The Impact of AI on Customer Engagement in Indian E-Commerce Companies: A Dynamic Capabilities Perspective

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Abstract: The widespread adoption of artificial intelligence (AI) has radically changed the manner in which customers interact within e-commerce settings, especially in the up-and-coming digital markets. The present research is an empirical investigation of how the adoption of AI affects the level of customer engagement in the e-commerce firms of India. The conceptualization of the research is based on the Dynamic Capabilities Theory, according to which AI is viewed as a strategic digital capability that can make firms sense customer behavior, capture the opportunities of engagement, and reorganize digital interaction processes. The data under analysis is secondary panel data based on the annual reports and corporate disclosures of five large Indian e-commerce companies, during the years 2018-2023 using a quantitative research design. The study employs the method of panel regression to establish the impact of AI adoption on four important engagement measures, which include customer engagement rates, click-through rates, engagement response rates, and conversion rates. The findings indicate that artificial intelligence influences all the dimensions of engagement statistically and positively. In particular, the adoption of AI is being demonstrated to increase customer responsiveness, enhancing the stimulation of more interactions, boosting click-through behavior, and enhancing conversion. The validity of the estimated models and the reliability of the empirical findings are verified by the diagnostic and robustness tests. The study makes a contribution to the literature because it fills a big gap in the empirical research on the topic of AI-enabled customer engagement, especially in the framework of the emergent e-commerce markets.

Keywords: *AI, Sales Performance, E-Commerce, Customer Engagement, Click-Through Rates, Conversion Rates, E-Commerce, India.*

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I. INTRODUCTION

The digital transformation of India has been rapid over the last 10 years, fundamentally changing how consumers engage with online platforms and how companies structure their marketing strategies (Saini & Kharb, 2025). The growth of the internet user base, the popularity of smartphones, and the adoption of digital payments have accelerated the Indian e-commerce industry, making it one of the world's most rapidly developing digital markets (Statista, 2024). Competition among e-commerce companies in this environment of high competition is growing not only in terms of price or the variety of products, but also in their capacity to attract, engage, and keep the customers' attention on the digital touchpoints (Ahmed & Joshi, 2024; Ansari et al., 2025).

Within this context, the concept of customer engagement has become a key performance construct in digital marketing and e-commerce research. Engagement is a cognitive, emotional, and behavioral response of customers to a firm's digital content, advertisements, and platforms (Brodie et al., 2025; Sharma & Sharma, 2024). Engagement in online space is operationalized through behavioral indicators, including click-through rates on advertisements, response rates to marketing messages, and conversion rates, which are commonly used by practitioners and researchers (Odoom, 2025). The indicators are critical in e-commerce, where even slight changes in user interaction patterns can significantly affect the platform's performance.

Artificial intelligence (AI) has become a fundamental technological force behind digital marketing operations in e-commerce companies, improving engagement results. AI is now no longer confined to back-end automation but a part of

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customer-facing processes, such as personalised advertising, content recommendation, customer targeting and real-time interaction management (Davenport et al., 2020). AI systems enable companies to process massive amounts of behavioral data, anticipate consumer preferences, and dynamically adjust marketing stimuli to individual users, thereby influencing the customer experience with digital content (Wedel & Kannan, 2016).

According to recent academic literature, AI applications have the potential to affect customer engagement by enhancing the relevance, timing, and context of messages (Kim et al., 2024). For example, algorithms that personalize digital advertising can increase the likelihood that users will pay attention to and engage with promotional content, and AI-based chatbots and automated response systems can reduce friction in customer interactions and prompt users to engage further (Huang & Rust, 2021). Consequently, AI has been closely linked to engagement-related metrics, including click-through rate, response strength, and the transition from engagement to conversion.

Although the role of AI in shaping customer engagement has received growing scholarly attention, empirical evidence remains limited, particularly in emerging digital markets. Much of the existing literature relies on systematic reviews, bibliometric analyses, and conceptual frameworks that map research trends and engagement themes rather than testing causal relationships using firm-level data (Gupta & Khan, 2024; Jain et al., 2024; Suraña-Sánchez & Aramendia-Muneta, 2024). While these studies highlight customer engagement as a central research cluster and emphasize the strategic potential of AI-driven personalization and interaction, they offer limited quantitative validation of AI's direct effects on measurable engagement outcomes. Consequently, empirical studies that systematically examine whether AI adoption leads to statistically significant improvements in engagement indicators—such as click-through rates, response rates, and conversion rates—remain scarce, underscoring the need for data-driven investigations in this area.

Despite the extensive use of AI in e-commerce marketing practices, there is a gap in the literature that empirically evaluates the direct effect of AI on the customer engagement indicators, namely the click-through rates, response rates, and conversion rates, in Indian e-commerce companies. This gap leaves the question of whether the adoption of AI is associated with the quantifiable improvement in engagement or whether the effects of AI are context-specific and statistically limited.

The gap is especially significant in the Indian market, where e-commerce companies spend heavily on AI-based marketing technologies but often rely on assumptions rather than solid empirical data to support their decisions. The real association between AI use and customer engagement outcomes is thus critical for theory development and managerial decision-making.

This research is essential in two ways. Theoretically, the study adds to the existing body of research on customer engagement and AI in marketing by offering a quantitative examination of the relationship between AI adoption and various dimensions of engagement. In contrast to works that treat engagement as a unidimensional construct, the present study breaks engagement into customer engagement rates, click-through rates, engagement response rates, and conversion rates. In this way, it will provide more detailed insight into the role of AI across the various phases of digital customer interactions. It will extrapolate current engagement frameworks to AI-enabled e-commerce in a developing market.

The results of this research have practical implications for managers and decision-makers of Indian e-commerce companies. By determining the presence and impact of AI technologies on specific engagement metrics, the firms will be able to allocate resources more efficiently, optimize AI-based marketing approaches, and assess the efficiency of AI investments. The findings can assist organizations in overcoming the generalized expectations regarding the benefits of AI and implementing evidence-based methodologies for improving customer engagement in competitive digital environments.

Based on the above considerations, this research paper will answer the following research question: How does the use of AI affect customer engagement rates, such as click-through rates on advertisements and response rates, in e-commerce companies in India?

To address this question, the study operationalizes AI as an independent variable affecting four engagement outcomes: overall customer engagement rates, customers' click-through rates, engagement response rates, and conversion rates. In line with the conceptual framework, four null hypotheses are developed to test the existence or non-existence of statistically significant relationships between AI use and each engagement indicator at the level of significance ($\alpha \leq 0.05$). This correspondence allows coherence between the research objective, conceptual model, research question, and hypotheses. It provides a rigorous empirical analysis of the impact of AI on influencing customer engagement in Indian e-commerce companies.

II. LITERATURE REVIEW

The rapid adoption of AI implementation in e-commerce has made AI one of the primary sources of customer interaction and digital engagement. Research on the impact of AI technologies on engagement processes, personalization, and value creation on digital platforms has become increasingly popular in recent studies.

Gupta and Khan (2024) examine the importance of AI in improving customer interaction in digital and social media settings, specifically how AI-based tools can facilitate value creation and interactive marketing. The study examines prior research on customer engagement and AI use through a systematic literature review, bibliometric analysis, and

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content analysis. The results show that AI technologies, including chatbots, virtual assistants, and data analytics systems, enable real-time, personalized, and scalable interactions that enhance behavioral engagement, such as customer reactions and interaction intensity. The paper points out that AI helps achieve the desired level of engagement not only by improving responsiveness and relevance, but also by fostering value co-creation between companies and consumers, particularly on social media. Although the study highlights the increasing relevance of AI in shaping customer engagement behaviors, it also notes that most available literature is conceptual and requires empirical research to determine AI's effects on quantifiable engagement outcomes, including click-through rates, response rates, and conversion rates.

