applies statistical techniques such as standard deviation to assess data dispersion, "uses correlation analysis to examine relationships between variables, and applies regression analysis to evaluate direct effects." The researchers use SEM to explore intricate relationships that include CE as a mediation factor and technological readiness as a moderation factor (Sarker, 2024).

3.6Ethical considerations

This study ensures that an ethical process is employed during research by observing the set of ethics that need to be observed during the research process. For a research study to take place, informed consent is obtained from participants to carry out the research activities. The research study employs techniques that ensure the anonymity of all the respondents. Security for the research study will be achieved by making sure that the data will not be used for anything other than academic research.

4.Results

"This section presents the findings and interpretations derived from the data analysis. The results have been organised according to the demographic characteristics of the respondents, the study objectives and the hypotheses." Each hypothesis is supported by corresponding statistical evidence, which displays results in tables that researchers explain in detailed interpretations. The use of tables improves understanding of the content, whereas the narrative description shows how important the study results are to the research findings.

Table 1 Reliability and Validity Statistics

Variables	Cronbach's Alpha	N of Items	KMO and Bartlett's value	Sig. value
AI-Driven Marketing Strategies	.736	6	.753	.000
Market Performance	.843	6	.852	.000
Customer Engagement.	.882	6	.890	.000
Technological Readiness	.802	6	.840	.000

Table 1 provides information about both reliability measures and complete sampling adequacy regarding all variables, such as AI-DMS, Market Performance, CE, and Technological Readiness. The level of internal consistency in all variables ranges from good to very good due to the high estimate of "Cronbach's Alpha (it fluctuates from 0.736 to 0.882), which means that the criterion of reliability of the measurement instrument exceeds the acceptable level (above 0.70) (Taber, 2017). Estimates of the Kaiser-Meyer-Olkin (KMO) criterion range from 0.753 to 0.890, which means that the size of the sample is sufficient for conducting factor analysis (Kaiser, 1974). In addition, it was found that based on Bartlett's Test of Sphericity, correlations between constructs were statistically significant at the 0.000 level."

4.1Result Based on demographics

Table 2 Demographic Characteristics of the Respondents

Sr. no.	Demographic characteristics	Category	N	%
1.	Gender	Male	208	53.3
		Female	182	46.7
2.	Age group	Below 25 years	53	13.6
		25–35 years	76	19.5
		36–45 years	100	25.6
		46–55 years	72	18.5
		Above 55 years	89	22.8
3.	Educational Qualification	Graduate	75	19.2
		Postgraduate	114	29.2
		Professional	93	23.8

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		Other	108	27.7
4.	Designation	Manager	107	27.4
		Marketing Specialist	99	25.4
		Owner	90	23.1
		Other	94	24.1
5.	Work Experience	Less than 5 years	124	31.3
		5–10 years	122	31.8
		More than 10 years	144	36.9

Table 2 depicts demographic data regarding respondents, including gender, age group, educational qualification, designation, and work experience. It can be observed that 53.3% respondents belong to the male gender category, whereas female gender respondents are 46.7%. With regards to age group data, "The result indicated that 25.6% respondents belong to the age group of 36–45 years, while 22.8% belong to the age group above 55 years, and 19.5% respondents belong to the age group 25–35 years, while 18.5% respondents belong to the age group 46–55 years, and 13.6% respondents belong to the age group below 25 years, indicating that the respondents belong to various age groups. In relation to the educational qualifications of the respondents," it can be noted that 29.2% of respondents have postgraduate qualifications, while 27.7% belong to other qualification categories, 23.8% of respondents have professional qualifications, while 19.2% respondents have graduate qualifications, indicating that the respondents have diversified educational qualifications. About designation-wise distribution, 27.4% of respondents occupy managerial designations, while 25.4% of respondents belong to the marketing specialist category, while 24.1% belong to the other category, while 23.1% respondents are owners. Based on the distribution of work experience, it can be seen that a greater percentage of participants (36.9%) have more than 10 years of experience, 31.8% of respondents have 5–10 years of experience, while 31.3% of participants have less than five years of experience, and thus, there are respondents with diverse professional experiences included in this study. The demographic information reveals that participants belong to various backgrounds professionally and educationally.

