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The Impact of Artificial Intelligence oOn Sales Performance in Indian E-Commerce Companies: A Dynamic Capabilities Perspective

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Abstract
This paper examines how Artificial Intelligence (AI) impacts sales performance, as measured by sales volume and growth rates, across five Indian e-commerce firms. The study builds on the Dynamic Capabilities Theory to conceptualize AI as a strategic capability that can strengthen firms' capacity to sense market trends, capture commercial opportunities, and restructure internal processes to improve performance outcomes. Based on secondary quantitative data from the annual reports of the selected companies, the study uses a set of preliminary statistical tests before conducting regression analysis to examine relationships among the variables. The empirical results show that adopting AI has a substantial, statistically significant positive impact on sales volume, indicating that AI-based personalization, targeting, and operational efficiency directly drive increased transactional output. Also, AI shows a substantial but comparatively small positive influence on sales growth rates, implying that, although AI can improve performance in the long term, the growth trends are still determined by the overall market and strategic variables. The findings provide strong support for the argument that AI is a transformative force in digital commerce. The research contributes to the current literature by providing empirical confirmation of the commercial impact of AI in an emerging-market setting and offering managers a practical understanding to justify investment in AI-based systems. By doing so, it implies the strategic value of AI in ensuring competitiveness and sustainable growth in the fast-changing digital markets.

Keywords: Artificial intelligence, sales performance, e-commerce, sales volume, sales growth rate, dynamic capabilities theory, India.

INTRODUCTION

India has experienced a tremendous economic and digital revolution over the recent years; this is evident through the growth of its e-commerce industry (Kolluru et al., 2025). The prevalence of internet services, the high rate of smartphone users, and the introduction of digital payment systems have all led to a boom in online shopping (Ansari et al., 2025). Some companies in India have already become the leaders in the Indian e-commerce industry, which is why the specified sector is one of the most competitive and fastest-growing in Asia.
In the face of this rising competition, businesses have been seeking tools and technologies to enhance

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performance and drive expansion. Among the most significant inventions that have transformed e-commerce is Artificial Intelligence (AI). Its use has become a necessary component of e-commerce operations, including first recommendation systems that propose relevant products to users (Xu et al., 2025). Second, anticipatory analytics that are predictive of customer behavior (GhorbanTanhaei et al., 2024). Third, chatbots as a means of instant support (Vashishth et al., 2024). Fourth, dynamic pricing systems based on facts (Najafabadi et al., 2022). AI, with the help of these applications, has become a key component of the online experience and a promising means of expanding the sales field and enhancing the conversion rates.

This context provides the natural environment from which the study originates, highlighting the importance of understanding the factors that influence the performance of companies operating in the Indian digital market.

Although AI is widely used in e-commerce firms, the literature in the field identifies a clear gap in studies that quantitatively and causally determine the effects of AI on sales. The majority of existing research focuses on descriptive aspects of AI use (Dosovitsky et al., 2020; El Yaccoubi et al., 2025), limited case studies (Rong et al., 2020), and a theoretical discussion without statistical testing. This leaves a crucial question unanswered: Does AI actually lead to increased sales volume and sales growth rate? This research gap necessitates a scientific analysis based on quantitative data to understand the relationship between AI and sales.

Given the gap outlined above, this study will conduct a scientific examination to quantify AI's influence on sales in the selected Indian e-commerce firms: Nykaa, Reliance Digital, Info Edge, Amazon India, and Zomato. The study aims to measure the impact of artificial intelligence on sales volume in selected e-commerce companies in India. So, it is essential to determine two critical relationships: the impact of AI on sales volume and on sales growth rates. Furthermore, to meet this research objective, this study employs a multivariate causal model to test the formulated research hypotheses. In this way, the research makes a new contribution to the field of AI impact analysis, both theoretically and practically.

Many companies believe that investing in AI tools will automatically increase sales. Yet, such an assumption is not always supported by precise quantitative data. The effects of AI depend on the nature of the company, the degree of implementation, the market type, and the marketing processes used.