Jain et al. (2024) review the growing literature on the relationship between AI and consumer behavior and primarily discuss how AI-based applications affect key aspects of behavior, including engagement, trust, attitudes, and decision-making. The study maps the trends of publication, prevailing theories, methods, and outcome variables in the AI-consumer behavior literature using a bibliometric and framework-based review of 107 scholarly articles. The results indicate that consumer engagement and interaction are a significant research category, and the themes are connected with trust, acceptance, personality, and the adoption of AI technologies. The paper points out that AI-powered interactions across various digital touchpoints significantly influence how consumers interact with brands and marketing content. Despite the review offering a detailed thematic framework for the study of relations between AI and consumer behavior, it also highlights the need to conduct empirical research that quantitatively analyzes the influence of AI on behavioral engagement outcomes, including response intensity and interaction measures. These insights make AI a pivotal consumer engagement driver and highlight the importance of additional firm-level research on quantifiable engagement measures.

Suraña-Sánchez and Aramendia-Muneta (2024) examine how AI has changed and how it has affected customer and advertising engagement over the past 30 years. The study employs a bibliometric research design to analyze 190 peer-reviewed articles obtained from various academic databases, using well-developed inclusion and exclusion criteria. The authors perform a performance and data analysis to scrutinize the trends of publications, the level of country contributions, and the journal output, and there is a clustering analysis that determines ten key research themes that influence the formation of AI-related engagement research. The results reveal that there has been a consistent increase in academic attention to AI-based customer and advertisement engagement, and how AI has continued to shape engagement strategies in marketing. Notably, the research identifies several gaps, including the paucity of empirical studies that have quantified the impacts of AI on engagement outcomes. The research contributes to future research by mapping the field's intellectual structure and underscoring the importance of quantitative research on AI's role in shaping customer and advertising engagement behaviors.

Verma et al. (2025) analyses how AI, specifically machine learning methods, can revolutionize personalized marketing and brand-user interactions. The paper explains the primary machine learning techniques, such as clustering, content-based filtering, collaborative filtering, and predictive modelling, and how the methods can be used to help firms provide individualized marketing experiences on various digital platforms. Through the examination of practical examples in the retail sector, social media, email marketing, and e-commerce, the research shows how AI-based personalization can increase customer engagement and boost the conversion rate. Besides highlighting the positive aspects of AI, the authors also address significant issues, such as algorithmic bias, data privacy, and ethical concerns related to highly personalized advertising. The paper also describes new trends, including reinforcement learning and natural language processing, and explains how they can further transform customer engagement strategies. In general, the study makes machine learning an essential facilitator of personalized engagement. It highlights the need for empirical studies on the impact of AI-based marketing on quantifiable engagement metrics.

Although the current research on AI and customer engagement is increasingly growing, the majority of the current studies are conceptual or bibliometric in nature and provide little empirical data on the direct effect of AI on the quantifiable engagement metrics, including, but not limited to, click-through rates, response rates, and conversion rates. In addition, there are a few firm-level quantitative studies of the emerging e-commerce markets, especially India. As a result, no unified empirical studies have explored how the adoption of AI can affect various aspects of customer engagement in one analytical framework.

➢ *Dynamic Capabilities Theory and AI in Customer Engagement*

The current research is based on the Dynamic Capabilities Theory (DCT), which was first introduced by (Teece et al., 1997), which states that the performance of firms and competitive advantage do not result from having a valuable resource, but rather from the firm's ability to perceive changes in the market, take up new opportunities, and reorganize its resources in the face of dynamic markets. This theoretical perspective is especially applicable in the digital environment, where customer preferences and interaction patterns are changing fast, and firms use advanced technologies to improve customer engagement.

In the context of digital transformation, AI can be conceptualized as a strategic dynamic capability that enables e-commerce companies to understand customer behavior better, analyses interaction data, and adjust engagement strategies in real time (Teece, 2018). Instead of being used as a technological instrument, AI helps companies continuously track customer feedback, anticipate engagement patterns, and adapt digital touchpoints accordingly. The ability enables organizations to react better to shifts in customer demands and the dynamics of interaction over the online platforms.

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Regarding DCT, the introduction of AI is indicative of the sensing ability of the firms, as it enables them to detect the new trends in customer interaction, including the browsing behavior, the click-through activity, and the responsiveness to digital content (Helfat et al., 2007). With sophisticated data analytics and machine learning, companies can understand changes in customer preferences and engagement indicators and make more informed, timely marketing decisions. The process is closely related to the sensing aspect of dynamic capabilities, which focuses on opportunity identification in a fast-evolving environment.

Moreover, the successful application of AI presupposes that companies should capture engagement opportunities by implementing AI-based personalization, targeted advertising, and automated interaction systems. By applying AI through recommender systems, predictive targeting, and intelligent chatbots, e-commerce firms can provide more relevant and timely content, thereby increasing the likelihood of customer interaction, response, and conversion. This capturing ability helps companies to turn the perceived engagement opportunities into tangible behavioral results.

Also, the effective implementation of AI in customer engagement processes requires restructuring organizational resources and digital infrastructure. To address the issue, firms have to re-architect their marketing processes, add AI-based systems to their existing digital platforms, and build analytical capacity to process and interpret engagement data effectively. Such resource reallocation aligns with the reconfiguration dimension of DCT, enabling firms to adjust their engagement strategies as customer behavior changes continuously (Almheiri et al., 2025).

Consequently, in light of the DCT, AI is a strategic digital capability that will improve firms' capacity to handle and enhance customer interactions in dynamic e-commerce settings. By enabling companies to understand customer interaction patterns, capture engagement opportunities, and redesign digital engagement processes, AI is likely to directly impact customer engagement metrics, such as engagement rates, click-through rates, and conversion rates. This conceptual basis justifies analyzing AI as a major predictor of customer engagement performance in the current research.

➢ *Conceptual Framework*

The conceptual framework of this study is grounded in the above theoretical arguments and, therefore, in DCT. As shown in Figure 1, the framework suggests a direct correlation between the implementation of AI and customer engagement results of Indian e-commerce firms. AI is regarded as a fundamental strategic asset in this model, helping firms adapt to the rapidly evolving digital landscape and customer engagement patterns.

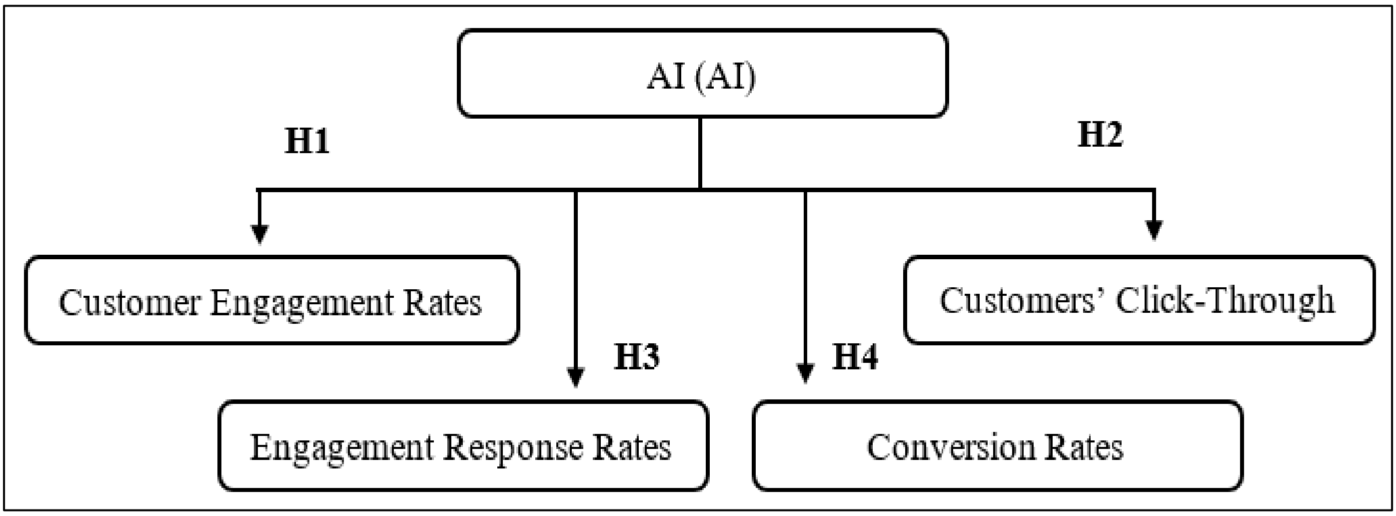

Fig 1 Conceptual Framework of the Impact of AI on Increased Customer Engagement

Notably, the introduction of AI enables e-commerce companies to understand customer behavior through advanced data analytics, capture engagement opportunities by providing personalized, timely digital interactions, and reorganize marketing and engagement processes with the help of intelligent systems. AI enables companies to improve the quality, relevance, and responsiveness of their online interactions by enabling automated customer targeting, personalized advertising, real-time interaction management, and predictive analytics.