4.2Results Based on Hypothesis

Common Method Bias Test: In this test, "the findings of Harman's one-factor test, based on Principal Axis Factoring used to determine whether there was a common method bias in the dataset. The findings reveal that the first factor possesses an eigenvalue of 13.348, accounting for 58.035% of the total variance in initial eigenvalues. The first factor also accounts for 58.035% of the total variance after extraction." Several factors have contributed to the dataset as the total variance accounted for after extraction is 78.290% with the top four. The variance accounted for by the first factor is however higher than 50%, suggesting that the variance among the measurement items is dominated by one factor. "Therefore, the results show that common method bias may present a concern in this study. Tehseen et al. (2017) explain that when a single factor explains more than 50% of the variance, then common method bias may affect the validity of the collected data."
Dropped variable: CE4 is excluded from the study because its extraction value seems too high when compared to the other measurement items; this can impact the overall balance of the measurement model. The extraction value is unusually high, suggesting the item has more variance in the construct than in the rest of the data. Thus, the deletion of CE4 does not significantly change the factor structure's stability and the appropriateness of its factor structure. The modification also enhances the overall appropriateness and uniformity of the measurement model for further analysis.

- **Factor Analysis**

Table 4 Rotated Component Matrix and Communalities

Rotated Component Matrix						
	Component				**Communalities**	
	1	2	3	4	Initial	Extraction
AI1		.809			1.000	.728
AI2		.797			1.000	.744
AI3		.793			1.000	.745

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AI4		.720			1.000	.690
AI5		.741			1.000	.692
AI6		.717			1.000	.669
MP1			.793		1.000	.834
MP2			.740		1.000	.800
MP3			.777		1.000	.806
MP4			.745		1.000	.781
MP5			.751		1.000	.803
MP6			.774		1.000	.661
CE1				.745	1.000	.824
CE2				.765	1.000	.807
CE3				.788	1.000	.797
CE5				.745	1.000	.823
CE6				.759	1.000	.782
TR1	.787				1.000	.866
TR2	.795				1.000	.848
TR3	.756				1.000	.823
TR4	.743				1.000	.819
TR5	.757				1.000	.839
TR6	.750				1.000	.826
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalisation.						
a. Rotation converged in 6 iterations.						

Table 4 “presents the findings from the Principal Component Analysis (Varimax rotation with Kaiser Normalisation) of the Rotated Component Matrix and Communalities. All the factor loadings are greater than the minimum value of 0.50 (Laher 2010) as indicated in the results. The items with Technological Readiness (TR1–TR6) have good factor loading values in the range of 0.743 to 0.795 for the Component 1.” The variables in the AI-DMS (AI1–AI6) have strong loading coefficient (range: 0.717 to 0.809) in Component 2 while the variables measuring MP1–MP6 have strong loading coefficient (range: 0.740 to 0.793) in Component 3. On the other hand, variables used in Customer Engagement (CE1–CE6) have a strong loading coefficient of between 0.745 and 0.788 in Component 4. The communalities remove from the matrix “range from 0.661 to 0.866, which is higher than the suggested value by Costello & Osborne (2005) of 0.40. This is because that much of the variance of each item is being explained by the factors, which were extracted. All items were obtained that loaded well onto their constructs. CE4 was omitted from the CE construct in the factor analysis due to the communality (extraction loadings). The removal of the item enhanced the overall quality of measurement and boosted the construct's psychometric properties without compromising the concept. The reliability and validity of the CE construct after the deletion of CE4 were very high, with Cronbach's Alpha of more than 0.937, Composite Reliability of more than 0.952, and Average Variance Extracted (AVE) of more than 0.799. Overall, the findings indicate that the retained items adequately represent the measurement scales for AI-DMS and satisfy the recommended criteria for construct reliability and convergent validity.” Market Performance, CE, and Technological Readiness, demonstrating good construct validity for the measurement scale.