On the other hand, the literature shows that no studies have directly investigated this relationship, particularly in the fast-growing Indian market. Thus, the research problem is as follows: To what extent does artificial intelligence affect sales volume and sales growth rates in Indian e-commerce companies?

The research questions stem from the research problem, as follows:

what is the impact of AI on sales volume in Indian e-commerce companies?

What is the impact of AI on sales growth rates in Indian e-commerce companies?

The null hypotheses in this study test the relationship between sales performance indicators and the adoption of AI technologies by Indian e-commerce firms. The null hypotheses chosen are consistent with the statistical analysis methodology that involves testing the presence or absence of a significant effect at the level ($\alpha \leq 0.05$). Through testing these hypotheses, the research will be used to find out whether the application of AI indeed leads to an increase in sales volume or growth rate, or whether the impact is ambiguous or statistically constrained.

The importance of this study lies at two levels: First, scientifically, it addresses a clear gap in the literature on AI's influence on sales. It offers a causal model that other researchers can use in their studies. It helps to build knowledge regarding the role of AI in new digital markets. Second, in practice, it allows firms to

make the right decisions about investing in AI technologies. It identifies AI applications linked to higher sales volume and growth. It improves companies' ability to manage their marketing processes with data.
To provide an accurate analysis, the study has several limitations: (1) The study focuses only on e-commerce firms in India. (2) It is limited to the impact of AI on sales volume and growth only, excluding other indicators such as customer satisfaction or operational efficiency. (3) The analysis is based on the annual reports of the selected companies from 2019 to 2024, as this was the period of the Indian e-commerce boom.

Literature Review

A massive rise in the usage of AI technologies in the e-commerce industry has marked the last few years. These technologies have now become a critical component of the digital infrastructure on which companies depend to analyze data, understand consumer behavior, and improve marketing performance. Recent research has examined this transition in various ways, with interest in the effects of AI on consumer behavior and on the outputs of business processes, especially sales. Madanchian (2024) overall review of the research found that the use of AI applications, including automated personalization, recommendation engines, and predictive analytics, is an effective way to enhance conversion rates and sales opportunities on e-commerce sites. The study's analysis of 50 papers published in the Scopus database showed that companies that invest in AI achieve better marketing performance than those that use traditional approaches.
Equally, a recent Indian study by Kumawat and Mathur (2025) found that AI-based personalization is among the most critical factors in consumer purchasing behavior. The researchers used a regression model and analyzed data from a sample of consumers in the Indian market and found that AI-driven personalization increases purchase intent and the likelihood of purchase. It proves that the role of AI is more than mere enhancement of the user experience; it directly affects purchasing behavior, which in turn affects sales volumes.
Another study by Singh et al. (2024) provides a comparative analysis of the performance of e-commerce companies before and after the implementation of AI technologies. The findings indicated that sales growth had increased significantly since the introduction of AI solutions, such as product recommendations, campaign management, and user interface optimization. This paper is particularly applicable, as it focuses on the Indian market and draws on actual company information, making it one of the most relevant studies to the present study topic.
These results support the work of Chugh and Jain (2024), who discussed the strategic role of AI in reshaping business processes, particularly in e-marketing. They indicated that AI is not an add-on to technology but a competitive requirement, as it enables corporations to improve operational efficiency and boost sales by accurately forecasting customer needs and providing personalized solutions.
Similarly, in an Indian context, Dixit et al. (2025) examined the effects of AI technologies on purchase intention and consumer behavior in the Delhi-NCR region using structural equation modeling. Their results revealed that companies' use of AI tools, especially predictive analytics and user interactions, increases interest in the online platform and boosts the likelihood of purchase. Even though the paper pays more attention to purchasing behavior than to sales data, it presents systematic evidence of AI's potential to alter the initial phases of the buying process, which ultimately results in higher sales.
On a broader scale, Lari et al. (2022) examined the various uses of AI in e-commerce. They observed that these uses extend beyond customer interaction to encompass inventory management, demand forecasting,

and process planning. Although the paper is focused on operational matters, it shows that implementing AI in digital marketing initiatives will improve the company's overall performance, aligning with the hypothesis that AI will have a positive effect on sales indicators.