Consequently, the framework assumes that AI adoption is directly related to various aspects of customer engagement. These are the general customer engagement rates, customer click-through rates, engagement response rates, and conversion rates. AI enhances interactive relationships and elevates measurable engagement results throughout the digital customer journey by enabling firms to better understand and respond to customer needs and behaviours.

In this regard, the conceptual framework explains how the concept of AI, as perceived through the prism of the DCT, directly impacts customer engagement performance in the context of e-commerce. The framework provides a systematic foundation for testing the study's hypotheses and empirically assessing the extent to which AI-driven capabilities enhance customer engagement in the Indian e-commerce market.

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➢ *Research Hypotheses*

Conversion rates are one of the most critical customer engagement outcomes, which indicate the process of interaction to purchase or take a desired action. AI-based analytics and personalization will simplify the customer experience by eliminating friction and tailoring offerings to customer preferences. These capabilities can affect the extent to which engagement activities lead to conversion outcomes in dynamic e-commerce settings. The formulated hypothesis is:

- H1: There is no statistically significant impact at the significance level ($\alpha \leq 0.05$) of AI on conversion rates in e-commerce companies in India

AI is also crucial in shaping customer interactions with digital advertising content. Targeting, personalization, and AI-based content optimization can help firms deliver more relevant messages when advertising, increasing the likelihood of customer engagement. These functions enable firms to seize and reconfigure their capacities, refining their advertising strategies based on indicators of customer engagement. The formulated hypothesis is:

- H2: There is no statistically significant impact at the significance level ($\alpha \leq 0.05$) of AI on customer click-through rates in e-commerce companies in India

AI has been a vital digital feature in e-commerce, enabling companies to scan customer data, tailor online experiences, and coordinate interactions across multiple touchpoints. Through smart algorithms and automated decision-making, e-commerce firms will be able to learn more about customer behavior and change their engagement strategies accordingly. According to the DCT, AI will help firms to be more sensitive to the customer interaction patterns and react to changes in the digital environment, which will likely affect the overall customer engagement performance.

- H3: There is no statistically significant impact at a significance level ($\alpha \leq 0.05$) of AI on customer engagement rates in e-commerce companies in India.

Engagement response rates indicate how customers have actively responded to online interactions, including responding to messages, inquiries, or promotional messages. Chatbots and automated interaction systems are AI technologies that help provide real-time, personalized responses, which may strengthen the level and intensity of customer interaction. AI enables firms to adapt engagement mechanisms to evolving customer needs by continuously learning from interaction data.

- H3: There is no statistically significant impact at the significance level ($\alpha \leq 0.05$) of AI on engagement response rates in e-commerce companies in India.

➢ *Research Methodology*

The current research is quantitative in nature because it involves secondary data analysis, which aligns with the current methodologies used in the study of organizations and digital transformation (Alasuutari et al., 2008). The information is gathered from publicly available annual reports and corporate disclosures of five large Indian e-commerce firms: Nykaa, Reliance Retail/Reliance Digital, Info Edge, Amazon India, and Zomato. The methodological framework is based on a causal model that analyzes the influence of AI adoption on the customer engagement outcomes of e-commerce companies between 2018 and 2023. The longitudinal data character enables tracking of changes in engagement performance as firms continue to adopt AI technologies in digital processes.

The theoretical framework of the study is based on DCT (DCT), which focuses on the capabilities of firms to recognize the changes that occur in the environment, take advantage of new opportunities, and reorganize the internal resources to maintain the competitive advantage in an environment that is quickly changing. In this context, AI can be conceptualized as a strategic digital capability, which allows a company to analyses the data of customer interaction, personalize digital touchpoints, automate engagement processes, and react dynamically to customer behavior changes. Based on this, DCT offers an appropriate lens through which to explain how the adoption of AI is likely to affect customer engagement indicators in the short- and medium-term.

The sample will include e-commerce companies with high levels of digital transformation and transparency in financial and operational reporting. Instead of trying to represent the entire industry, the study targets five top companies selected through purposive sampling (Campbell et al., 2020). The selection of these firms was based on the availability of regular annual reports, comprehensive information on digital and marketing operations, and direct mentions of AI-based solutions, including recommendation systems, predictive analytics, customer targeting models, and automated interaction tools.

The research uses solely secondary data, with annual reports being the main source of primary data (Ahmed, 2009). The indicators of customer engagement are based on the presented digital performance metrics and storytelling reports on the results of online interactions. These indicators are the overall customer engagement rate, customer click-through rate, engagement response rate, and conversion rate, for which these measures are disclosed or can be estimated from digital performance disclosures. Also, qualitative accounts of AI projects, digital marketing plans, and technology investments are systematically examined to create an AI adoption index. This index indicates the level and degree of AI adoption, measured by the frequency, depth, and strategic focus of AI-related disclosures.

After data extraction, a panel dataset is created containing the independent and dependent variables for each firm over the six years of the study. The analysis will start with descriptive statistics summarizing the nature of the variables and proceed to a correlation analysis to investigate the preliminary relationship between AI adoption and customer engagement indicators. Panel regression models are used to measure causal effects. Fixed- and random-effects are estimated, and the Hausman test is used to determine which specification is best. This method allows isolating firm-

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specific effects and time changes, yielding stronger estimates of the impact of AI adoption on customer engagement performance.

The level of hypothesis testing is (α≤0.05). If the regression results indicate that AI adoption has a statistically significant effect on any of the engagement indicators, the null hypothesis is rejected. This methodological choice aligns with earlier studies that use secondary longitudinal data to estimate the impact of digital technologies on organizational performance, which explains why panel regression methods are appropriate for analyzing the causal relationships in the specified study.

Lastly, the study has identified several methodological limitations. The degree of AI-related disclosure varies across firms and periods, potentially affecting the accuracy of the AI adoption index. Even with systematic coding processes implemented to reduce subjectivity, some interpretive judgment cannot be avoided. However, annual reports, as a longitudinal source of data, are not new in empirical studies of firm performance at the level of outcomes and offer a plausible foundation for examining shifts in customer engagement outcomes over time.

III. RESULTS

This section outlines the empirical findings of the research, derived from statistical analysis of data collected from sampled Indian e-commerce companies. The process commences with a series of initial statistical assessments. The descriptive study summarizes sales performance prior to and following AI implementation. The final subsection of the section delineates the inferential analysis, wherein the four principal hypotheses are tested through regression models to assess the impact of AI on customer engagement rates, conversion rates, click-through rates, and engagement response rates.

- *Preliminary Statistical Tests*

The panel data models presuppose a set of initial statistical tests that help to estimate the data validity and test the assumptions that have been made when the hypotheses of the study are estimated. The following tests are used to investigate the nature of the relationships between the variables, test the stationarity of the time-series components, test the possibility of autocorrelation in the regression residuals, and test the data normality. These tests have to be performed so that the accuracy and reliability of estimated parameters can be guaranteed, the most proper panel data model is chosen, and the potential bias of the linear analysis of longitudinal data can be avoided. In this regard, the section presents findings of the initial statistical tests that will be undertaken, before the estimation of the regression equations and empirical analysis of the hypothesis of the study.