- **Constructs Validity and Reliability**

Table 5 Convergent Validity of the Constructs

	Construct	Items	Standardized Loadings	Collinearity (VIF)	Cronbach’s Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
1.	AI-Driven Marketing Strategies	AI1	.833	2.479	.917	.936	.708
		AI2	.852	2.724			
		AI3	.860	2.742			

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		AI4	.838	2.342			
		AI5	.837	2.342			
		AI6	.826	2.242			
2.	Market Performance	MP1	.915	4.209	.942	.954	.775
		MP2	.902	3.713			
		MP3	.900	3.678			
		MP4	.889	3.307			
		MP5	.905	3.946			
		MP6	.763	1.968			
3.	Customer Engagement.	CE1	.910	3.900	.937	.952	.799
		CE2	.895	3.898			
		CE3	.882	3.112			
		CE5	.911	4.020			
		CE6	.871	2.933			
4.	Technological Readiness	TR1	.925	4.965	.960	.968	.835
		TR2	.914	4.319			
		TR3	.909	4.082			
		TR4	.907	3.926			
		TR5	.916	4.364			
		TR6	.910	4.128			

Table 5 "presents the outcomes of the confirmatory factor analysis (CFA), which includes standardised loadings, collinearity values through VIF measurements, Cronbach's Alpha, Composite Reliability, and Average Variance Extracted, which measure the AI-Driven Marketing Strategies, Market Performance, Customer Engagement, and Technological Readiness constructs. The standardised loadings, which all measure between 0.763 and 0.925, confirm strong indicator reliability as their values exceed the 0.70 threshold (Cheung et al., 2024). The VIF values range from 1.968 to 4.965, which remain below the critical limit of 5, because all indicators of the study show no multicollinearity (O'Brien, 2007). The internal consistency of AI-DMS (0.917), Market Performance (0.942), Customer Engagement (0.937), and Technological Readiness (0.960) shows strong results because Cronbach's Alpha values exceed the acceptable threshold of 0.70 (Bland & Altman, 1997). The Composite Reliability values range from 0.936 to 0.968, while the AVE values range from 0.708 to 0.835, which both exceed the recommended cutoffs of 0.70 and 0.50 (Cheung et al., 2024). The Technological Readiness construct demonstrates the highest reliability and convergent validity (α = 0.960, CR = 0.968, AVE = 0.835), followed by Market Performance (α = 0.942, CR = 0.954, AVE = 0.775), while Customer Engagement (α = 0.937, CR = 0.952, AVE = 0.799) and AI-DMS (α = 0.917, CR = 0.936, AVE = 0.708)" also show strong measurement quality. Overall, it is clear from the results that all the constructs have high reliability along with satisfactory convergent validity, which indicates that the measurement model effectively measures the following structural model test.

Table 6 Discriminants Validity Table

	AI	CE	MP	TR
AI	.841			
CE	.573	.894		
MP	.644	.653	.881	
TR	.631	.764	.691	.914

Table 6 shows "the results of the discriminant validity test conducted based on the Fornell-Larcker criterion. This confirms that the constructs of the research possess unique conceptual meaning and empirical distinctiveness. The square roots of the Average Variance Extracted (AVE), presented in the diagonal of the

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matrix, exceed correlations between the constructs. Thus, this means that the discriminant validity Fornell-Larcker criterion is satisfied (Cheung et al., 2024). For example, the square root of the AI-DMS construct's AVE equals 0.841, which is higher than the correlations with CE (0.573), Market Performance (0.644), and Technological Readiness (0.631). CE shows a square root of AVE value of 0.894, which exceeds its correlations with Market Performance (0.653) and Technological Readiness (0.764). Market Performance shows a square root of AVE value of 0.881, which exceeds its correlation with Technological Readiness (0.691). Technological Readiness shows a square root of AVE value of 0.914, which exceeds its correlations with all other constructs. Overall, the results prove that all the constructs have a stronger relationship with their respective indicators than with those from other constructs within the model." The results illustrate that all the constructs enjoy good discriminant validity as the model can differentiate among various theoretical constructs.