The analysis of the existing literature shows that modern literature is inclined to focus on the prominent role of AI in increasing the marketing and sales indicators. Nevertheless, one of the most essential points to note is that there is limited research offering direct quantitative results on the effect of AI on sales volume and growth, especially in the context of India. This research gap shows that there is a lack of studies in quantitative data and robust causal designs to investigate the association between AI applications and sales, which the current research will attempt to address.

Rationale and Research Hypotheses

The current study is based on the Dynamic Capabilities Theory (DCT), developed by Teece et al. (1997), which states that a company's superiority and performance are not determined solely by its ownership of resources but also by its ability to identify and capture market opportunities and to redefine its resources to match the rapidly emerging new business environment (Bleady et al., 2018). AI is a strategic dynamic capability in the digital transformation context that allows e-commerce organizations to study the demand, learn the consumer behaviour, make sound pricing decisions, automate sales, and react to the market changes more quickly (Teece, 2018). In line with that, the study indicates that the direct adoption of AI will lead to increased sales volume and sustainable growth by enhancing a company's responsiveness and competitiveness in digital markets.

The DCT emphasizes a company's capacity to integrate, build, and redesign internal and external resources in a fast-evolving environment (Teece et al., 1997). According to the theory, a firm's competitive advantage is based on its ability to identify market opportunities, capture them, and reallocate its resources in response to a changing environment. The DCT offers a valuable framework for understanding digital transformation in enterprises that improve sales performance through the use of AI (Helfat et al., 2007).

To start with, being a new digital technology, AI adoption is essentially how companies view and seize digital opportunities in the market. The companies should properly assess market trends, consumer behavior patterns, and the potential of AI technologies, and make relevant adoption decisions based on their strategic and operational circumstances (Gao et al., 2025). This is very much aligned with the sensing ability emphasized in the DCT. Second, the successful implementation of AI technologies presupposes that enterprises will have to restructure their current organizational processes and business models. Companies need to modify their business models, acquire digital and analytical capabilities, and redesign their technical architecture. This reconfiguration is a reconfiguring ability in the DCT. With such reconfiguration, businesses will be able to connect AI technology to their current marketing and sales resources, thereby directly boosting their sales capabilities and ensuring continued sales growth (Almheiri et al., 2025).

In this regard, based on the DCT, AI can be viewed as a strategic digital capability that helps companies to react better to market demand, to optimize their sales process, customize the offerings of their customers, and to enhance the activities that generate revenue in dynamic e-commerce settings.

Conceptual Framework

The above theoretical arguments constitute a direct theoretical model for this study, grounded in dynamic capabilities theory. The model, as shown in Figure 1, demonstrates the direct impact of AI adoption on sales performance, measured by sales volume and sales growth rates, in Indian e-commerce companies. In particular, AI adoption is an indicator of the capability of firms to recognize and exploit the technological and market opportunities and redesign their sales and marketing resources by using smart data processing, autonomous decision-making, customer targeting, and price optimization. These abilities eventually increase sales levels and sales growth.