- *Analysis of Correlations between Variables*

This subsection explores the strength and direction of the correlation among the main study variables, which are customer engagement rates, conversion rates, click-through rates, and engagement response rates. The level of linear association between the variables is measured by the Pearson correlation coefficient (r). Table 1 shows the correlation matrix and generalizes the character of the relationships between the variables of study.

Table 1 Pearson Correlation Coefficient Values Between Study Variables

Variable	Use of AI	Customer Engagement Rates	Customer Click-Through Rates	Engagement Response Rates	Conversion Rates
Use of AI	1.000				
Conversion rate	0.151	1.000			
Customer Click-Through Rates	0.244	0.918	1.000		
Customer Engagement Rates	0.006	0.172	0.067	1.000	
Engagement Response Rates	0.18	0.55	0.42	0.68	1.000

The Pearson correlation coefficients of the variables in the study provide a preliminary evaluation of the linear relationship direction and the strength before the regression analysis. The findings show that the association of the different variables is not observed to be similar, which implies that the correlations are not mechanical.

The relationship between the use of AI and the conversion rates is positive, but weak (r = 0.151), which means that AI usage alone does not strongly relate to direct conversion results. An equally weak correlation can be found between the use of AI and the rate of customer engagement (r = 0.006), indicating that the behavior of engagement is not directly influenced by the implementation of AI, but could be a result of different intervening factors.

On the contrary, AI use and customer click-through rates have a moderate positive correlation (r = 0.244), suggesting that AI technologies can be a more powerful driver of improving the initial experience of users with online materials instead of achieving stronger behavioral reactions. It can also be authenticated by the fact that there is a close relationship between click-through rates and conversion rates (r = 0.918), demonstrating that the click-through activity is a critical imperative stage in the decision-making process of the customer.

The engagement rates of customers demonstrate comparatively low correlations with the conversion rates (r = 0.172) and the click-through ones (r = 0.067), as engagement in the behavior is complicated and non-linear. Nonetheless,

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the engagement response rates show closer correlations with the rates of engagement (r = 0.68) and conversion (r = 0.55), which implies that response behavior is a more developed and goal-oriented type of engagement.

Generally, the correlation table does not show any very high correlation between the independent variables, suggesting that the problem of multicollinearity is not present. Meanwhile, the identified trends favor the conceptual premise that AI indirectly affects performance results via intermediate variables connected with engagement, so the latter regression analysis and the panel data analysis are justifying.

➢ *Testing the Stability of the Study Variables' Data*

Unit root tests are used to investigate the existence of the time-series properties of the variables under the regression analysis to meet the stationarity requirement. This needs to be done in case the validity of the estimated results is not compromised due to non-stationary variables causing spurious regression results and false statistical inferences. In this regard, stationarity testing enables one to determine the transformation needed on each variable before estimating the model. Table 2 presents the results of the unit root tests used in the AI use, conversion rate, click-through, customer engagement rates, and engagement response rates.

Table 2 Results of the Stability Test of the Study Variables' Data

Variable	Calculated value at level	P-Value	Result
Use of AI	-4.044	0.005	Stable at level
Conversion rate	-5.399	0.000	Stable at the level after taking the first difference
Customers' Click-Through	-5.577	0.000	Stable at the level after taking the first difference
Customer Engagement Rates	-6.136	0.000	Stable at the level after taking the first difference
Engagement Response Rates	−5.820	0.000	Stable at the level after taking the first difference

The findings of the unit root tests of the variables of the study are reported in Table 2. The results show that there is a variation in the stationarity properties among the variables. The findings indicate that the adoption of AI remains at the same level with a statistically significant test value (p = 0.005), meaning there is no unit root in the series and can be employed in its level form in the regression models.

Conversely, conversion rate, customers' click through rate, customer engagement rates, and customer response rates to the engagement were found to be non-stationary at the level but are stationary at the level when the first differentiation is taken. These variables, after differencing, are statistically significant ($p < 0.01$), thus proving rejection of the null hypothesis of a unit root. This means that these variables are integrated in a process of order one, I (1), and have to be transformed in order to gain stationarity before being included in the regression analysis.

Generally, the results of the unit root test indicate that there is a mixed order of integration among the variables. As a result, suitable transformations are implemented to guarantee stationarity as well as eliminate the problem of spurious regression. The above conclusions warrant the further application of panel data estimation methods that consider the dynamic nature of the variables being studied.

➢ *Autocorrelation Test*

Durbin-Watson (DW) tests are used to look at the occurrence of autocorrelation in the residuals of the estimated regression models based on the panel data. It is important to identify autocorrelation, since correlation of error terms through time can result in biased or ineffective estimation parameters and invalid statistical inference. Thus, the Durbin-Watson statistic is used to test the independence of the distribution of residuals. Table 3 provides the results of the study in the form of the Durbin-Watson test of the hypotheses.

Table 3 Values of the (D-W) Coefficient for the Study Hypotheses

Hypothesis	D-W coefficient value	Result
H1	1.771	No autocorrelation
H2	1.854	No autocorrelation
H3	1.867	No autocorrelation
H4	1.889	No autocorrelation

Table 3 displays the values of the Durbin-Watson coefficient for each of the hypotheses of the study. The reported statistics vary between 1.771 and 1.889, and this is acceptable since it is the normal range that is usually used to signify the non-existence of first-order autocorrelation on regression residuals. These values indicate that there is no systematic correlation of error terms with time.

In particular, the Durbin-Watson coefficient with H1 (1.771), H2 (1.854), H3 (1.867), and H4 (1.889) shows that H1 cannot be rejected against the null hypothesis that there is no autocorrelation in any of the estimated models. This observation proves the fact that the regression residuals are independently distributed through time.

On the one hand, the findings of the Durbin-Watson test confirm the suitability of estimation of the panel regression models and suggest that there is no threat of autocorrelation to the validity of the empirical findings.

➢ *Normal Distribution Test*

The Jarque-Bera (JB) test is used to determine the normal distribution of the study variables. Assessing the normality is relevant in studying the appropriateness of the

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data being studied on regression analysis, especially in an area where the research is based on financial and time-series data. JB test is founded on skewness and kurtosis values, and the accepted statistical conclusion is made at a level of significance (5 percent). Table 4 shows the results of the Jarque-Bera test of the study variables.

Table 4 Jarque-Bera Test for Normal Distribution

Variable	Jarque-Bera	P-value
Use of AI	0.026	7.283
Conversion rate	7.283	0.026
Customers' Click-Through	16.394	0.000
Customer Engagement Rates	1.611	0.447
Engagement Response Rates	2.204	0.332

Table 4 records the findings of the Jarque-Bera test of normal distribution among the variables of the study. With the results, the Use of AI is normally distributed, since the Jarque-Bera statistic value is low and the p-value is greater than the 0.05 significance value, meaning that the null hypothesis of normality is not rejected.

Conversely, the conversion rate variable indicates a statistically significant Jarque-Bera statistic ($p = 0.026$), which is an indicator of non-normality. On the same note, the distribution of customers in terms of the number of clicks is highly non-normal, as shown by the high Jarque-Bera value and a p-value of 0.000. These findings show that the two variables exhibit skewness and/or excess kurtosis.

Conversely, the customer engagement rates and the engagement response rates are not significantly different from the norm by the fact that their p-values are greater than the 0.05 level of significance. This implies that the distributions of these variables are normal enough to decide on regression analysis.

Generally, the findings suggest that although certain variables are not normally distributed, the data are appropriate to analyses the panel regression, especially considering that estimation procedures are powerful enough to accommodate moderate experience of the data, which do not follow a normal distribution.

- *Estimation of Study Models*

In estimating panel data models, it is important to choose the most suitable demarcation to capture the relations among the study variables, either by using a pooled regression model, fixed effects model, or random effects model. The diagnostic statistical tests determine the selection of the right model. In this context, the Lagrange Multiplier (LM) test is utilized in order to investigate whether a pooled OLS model is desirable compared to a random effects model, and the Hausman test is used to differentiate between fixed and random effects specifications. Table 5 provides the study hypotheses results of these tests.