Table 7 Goodness of Model Fit Indices

	Saturated model	Estimated model
SRMR	0.040	0.123
d_ULS	0.438	4.154
d_G	0.348	0.463
Chi-square	782.859	945.970
NFI	0.915	0.897

Table 7 presents "the model fit indices that apply to both the saturated model and the estimated model, proving the overall suitability of the measurement model. The SRMR value of the saturated model is 0.040, which remains below the recommended threshold of 0.10 and shows that the saturated model possesses adequate fit (Hu & Bentler, 1999). However, the SRMR value of the estimated model is 0.123, which exceeds the acceptable threshold and indicates comparatively lower model fit. The discrepancy measures d_ULS (0.438; 4.154) and d_G (0.348; 0.463) represent the differences between the empirical correlation matrix and the model-implied correlation matrix, which are commonly reported in PLS-SEM to assess model approximation (Hair et al., 2022). The values of Chi-square for the saturated model and the estimated model are stated at 782.859 and 945.970, respectively. This is common practice in structural equation modelling with large sample sizes and models due to the increased sensitivity of the Chi-square statistics when dealing with increased sample sizes (Kline, 2016). The Normed Fit Index (NFI) for the saturated model is stated as 0.915, a value that is beyond the recommended threshold level of 0.90, thus demonstrating" good comparative fit (Hooper et al., 2008; Nervilia, 2024). On the other hand, the NFI for the estimated model is stated as 0.897, a value that is slightly below the acceptable cutoff. In summary, from the results, the saturated model fits the data adequately while the estimated model fits moderately, but there is room for improvement. The structural model remains a solid foundation for analysing the association between AI-DMS, CE, Market Performance, and Technological Readiness.

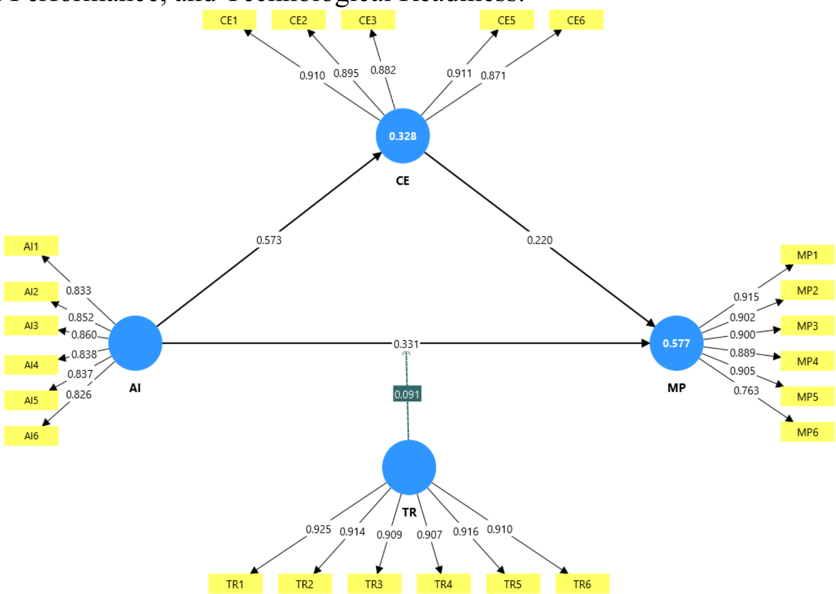

Figure 2 SEM Model

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Figure 2 depicts "the structural model demonstrating the effects among AI-Driven Marketing Strategies (AI), Customer Engagement (CE), Market Performance (MP), and Technological Readiness (TR). AI-Driven Marketing Strategies have positive effects on Customer Engagement ($\beta = 0.573$) and direct effects on Market Performance ($\beta = 0.331$). On the other hand, CE affects Market Performance ($\beta = 0.220$), thus indicating that CE partially mediates the connection. Moreover, Technological Readiness moderates the association between AI-Driven Marketing Strategies and Market Performance ($\beta = 0.091$). The model accounts for 32.8% of the variance in CE ($R^2 = 0.328$) and 57.7% of the variance in Market Performance ($R^2 = 0.577$). Therefore, it can be concluded that using AI-based marketing strategies" along with CE and TR improves MP.