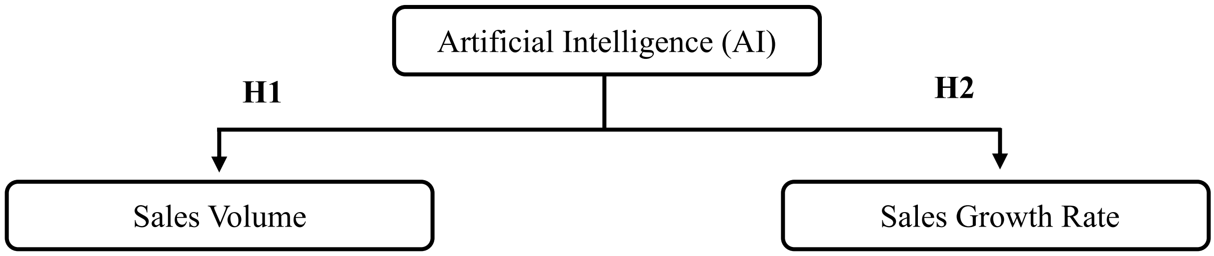

Figure 1: Conceptual framework of the impact of AI on sales performance

Research Hypotheses

According to the DCT, the adoption of AI indicates a business organization's capacity to recognize and exploit technological opportunities and convert them into high-quality sales results. Artificial intelligence is vital in improving sales performance in the following ways. To begin with, AI greatly enhances firms' data processing and analytical capabilities, enabling more accurate identification of market demand and customer buying behavior. Second, AI helps automate and improve the efficiency of sales and marketing activities, enhancing transaction speed, conversion rates, and overall sales volume. Third, the use of AI enhances firms' competitive advantage in the digital market and supports sustainable revenue growth.

In line with the objectives of this study and its null-hypothesis testing approach, the following research hypotheses are formulated:

H1: There is no statistically significant impact at the significance level ($\alpha \leq 0.05$) of artificial intelligence on sales volume in e-commerce companies in India.

Furthermore, DCT also supports the examination of performance over time. Through continuous data-driven decision-making, demand forecasting, and personalized marketing enabled by artificial intelligence, firms are expected to improve their ability to sustain revenue growth. Therefore, this study also proposes:

H2: There is no statistically significant impact at the significance level ($\alpha \leq 0.05$) of artificial intelligence on sales growth rates in e-commerce companies in India.

Research Methodology

The study's analytical methodology is a quantitative analysis of secondary data gathered (Alasuutari et al., 2008) from annual reports and financial statements of five major Indian e-commerce organizations: Nykaa, Reliance Retail/Reliance Digital, Info Edge, Amazon India, and Zomato. The methodological design is based on a causal model that quantifies the effect of AI implementation (Joshi et al., 2025) on the sales performance of these companies, measured by sales volume and sales growth rates from 2019 to 2024. The design is appropriate given the study's panel data and focus on the company's behavior over several years, which allows us to see how sales performance changes with increasing AI adoption.

The methodology will be based on DCT, which holds that a company's capacity to identify, exploit, and refocus its resources and strategies is the key to attaining a competitive edge and enhancing performance.

In that regard, the adoption of AI can be seen as an evolving strategic capability, which can help the business redefine its sales process, become more responsive to the market, and increase its capacity to analyze data and tailor the consumer experience. The theory can therefore be a strong tool for explaining AI's influence on sales development in the short and medium term, which is more than adequate for the goals of this study.

The study's sample comprises e-commerce firms with a clear level of digital transformation and financial disclosure. The study, however, is not intended to cover all firms in the industry. Instead, it will concentrate on five highly transparent companies, report on their operations, and state that they depend on AI technologies in their marketing and operational decisions. Purposive sampling was used to select these companies that had regular annual financial statements (Campbell et al., 2020), covered operational performance in detail, and indicated in their reports that they used AI-based solutions, e.g., recommendation systems, predictive analytics, or customer targeting models.

This study is based solely on secondary data, with annual reports as the primary source (Ahmed, 2009) for both sales volume (the revenue of the company for its e-commerce operations or online services) and sales growth rates (the change in revenue per year) (Varian, 1980). Narrative disclosures on digital strategies, AI initiatives, and the extent to which the technologies are involved in the company's operations or marketing processes are also presented in annual reports. These announcements are employed to create an AI adoption index by assessing the content and identifying the level of attention to innovative technologies and the volume of announced digital investments.