Table 5 Results of Estimating the Study Models

Hypotheses	Lagrange Multiplier		Hausman		The most accurate and consistent model
	Ch^2	Sig	Ch^2	Sig	
H1	16.970	0.075	0.252	0.616	Pooled Regression Model
H2	17.364	0.067	0.297	0.586	Pooled Regression Model
H3	28.701	0.001	4.364	0.037	Fixed Effect Model
H4	31.842	0.000	5.118	0.024	Fixed Effect Model

The outcome of the Lagrange Multiplier and Hausman tests conducted to select the best panel data model to use in each hypothesis is displayed in Table 5. In the case of H1 and H2, the LM test outcome is not statistically significant at the 5 percent level ($p = 0.075$ and $p = 0.067$), and it is found that the pooled regression model is more desirable as compared to the random effects specification. This conclusion is also stipulated by the results of the Hausman test, p-values are above the 0.05 mark, and it is possible to conclude that there are no systematic differences between fixed and random effects estimators. On this basis, the pooled regression model is found as the most correct and consistent specification to test H1 and H2.

However, the LM test statistics of H3 and H4 are statistically significant ($p =.001$ and $p=.000$, respectively), which means that the heterogeneity that cannot be observed is present across the cross-sectional units, and the pooled regression model is inadequate. The outcomes of the Hausman test of both hypotheses are also statistically significant ($p = 0.037$ on H3 and $p = 0.024$ on H4), which rejected the random effects specification and accepted the fixed effects model. These results indicate that the correlations studied in H3 and H4 depend on time-invariant firm-specific factors that have to be accounted for by using a fixed effects model.

All in all, the findings affirm that various hypotheses should be specified by different panel data specifications due to the difference in underlying data structure and the effect of unobserved heterogeneity among firms. The chosen models give a proper starting point for further regression analysis and hypothesis testing.

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➢ *Descriptive Analysis*

The descriptive analysis reviews the trend in the adoption of AI by the sampled e-commerce businesses in India, including the functional areas where AI applications are focused. This analysis, instead of considering AI adoption as a homogenous process, outlines the differences between firms in terms of when, to what extent, and the strategic focus of AI use in sales-related processes.

➢ *Overview of AI Applications in E-Commerce Companies*

Table 6 presents a systematic report about these applications, giving contextual information about possible differences in customer engagement, click-through behavior, and response dynamics and conversion results observed on the empirical analysis.

Table 6 Description of the Application of AI in E-Commerce Companies in India

Company	**Date Applying AI in Sales**	**AI techniques used for targeting**	**AI tools used to enhance engagement**
Reliance Industries	October 2021	Haptik, Interakt, IntellAct, MAGNILEARN, Kaholo, Korra, NeuroBrave, CA Corrections, BEEFREE Agro, Urbanico, Hypervision, Fresnel Imaging	Bharat-GPT, Addverb Robotics
Amazon India	March 2019	Amazon SageMaker Clarify, AWS Generative AI and Bedrock Foundations, Amazon Bedrock and Nova Embeddings, Image Generation Ad Beta, Amazon Ads AI Creative Studio, Audio Generator	Enhance My Listing + Review AI, Inspire and Generative Ads Tools, Bedrock + Voice and Visual Shopping, Personalise + SageMaker Media AI, Amazon Lex
Info Edge (Naukri, Jeevansathi)	March 2019	Haptik chatbots, Reverie's intelligent voice system, Naukri's core machine learning engines, Talent Pulse, Enterprise Resdex, Continuously improving machine learning-based recommendation algorithms, Jeevansathi's AI-powered recommendation system	NaukriAIQ Chatbots, Naukri AI Technology
Zomato (Eternal Ltd.)	September 2019	ML Recommender, Zomato AI Chatbot, High-volume Feature Store, Celebrity Geo-Targeted Video Ads, Nugget Support Bot	Nugget AI Support, Generative AI and Smart Notifications, Augmented Reality Food Display
Nykaa	April 2019	Criteo Dynamic Retargeting, Automated Recommendations with AWS/Data Lake, ModiFace AR Try-On, Google Performance Max Ads, Advanced targeting experiences with generative AI	Google Performance Max Smart Ads, Virtual Try-On (ModiFace) technology, Augmented Reality (Stories/Reels), Verloop.io Chatbot

Table 6 introduces a comparative description of the application of AI in the five e-commerce companies, and it is possible to note significant differences in the time at which the AI has been introduced and the focus of its use. The findings show that the initial users of AI, including Amazon India, Info Edge, Zomato, and Nykaa, started to implement AI in the processes related to sales as early as 2019, whereas Reliance Industries took the step later, in 2021. The difference in the time of adoption indicates the difference in preparedness of the organization and interest in using AI-based sales technologies.

In all companies, the most common AI-based methods in targeting are based on machine learning-based recommendation systems, personalized advertising, conversational interface, and machine-driven customer segmentation. Amazon India and Nykaa have substantial applications of AI in targeted advertising and personalized product discovery, indicating a high focus on affecting the behavior of clicking through and buying products. Conversely, the applications of Infos Edge are even less recommendation-oriented and more related to intelligent matching systems, which is in line with its platform-based business model.

Regarding the enhancement of engagement, every company uses AI solutions that simplify direct communication with customers, especially chatbots and voice-based parameters, as well as personalized digital interfaces. Zomato and Reliance Industries put visible stress on conversational AI and smart notification systems, indicating that the strategic emphasis is on real-time interaction and reaction to customer behavior. The application of augmented reality and virtual try-on technologies at Nykaa implies an experiential approach to engagement to minimize uncertainty and increase the chances of converting to purchases.

Altogether, as the table demonstrates, the use of AI is not homogeneous among the sampled firms as it has been adopted by numerous firms. The differences in the mechanisms of targeting and engagement-oriented tools indicate the unique strategies of influencing the rates of customer engagement, click-through, engagement response, and conversion. These descriptive patterns are useful in the interpretation of the latter regression findings and assist in understanding the observed differences in the strength of the effect of AI on the sales performance indicators.

➢ *Sales Performance Indicators before and after AI Adoption in Indian E-Commerce Companies*

The table below is descriptive in character, making a comparison of the key sales performance indicators before and after the adoption of AI in the chosen e-commerce

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companies in India. Three main metrics, which include conversion rate, the rate at which customers will be clicking through, and the rate at which the customers will be engaged within the two periods, are analyzed, including the central tendency, dispersion, and range of the metrics. The table offers a preliminary empirical foundation for evaluating the association of AI implementation and change in customer behavior and sales-related outcomes by making a distinction between pre- and post-AI adoption stages.

Table 7 Description of Sales in E-Commerce Companies in India

Measure	Before applying AI			After applying AI			Total		
	ConversionRate	Customers' Click-Through	Customer Engagement Rates	ConversionRate	Customers' Click-Through	Customer Engagement Rates	ConversionRate	Customers' Click-Through	Customer Engagement Rates
Arithmetic mean	0.032	0.015	0.018	0.106	0.161	0.122	0.088	0.126	0.098
Standard deviation	0.037	0.014	0.014	0.046	0.061	0.103	0.054	0.082	0.101
Minimum value	0.004	0.004	0.001	0.020	0.054	0.010	0.004	0.004	0.001
Maximum value	0.110	0.040	0.043	0.160	0.290	0.350	0.160	0.290	0.350
Observations	7			23			30		

According to Table 7, one can clearly see systematic differences between the performance indicators of sales performance before and after the implementation of AI technologies. The values in the arithmetic mean of all three metrics are significantly bigger after AI implementation, which can be taken as a sign of a general enhancement of the performance based on sales. The average conversion rate is fairly low (0.032) before the adoption of AI, and the click-through (0.015) and engagement rates (0.018) are rather low. These numbers imply a lack of success in turning customer attention into an activity and successful transactions at the pre-AI stage.