Table 8 Hypothesis Testing Table

Hypothesis	Predicted Relationship	Original sample	Sample mean	Standard deviation	T statistics	P values	Decision
H1	AI->MP	.331	.331	.057	5.811	.000	Supported
H2	AI->CE	.573	.576	.038	15.034	.000	Supported
H3	CE->MP	.220	.219	.069	3.165	.002	Supported
H4	AI->CE->MP	.126	.126	.040	3.114	.002	Supported
H5	TR x AI-> MP	.091	.088	.040	2.255	.024	Supported

Table 8 "presents the results of testing the hypotheses based on bootstrapping in the structural model. The criteria used to prove the significance of the hypothesis are as follows: when the t-value is more than 1.96, and the p-value is less than 0.05, as per the criteria set out by Hair et al. (2021). Statistical support is provided for all hypotheses tested from H1 to H5. H1 demonstrates that AI-Driven Marketing Strategies have a substantial positive impact on Market Performance (MP) with an original sample value of 0.331, a t-statistic of 5.811, and a p-value of 0.000, which shows that AI-DMS lead to better market performance. H2 demonstrates that AI-DMS brings about a strong effect on CE with an original sample value of 0.573, a t-statistic of 15.034, and a p-value of 0.000, which shows that customer engagement increases through the adoption of AI-DMS. H3 shows that Customer Engagement creates a positive impact on Market Performance with an original sample value of 0.220, a t-statistic of 3.165, and a p-value of 0.002, which indicates that increased customer engagement leads to better market performance results. H4 demonstrates that Customer Engagement serves as a mediator between AI-DMS and Market Performance through an indirect effect value of 0.126, a t-statistic of 3.114, and a p-value of 0.002, which shows that AI-DMS leads to better market performance through increased customer engagement. Furthermore, H5 examines the moderating effect of Technological Readiness on the relationship between AI-DMS and Market Performance. There is evidence of a moderating influence with an initial sample of 0.091, a t-value of 2.255, and a p-value of 0.024, meaning that technological readiness influences the connection between AI marketing strategy and market performance." The results point out that an AI marketing strategy increases the level of market performance directly as well as indirectly through CE. In contrast, technological readiness further improves the connection between them.

5.Discussion

The "study examines the effect of AI-Driven Marketing Strategies (AI-DMS) on Market Performance in SMEs by considering the mediating role of Customer Engagement and the moderating role of Technological Readiness. The results suggest that AI-DMS can be a transformative tool for improving Customer Engagement and Market Performance, underscoring the power of AI in marketing to generate business value through better decision making, personalization and customer interactions." The results align with the previous research that identified AI as a strategic capability for enhancing the performance of the organization through data-driven marketing and digital transformation (Al-Surmi et al., 2021; Dash & Chakraborty, 2021; Jin et al., 2024). The current study builds on previous research, which mainly focused on the direct connection between the adoption of AI and the firm's performance, by elucidating the mechanism by which AI enables marketing strategies to create better market performance in SMEs.

The study also shows that AI-DMS has a positive impact on CE, which aligns with the findings of other

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studies that indicate that AI-driven personalization and digital marketing technologies, and intelligent customer interactions, improve customer relationships and CE (Algharabat et al., 2020; Beyari & Hashem, 2025; Salih et al., 2025). More importantly, CE is shown to "partially mediate the relationship between AI-DMS and Market Performance, suggesting that AI for marketing has two complementary pathways that are shown to boost Market Performance." The primary advantage of AI for businesses is its ability to boost efficiency, decision-making, and resource allocation, all of which directly impact performance. Second, AI indirectly supports performance by enabling better CE, which leads to higher customer satisfaction, loyalty and value. The partial mediation indicates that while CE is a key mechanism, there are potentially other factors within the organization that can also impact the effectiveness of using AI-driven marketing efforts to enhance market performance.

The results also show the significant strengthening of the link between AI-DMS and Market Performance by the Technological Readiness. This indicates that SMEs with the proper digital infrastructure, workforce talents, and organizational preparedness are more likely to maximize the utility of AI technologies and translate AI-powered marketing efforts into business results. This result confirms previous research that cited the importance of organizational readiness for the successful implementation of AI (Flavián et al., 2021; Pillai et al., 2020). The present study further builds on this literature by showing that technological readiness acts as a boundary condition that can improve the effectiveness of AI-based marketing strategies, but cannot simply be equated with adoption of AI.