Following data extraction, a longitudinal database is created that includes independent and dependent variables for each company and year in the given period. The analysis will start with a description of the variables and proceed to the primary relationships between AI adoption and sales testing using correlation coefficients. Causal impact is then measured by using panel regression models. To test the suitability of fixed- or random-effects models, tests such as the Hausman test are conducted to ensure the most suitable model is selected. In this way, it is possible to separate the effect of the company-specific factor from the impact of changes in the company over time, yielding a more precise estimate of how AI will influence sales performance.

The level of significance used in testing the hypothesis is 0.05. If the regression coefficients indicate that AI adoption significantly affects sales volume or sales growth, then the null hypothesis (no effect) is rejected. This process is consistent with past research that used secondary data to gauge the impact of digital transformation or technological innovation on financial performance, which supports the feasibility of longitudinal regression models for studying causal relationships in this context.

The research has noted a range of methodological weaknesses, the most prominent of which is the inconsistency in the amount of AI disclosure across companies and in the details presented in the annual reports. Moreover, the AI adoption index can be partially subjective, despite efforts to reduce this bias through clear, consistent coding criteria. Nevertheless, yearly data is a valuable and widely used source in scholarly research on companies' performance over time.

Results

This section presents the empirical results of the research, based on statistical analyses of data gathered from sampled Indian e-commerce firms. It starts with a set of preliminary statistical tests. Subsequently, the descriptive analysis will provide a summary of sales performance before and after AI implementation. The last subsection of the section presents the inferential analysis, in which the two primary hypotheses are verified using regression models to estimate the effects of AI on sales volume and sales growth rates.

Preliminary Statistical Tests

The panel data models presuppose a set of initial statistical tests to confirm the validity of the data and the validity of the assumptions underlying the estimation of the study's hypotheses. These tests are used to investigate the character of the relationships between the variables, to check the stability of the time-series components, to check whether there is no autocorrelation in the residuals, and to check whether the data are typically distributed. The importance of these examinations is to ensure that statistical estimates are accurate and reliable, as they determine which model is most suitable and help prevent problems related to linear analysis of longitudinal data. This section provides a detailed outline of the preliminary test results before estimating the regression models and testing the study's hypotheses.

Analysis of Correlations between Variables

The purpose of this section is to analyze the strength and the direction of the central relationship between the three study variables: AI adoption, sales volume, and the sales growth rate. Table 1 shows the linear relationship between the variables using the Pearson correlation coefficient (r).

Table 1: Pearson correlation coefficient values between study variables

Variable	Use of AI	Sales Volume	Sales growth rate
Use of AI	1.000		
Sales Volume	0.175	1.000	
Sales growth rate	0.031	0.230	1.000

The correlation analysis results indicate that the relationships between AI adoption and sales volume and sales growth rate are very weak. The correlation coefficient between the adoption of AI and sales volume ($r = 0.175$) is low and not enough to show a strong or even moderate correlation between the two variables. This implies that merely adopting AI applications in these firms is not directly or strongly associated with sales during the study period.

This correlation between AI adoption and the sales growth rate was significantly lower ($r = 0.031$), which is near zero, and this means that there is a near-zero linear relationship between the two variables. It implies that the rate of AI adoption by organizations does not always indicate a positive change in the annual growth rate of sales.

Regarding the correlation between sales volume and sales growth, the coefficient ($r = 0.230$) was low but higher than the correlation between AI and other factors. This indicates that sales growth might improve with increased sales volume, but the association is not strong enough to be statistically significant.

Testing the Stability of the Study Variables' Data

The unit root test is an effort to determine whether the time series of variables to be included in the regression analysis are stable before incorporation into the model. This is necessary to verify the validity of the results, because when variables are unstable, spurious regression is often used. The results of the stability test for AI usage, sales volume, and sales growth rate are shown in Table 2.