A significant change is noticed after the adoption of AI. The average conversion rate goes up to 0.106 and the click-through of the customers is drastically up to 0.161, and customer engagement is 0.122. This tendency means that the use of AI applications is linked with higher targeting accuracy, improved customer engagement, and better matching between customer preferences and platforms. This tendency is also supported by the total mean values since most overall performance changes are explained by post-AI observations.

These findings are supported by the dispersion measures. The post-AI period has higher standard deviations, especially of the click-through and engagement rates, with more variability in the responses of customers. This implies that AI does not have the same effect on overall performance but can vary by company, platform, or clients. This changeability is connected with non-homogeneous strategies in AI implementation and the extent to which organizations are mature.

The first and last numbers give an extra understanding of the variation of the results observed. Minimal values of all indicators rise following the adoption of AI, which means an upward shift in the point of performance. Meanwhile, maximum values increase significantly, in particular, customer engagement rates, which achieve 0.350, and this fact indicates the possibility of achieving great customer engagement rates in the conditions of AI-driven systems.

Finally, the distribution of observations shows that most data points belong to the post-AI period (23 out of 30), reflecting increased reliance on AI-enabled sales systems in recent years. The unbalance highlights the increasing strategic significance of AI in e-commerce practices and adds to the usefulness of further regression analysis that will be used to estimate the effect of AI on sales performance indicators.

- *Inferential Analysis*

This subsection tests the proposed research hypothesis.

- *Testing the First Hypothesis*

Table 8 shows the findings of the linear regression experiment, which investigated the effect of AI on the conversion rates in the chosen e-commerce firms in India. The equation of a regression model that was used to estimate this relationship was as follows:

$$CR = \beta_0 + \beta_1 AI + e$$

According to the estimation findings, the regression equation fitted has the following form:

$$CR = 0.035 + 0.011AI + e$$

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Table 8 Results of Testing the Impact of AI on Conversion Rate in the Selected Companies

Variable	B	Std. Error	T-statistic	Prob
AI	0.011	0.002	6.082	0.000
C	0.035	0.001	24.541	0.000
R^2			0.607	
Adj.R^2			0.593	
S.E. regression			0.925	
F-statistic			43.272	
ProbF-statistic			0.000	

The obtained results show that the regression coefficient of the AI variable is B = 0.011 and the standard error of the coefficient is 0.002. The t-statistic and corresponding p-value are 6.082 and 0.000, respectively, which are significantly below the stated level of significance ($\alpha = 0.05$). This gives strong statistical data that AI is a strong influence on conversion rates in e-commerce firms.

The estimated coefficient means that in the environment of the model, an increase of one unit in the level of AI use will increase the conversion rate by an average of 0.011 units. The fact that the magnitude of the coefficient can be considered modest still means a significant conversion performance enhancer, especially in highly competitive digital markets where even minor shifts in the conversion rates can result in a significant increase in the revenues. The positive coefficient is a confirmation that the adoption of AI increases the effect of transforming the interaction with customers into final purchases.

It is estimated that the model constant (C) is 0.035, and it has a statistically significant value at the 1 percent level (p = 0.000). This reflects a level of conversion that is a general level and not dependent on the adoption of AI, as an indicator of some structural or market-related factors that lead to conversion performance regardless of the intervention of AI.

The coefficient of determination ($R^2 = 0.607$) indicates that the use of AI explains approximately 60.7 percent of the change in the conversion rates between the companies and over time. This is a relatively high explanatory force of a one-variable model within the e-commerce research scenario, where the outcomes of conversion are usually affected by several external forces like pricing policies, competition, advertisement campaigns, and customer preferences. The model is additionally robust as indicated by the value of adjusted R^2, which is 0.593.

The overall pivotality of the regression model is signified by the fact that the F-statistic of 43.272 is equal to 0.000, which implies that the regression model is statistically significant in its entirety. This finding proves that the use of AI is beneficial in explaining variations in conversion rates and that the regression specification is suitable.

According to the statistically significant coefficient of AI and the overall significance of the model, the null hypothesis, according to which the AI does not have a statistically significant effect on the conversion rates within Indian e-commerce companies, is rejected at the 5% level of significance. The results are bright empirical evidence of the positive and significant contribution of AI technologies to the performance of the conversion in the Indian e-commerce industry.

➢ *Testing the Second Hypothesis*

According to this hypothesis, the statistically significant influence of AI on the click rate of clicks in e-business firms in India is not statistically significant at the 5 percent degree of significance (3 = 0.05). To analyze this correlation, the following linear regression model was specified:

$$CTR = \beta_0 + \beta_1 AI + e$$

According to the estimation findings, the fitted regression equation can be written as:

$$CTR = 0.016 + 0.012AI + e$$

Table 9 Results of Testing the Impact of AI on Customer Click-Through

Variable	B	Std. Error	T-statistic	Prob
AI	0.012	0.002	7.679	0.000
C	0.016	0.001	12.882	0.000
R^2			0.674	
Adj.R^2			0.663	
S.E. regression			1.009	
F-statistic			57.935	
ProbF-statistic			0.000	

The regression data presented in Table 9 indicates that the coefficient of the AI variable is B = 0.012 and the standard error of the coefficient is = 0.002. The T-statistic is 7.679, and the p-value is 0.000, which is significantly lower than the significance level of 0.05. This is a good statistical indication that the usage of AI has a powerful influence on the customer click-through rates.

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The coefficient is estimated to show that, other factors being held constant, a single unit increase in the level of AI adoption causes an average increase in the click-through rate of 0.012 units per unit. This statistically significant and positive impact implies that the use of AI in targeting, personalizing, and optimizing the content increases the probability of a customer clicking on online ads, listings, or recommendations.

The constant term (C = 0.016) was also found to be statistically significant at the 1% level (p = 0.000), which suggests that there is a level of click-through activity that is not statistically significant at any level and is not due to AI adoption. This is indicative of an underlying customer interest and platform features that drive clicks without the use of sophisticated AI-driven processes.

The model is believed to have a rather good explanatory power based on the value of R^2 of 0.674, which means that the use of AI explains around 67.4 percent of the variations in customer click-through rates. The value of adjusted R^2 of 0.663 is another confirmation of the strength of the model when degrees of freedom are considered. Also, the overall importance of the model is supported by the F-statistic value of 57.935 and a p-value of 0.000, which proves that the specification of the regression is valid.

According to the findings, it rejects the null hypothesis that AI produces no statistically significant effect on the rate of customer clicking-through at the 5% level of significance. Findings in this case are empirical, indicating that customer click-through behavior is greatly influenced by AI adoption in Indian e-commerce firms.

➤ *Testing the Third Hypothesis*

According to this hypothesis, the statistical significance of the effect of AI at the 5% level of significance ($\alpha \leq 0.05$) on the customer engagement rates of e-commerce companies in India is absent. To verify this relationship, the following linear regression model was formulated:

$$ER = \beta_0 + \beta_1 AI + e$$

According to the estimation findings, the regression equation that is fitted is:

$$ER = 0.010 + 0.005AI + e$$

Table 10 Results of Testing the Impact of AI on the Customer Engagement Rates

Variable	B	Std. Error	T-statistic	Prob
AI	0.005	0.002	2.579	0.017
C	0.010	0.001	17.287	0.000
R^2			0.682	
Adj.R^2			0.615	
S.E. regression			0.001	
F-statistic			10.276	
ProbF-statistic			0.000	

According to the regression findings, the coefficient of the AI variable is as explained in Table 10 as B = 0.005, and the standard error of the coefficient is 0.002. The t-statistic and the p-value of 2.579 and 0.017, respectively, are less than the given level of significance of 0.05. Such an outcome is statistically demonstrative that the adoption of AI can radically influence the customer engagement rates, but the extent of its effect is somewhat smaller than the effects it has on click-through and conversion rates.