Theoretically, "the study adds to the study of the Resource-Based View and Technology–Organization–Environment (TOE) by showing that AI for marketing can be a partial solution to optimizing market performance. Rather, the ability of organizations to engage with customers and their technological readiness are the factors that account for how and when AI can be a source of competitive advantage. The study combines direct, mediating and moderating relationships into one framework, offering a more comprehensive understanding of the AI-enabled marketing performance of SMEs."

The results also have management implications for SMEs. Managers should not just pay attention to AI adoption but also harness customer-oriented engagement strategies, and invest in technological infrastructure, employee digital skills, and organizational readiness. This comprehensive strategy allows SMEs to build stronger customer relationships, optimize marketing strategies, and maximize the value they get from AI-powered marketing campaigns, thus ensuring their sustained competitiveness in today's digital business landscape.

6.Implications

- Theoretical Implications

"This study extends the Technology–Organization–Environment (TOE) framework and the Resource-Based View (RBV)" by explaining how AI-Driven Marketing Strategies (AI-DMS) improve Market Performance in SMEs. From the RBV perspective, CE acts as a strategic capability through which AI-driven marketing creates business value and competitive advantage. From the TOE perspective, Technological Readiness strengthens the effectiveness of AI-driven marketing, indicating that SMEs with better technological capabilities are more likely to achieve superior market performance. By integrating AI-DMS, CE, Technological Readiness, and Market Performance into a single framework, the study enriches the literature on AI-enabled value creation in SMEs.

- Managerial Implications

The findings suggest that SMEs should invest in digital infrastructure, AI-powered CRM systems, and data management capabilities to support AI-driven marketing. Managers should use AI-based customer segmentation, personalized marketing, chatbots, and customer analytics to strengthen CE and improve market performance. In addition, SMEs should provide employee training in AI and digital technologies to enhance technological readiness and ensure effective AI implementation. Combining AI adoption with customer-centric strategies and technological capability development can help SMEs achieve a sustainable competitive advantage.

7.Conclusion

"This study aimed at understanding the impact of AI-DMS on the performance of SMEs with mediating variable being CE and moderating variable being Technological Readiness." The findings indicate that AI-DMS can have a positive impact on market performance directly, and indirectly through its impact on CE. The findings confirm the importance of CE as one of the critical paths towards improving market performance through AI marketing. Moreover, the result shows the influence of technological readiness on the effectiveness of the use of AI-DMS, which means that the readiness of the digital infrastructure, technology and organization are important issues.

This study contribute to the "existing evidence on SMEs adoption of AI by providing empirical evidence of the interdependence between AI-DMS, CE and technological readiness and its impact on market performance. The findings show that investing in technology is a critical factor, but the right CE and organizational readiness are also key to the effective adoption of AI." Overall, the study extends the scope of the field of AI adoption for SMEs to understand how and when AI-based marketing strategies improve the marketing outcomes.

7.1Limitations

There are some "limitations of this study. However the sample used (390 respondents) strengthens the analysis, but it may not be representative of the general population of SMEs. Secondly the study was conducted on selected SME's of the Jaipur city, Rajasthan so results could not be generalized in other city or other related industries. Thirdly, there is the possibility of common method and social desirability biases when using self- presented data. The first factor was used in Harman's one factor test, but more than 50% of the variance is accounted for by this factor, which means that common method bias cannot be fully excluded. Fourth, as a cross-sectional design," it is only a snapshot of the data and causal conclusions are limited. Finally, other institutional and environmental determinants of market performance are not measured, and this could affect the all-encompassing nature of the results.

7.2Future Research

Future research should increase the number of SMEs (with a broader cross-section of industries and geographic areas) to improve "the generalizability of the findings of the study. Longitudinal studies are suggested to explore the impact of AI marketing over time on CE, technological readiness, and market performance. Other intermediate factors such as customer satisfaction, customer trust, customer loyalty, and organizational innovation capability can also be explored as other factors influencing the creation of value through AI. Finally, the necessity for mixed methods and comparative study between countries and/or institutional settings is highlighted to overcome the inherent bias and drawbacks of self-reported data and to provide more insights into the impact of AI" on SMEs.

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