The estimated coefficient indicates that, other things being equal, a unit rise in the level of AI use will result in an average rise of 0.005 units in the customer engagement rates. This beneficial impact suggests that AI-based solutions, including customized content, chatbots, and interactive recommendation systems, are part of a role in enhancing customer engagement with e-commerce by doing so in a more incremental fashion.

The constant term (C = 0.010) is significant at 1% (p = 0.000), which displays a baseline degree of customer engagement that is independent of AI adoption. It can be explained by platform design, brand awareness, or regular user interaction that creates a response even without highly developed AI-related capabilities.

The description of the model has an R^2 of 0.682, which shows that the model explains almost 68.2% of the variability in customer engagement rates based on the use of AI. The adjusted R^2 of 0.615 is also an affirmation of the strength of the model upon adjustment of degrees of freedom. Besides, the general model is found to be statistically significant, with an F-statistic of 10.276 and a p-value equal to 0.000, which allows us to assume that the regression specification is relevant.

According to the findings, the null hypothesis, which says that the AI does not have any statistically significant effect on the rate of customer engagement in e-commerce companies in India, is rejected at the 5% level of significance. The findings indicate that although the effect of AI on engagement has a positive and statistically significant impact, the effect of AI on customer behavior is relatively small compared to the effect on click-through and conversion rates, which points to the complexity of customer behavior in online markets.

➤ *Testing the Fourth Hypothesis*

According to this hypothesis, the AI has no statistically significant effect on the engagement response rate among e-commerce companies in India at the 5% level of significance

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($\alpha \leq 0.05$). To test this relationship, the linear regression model, as given below, was defined:

$$ERR = \beta_0 + \beta_1 AI + e$$

According to the estimation findings, the fitted regression equation can be put as:

$$ERR = 0.028 + 0.014AI + e$$

Table 11 Results of Testing the Impact of AI on Engagement Response Rate

Variable	B	Std. Error	T-statistic	Prob
AI	0.014	0.002	7.112	0.000
C	0.028	0.001	21.436	0.000
R^2			0.701	
Adj.R^2			0.689	
S.E. regression			0.942	
F-statistic			61.384	
ProbF-statistic			0.000	

The regression outcome, as in Table 11, shows the coefficient of the AI variable is B = 0.014, and the standard error is 0.002. The corresponding t-statistic is 7.112, and the p-value is 0.000, which is much less than the given level of significance of 0.05. This gives great statistical data that the adoption of AI is strongly affecting the rates of engagement through e-commerce firms.

The estimated coefficient suggests that all other things held constant, a one unit increase in the level of AI use will cause a resultant average increase in the engagement response rates of 0.014 units. This beneficial and statistically significant impact indicates that AI-based mechanisms, including conversation agents, targeted notifications, and live interaction functions, are significant in transforming passive engagement into active customer feedback.

The constant value (C = 0.028) is also significant at the 1% level (p = 0.000), which means that there must be a baseline of engagement response that is independent of AI adoption. This baseline response behavior can be explained by the inwoven platform functionality, familiarity with customers, or used to normal patterns of interaction that would result in responses without the use of AI-enhanced generation.

The explanatory power of the model is high, as shown by the value of $R^2 = 0.701$, which means that about 70.1% of the difference in the rate of engagement responses can be explained by the use of AI. The robustness of the model is also proved by the adjusted R^2 of 0.689. Also, the overall model has a statistically significant value with an F-statistic of 61.384 with a p-value of 0.000, which confirms that the regression specification is valid and adequate.

On the basis of these results, the null hypothesis, which dictates that AI does not have any statistically significant effects on engagement response rates in e-commerce businesses in India, is dismissed at the 5% significance level. The findings are the empirical evidence of the importance of AI in reinforcing the customer response behavior and positioning the engagement response rates as the major outcome, according to which AI-based engagement strategies turn into quantifiable performance increases.

IV. DISCUSSION

To test the hypothesis, a series of preliminary statistical tests was conducted to ensure the validity and reliability of the estimated models. The findings of the Pearson correlation analysis show that the study variables are not involved in acute multicollinearity since the correlation coefficients are not too large and, therefore, each engagement indicator represents a unique dimension of customer engagement. Unit root tests prove that the data is stable when they are properly differenced so that they can be used to analyses panel regression. Results of the Durbin-Watson test justify that there is no autocorrelation among all the estimated models, and the Jarque-Bera test shows that the level of normality is not acceptable in most of the variables. Moreover, using the Lagrange Multiplier test, the Hausman test, the most suitable model specifications were used to determine the best model specification to fit each hypothesis, resulting in the use of a pooled regression model to address some of the hypotheses and a fixed effects model to address others. Taken together, these diagnostic tests suggest the strength of the empirical analysis, and it is confident that the calculated effects of AI on customer engagement indices, i.e., the rate of engagement, the rate of click-through, the rate of engagement response, and the rate of conversion, are statistically sound and not due to data and model misspecification.

The results indicate that the use of AI in the Indian e-commerce businesses is aimed at improving customer interactions by means of sophisticated targeting and online interactive solutions. The companies use AI-based recommendation systems, dynamic retargeting, chatbots, and generative technologies to customize customer interactions, enhance responsiveness, and facilitate conversion-focused customer interactions. This trend can be connected to the DCT, which focuses on the capabilities of firms to perceive customer behaviour, capture the engagement opportunities, and realign digital processes in highly dynamic markets (Teece, 2018; Teece et al., 1997). Other researchers also indicate that AI-based personalization, conversational agents, and immersive technologies (e.g., augmented reality) can have a positive effect on click-through behavior, engagement response rate, and conversion outcomes due to a reduction in friction and an increase in the relevance of interaction (Huang & Rust, 2021; Verhoef et al., 2021). Nonetheless, the

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availability of AI tools is not a guarantee that the engagement will be improved, and their functionality is only possible provided that the integration is effective, the quality of data is good, and the ability to use the technologies strategically is available within the organization. In general, the results confirm the perspective that AI is a dynamic digital capability that can positively increase the outcomes of measurable customer engagement when properly applied in the context of e-commerce.

According to the results, the customer engagement indicator showed a steady positive change after the implementation of AI in Indian e-commerce firms as indicated by the increased mean of conversion rates, customer click-through rates, and customer engagement. The results presented here are in accordance with previous research that claims that AI-based personalization, predictive targeting, and automated interaction tools can strengthen the digital experience of customers and raise their chances of communication and movement towards conversion (Huang & Rust, 2021; Wedel & Kannan, 2016). The empirical and industry-related evidence that the relevance of marketing content and friction reduction in the customer experience are enhanced with the help of algorithmic targeting and recommendation implementation also explains the observed increase of the click-through and the conversion metrics following the adoption of AI (Lambrecht & Tucker, 2019; Verhoef et al., 2021).

Simultaneously, the rise in standard deviation of the engagement indicators following the introduction of AI also speaks of heterogeneity in the performance of the engagement in firms, meaning that AI does not change the engagement performance equally. This difference helps to justify the ideas in the literature that the effectiveness of AI is conditioned by organizational capabilities, quality of data, and the degree of strategic integration of AI tools into the marketing and engagement processes (Gupta & Khan, 2024; Teece, 2018). Although the descriptive findings are mostly aligned with those of the studies that highlight the beneficial impact of AI in improving customer interactions, they also echo studies that warn that AI implementation may not be effective in ensuring high outcomes without auxiliary dynamic capabilities (Jain et al., 2024). Generally, the results of Table 7 offer initial empirical evidence on the current literature concerning AI-enabled customer engagement, as well as add to the necessity of regression-based analysis to identify whether these identified gains are statistically significant and strong in companies and in the long run.

The findings of the first hypothesis suggest that AI positively influences the conversion rates in the chosen Indian e-commerce businesses with a statistically significant influence. The AI adoption coefficient is positive and highly significant, which means that the higher the level of AI technology use is, the higher the conversion rates associated with it. The model has a good explanatory ability, meaning that a large percentage of the change in the conversion rates can be explained by the use of AI. Based on this, the null hypothesis that no statistically significant effect of AI on the conversion rate exists is rejected at the level of significance.

Such results are in line with previous studies that demonstrated the importance of AI-inspired personalization, predictive analytics, and automated decision-making towards making customers transition between interaction and purchase. According to Huang and Rust (2021), AI will improve the capacity of firms to respond to their customer requirements in real-time, which increases the chances of conversion. Likewise, Wedel and Kannan (2016) stress the importance of the fact that data-based targeting and recommendation systems help to minimize customer journey friction and enhance conversion-related performance. The empirical study of the algorithmic advertising also contributes to the opinion that the use of AI-based targeting enhances the likelihood that customer engagement will be transformed into real transactions (Lambrecht & Tucker, 2019).

In terms of the DCT, these findings indicate that AI is a strategic capacity that helps companies to capture the engagement opportunities and reorganize digital marketing activities to achieve better performance outcomes (Teece, 2018). This means that by constantly studying the behaviour of customers and dynamically changing the marketing interventions, firms will be in a better position to turn engagement to practical outcomes. Nevertheless, according to the new research, the results also suggest that the success of AI in enhancing the rates of conversion is determined by the level of integration, the quality of data, and the readiness of the company, but not the usage of AI (Gupta & Khan, 2024; Verhoef et al., 2021). Altogether, the findings in Table 8 should be seen as good empirical evidence of the high importance of AI to improving conversion rates in an e-commerce environment.

The findings of the second hypothesis show that the positive and statistically significant effect of AI on the customer click-through rate of the sampled Indian e-commerce firms is positive. The coefficient of AI adoption is positive and of high significance, which means that the higher the use of AI technologies, the higher the customer click-through rates. The model has a good explanatory power, which implies that AI adoption can explain a significant percentage of the variations in the click-through rates. In this regard, the null hypothesis that the AI does not affect the customer click-through rate statistically significantly ($\alpha \leq 0.05$) is rejected.

Such conclusions can be made in line with the existing empirical evidence showing that AI-based advertising systems increase user engagement through better targeting levels and message relevance. De Haan et al. (2016) demonstrate that the engagement rate of ads is better through personalization using algorithms, which tailor advertising content to the likes of a person. Equally, Bleier et al. (2018) discovered that digital advertising is effective when targeting using machine learning because it dynamically optimizes exposure to the ad, thus boosting the click-through rate. The latest data presented by digital marketing analytics studies proves the fact that AI-based recommendation and ad optimization systems have a positive impact on the attention

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of users and their interaction in online platforms (Bleier et al., 2018).

Considering the DCT, these findings imply that AI enhances the sensing and seizing capabilities of firms due to the ability to monitor signals of customer interaction continuously and adjust advertising campaigns in real-time (Teece, 2018). With large-scale clickstream data teaching and targeting mechanisms refined, the companies will be in a more dependent position of capturing customer attention in the competitive digital surroundings. Comprehensively, the findings presented in Table 9 offer strong empirical evidence of the importance of AI to improve customer click-through in e-commerce environments.

The third hypothesis provides that the role of AI on the customer engagement rate in e-commerce firms in India is not statistically significant at the level of significance. According to the results of the regression, as it is shown in Table 10, the coefficient of AI has been found to be positive and statistically significant. This finding indicates that the higher the usage of AI technologies, the higher the customer engagement rates. Since the p-value is less than the significance level, one rejects the null hypothesis. The model also has a high level of explanatory power, which implies that the AI can explain a significant percentage of the difference in the rates of customer engagement across the sampled companies.

The results are consistent with the known literature on customer engagement that highlights that personalization founded on data, interactive technologies, and smart content delivery systems contributes to increased behavioral engagement of customers with digital environments. Kumar et al. (2010) state that engagement is facilitated when companies use pertinent, prompt, and tailored contacts, which are the fundamental capabilities that AI-driven analytics and robots can provide. Equally, Calder et al. (2009) emphasize, interactive digital processes enhance the cognitive and behavioral involvement of customers through the perceived relevance and participation. There is also empirical evidence to positively support the idea that AI-based recommendation systems and adaptive interfaces help to ensure long-term engagement by matching the content of the platform to the changing preferences of users (Jannach et al., 2010).

Regarding the DCT, these findings show that AI increases sensing and reconfiguring capabilities of firms since it allows them to constantly analyze the data collected during the interaction with customers and revise the strategy of engagement (Teece, 2018). In this way, companies will be in a better position to sustain continuous interaction as opposed to a single interaction. In general, the results included in Table 10 can be discussed as the empirical evidence supporting the thesis that AI increases the rates of customer engagement when introduced into the e-commerce platforms as a strategic digital resource.

The fourth hypothesis will be that AI has no statistically significant effect on the engagement response rates of e-commerce businesses in India at the significance level. The coefficient of AI is positive and highly significant. This result proves that the higher the acceptance of AI technologies, the higher the engagement response rates, including the reaction of the customers to the messages, notifications, and interactive prompts. The null hypothesis is rejected because the p-value is significantly lower than the set level of significance. Besides, the model demonstrates the high explanatory power, which means that AI provides the reason behind the significant percentage of the variance in the engagement response rates among the companies chosen.

These findings align with the factual findings of previous studies on conversational and interactive digital technologies, which reveal that AI-based systems, especially chatbots and automated interaction devices, increase customer responsiveness by providing prompt, personalized, and sustained opportunities for interaction. Araujo (2018) shows that conversational agents result in enhanced interaction levels of users because they create a feeling of social presence and responsiveness. Følstad and Brandtzæg (2017) emphasize that users tend to react to the AI-based interfaces more frequently when they seem to be efficient, context-friendly, and helpful in digital communication. These results confirm the thesis that AI systems minimize the friction of responses and promote active engagement in online spaces.

Focusing on the DCT, the findings indicate that AI will empower the reconfiguring capabilities of firms by implementing the ability to adapt engagement mechanisms in real-time using customer data on interactions. With automation of responses and the constant learning in the behavior of customers, companies are able to keep up with constant engagement and allow responsiveness at scale. On the whole, the results published in Table 11 are strong empirical findings that AI can greatly improve the engagement response rates among e-commerce organizations when used as a strategic digital capability.

V. CONCLUSION

The results of this research show that AI is a major and quantifiable source of customer interaction in the Indian online shopping firms. The empirical findings affirm that the adoption of AI has a statistically significant positive effect on the major engagement measures, such as the customer engagement rates, the click-through rates, the engagement response rate, and the conversion rate. Making firms better at analyzing customer data, enabling digital interactions to be more personalized, automating processes of engagement, and dynamically responding to customer behavior, AI allows e-commerce firms to deepen and make customer interactions more effective at digital touchpoints.

These findings are important not only because they prove the positive relation between AI and customer engagement. Customer engagement is a key source of sustainable competitive advantage in the very competitive and rapidly changing digital markets. The findings show that AI is not only a supportive technology, but it is also a strategic ability that enables businesses to intuit customer demands, capture engagement, and re-architect the digital marketing procedures according to the Dynamic Capabilities Theory. The use of AI is therefore a strategic requirement as opposed to an optional technological expenditure.

Academically, this research work can be seen as filling an important gap within the body of literature on AI-based customer engagement, specifically in new e-commerce markets. It builds on this conceptual and bibliographic pre-existing research by offering firm-level, quantitative data on the effect of AI on various aspects of engagement as a part of a single analytical framework. To practitioners, the results provide solid reasoning on why companies should invest in AI-based engagement tools since the results indicate that investments lead to visible customer interaction and conversion performances. To the policymakers, the findings help highlight the importance of AI in promoting more interactive, efficient, and competitive digital marketplaces to achieve wider policy goals of digital transformation and economic development.

This study reveals that artificial intelligence is technically redefining the way e-commerce companies interact with customers, and the impact of this is reflected in theory-building, managerial decision-making, and the development of national digital economies. Through empirical correlation of AI adoption to improved customer engagement performance, the study indicates the transformational character of AI in changing the dynamics of customer-firm relationships in modern e-commerce settings.

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