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

Sales Volume	- 45.645	0.000	Stable at the level after taking the first difference
Sales Growth Rate	-2.518	0.122	Stable at the level after taking the first difference

The findings suggest that the variable of AI usage is at the first level, and the calculated value of -4.044 is significant in terms of power and correlated with a significant value of P = 0.005, which is lower than the significance level used in this study (α = 0.05). This means that the unit root hypothesis is rejected, and thus, the AI usage data does not have the instability and it can be directly added to the regression model without considering the differences.
The sales volume variable, however, was not stable at the first stage, with a calculated value of -45.645, which is highly significant (P = 0.000). Even though the value indicates good stability, the nature of this test and the fluctuations in the financial series imply that the final decision is subject to the series' actions. The values showed that the stability was realized upon taking the first difference. This means that the data on sales volumes was not suitable for analysis at first. Still, it became ideal after being transformed into first differences, which is usually done for revenue and sales series that are highly prone to seasonal changes and other operational factors.
As to the sales growth rate variable, it was also unstable at that level, with a calculated value of -2.518 and a p-value of 0.122, which is greater than the level of significance of 0.05, indicating that the one-root hypothesis could not be rejected. Nevertheless, the series was stabilized by taking first differences, and the variable was therefore considered suitable for the statistical model. This is typical of growth rate variables, as they are affected by past values and subject to natural oscillations over time.
These findings indicate that the data model uses both at-level stable variables (use of AI) and variables that require first-difference transformation (sales volume and sales growth rate). This method aligns with the needs of time-series analysis in panel models and improves the accuracy of the final findings. In addition, the lack of significant change after transformation indicates that the model correctly captures the relationship between AI use and sales performance indicators, without being skewed by long-term trends or statistical distortions.
This is a crucial step before engaging in regression analysis, since it will be used to determine whether there is a single root problem that may affect the model's validity and yield false results. This makes all the variables now stable at the level. After transformation, the basic statistical requirements of estimating the causal model have been satisfied, and the H1 and H2 hypotheses can be tested using relevant regression models.

Autocorrelation Test

The Durbin-Watson (D-W) coefficient is used to test the hypothesis of autocorrelated errors in a regression model with time. The test is required in panel data research, as current values may be affected by past residual errors, leading to biased or misleading estimates if not addressed. The Durbin-Watson coefficient results are presented in Table 3 for both study hypotheses.

Table 3: Values of the (D-W) coefficient for the study hypotheses

Hypothesis	D-W coefficient value	Result
H1	1.831	No autocorrelation
H2	1.763	No autocorrelation

The results indicate that the Durbin–Watson coefficient for the H1 hypothesis was 1.831, a value within the statistically acceptable range (1.5–2.5). This demonstrates the absence of autocorrelation in the residuals of the regression model for the impact of artificial intelligence on sales volume. This means that the residual errors are independent across time periods, a prerequisite for the model's validity and for unbiased estimates.

For hypothesis H2, the Durbin-Watson statistic was 1.763, which falls within the acceptable range and indicates the absence of autocorrelation in the AI-driven sales growth model. This result suggests that changes in the growth rate are not dependent on residuals from previous years, thus strengthening the model's robustness and supporting the reliability of its subsequent results.

These findings indicate that the regression models used to test hypotheses H1 and H2 satisfy one of the most critical classical assumptions of linear regression: the independence of errors. This is necessary to ensure that regression estimates are not affected by time trends in the data, which could lead to misinterpretation of the relationship between the variables.

In addition, there is no autocorrelation; this means that the data, having undergone processing (both at the level and by first differences), are ideally suited to building a stable regression model, and the results obtained in the following section, when verifying the hypotheses, will be more stable and general.

These findings also demonstrate the usefulness of integrating the three variables into the longitudinal data model, without the need for special corrective models such as AR or GLS, to simplify the analysis and make OLS or Fixed/Random Effects models statistically suitable.

Normal Distribution Test

The Jarque-Bera (JB) test is one of the most widely used tests for assessing whether variables are normally distributed. This is a condition that helps determine the appropriateness of data for regression models, particularly when conducting a study based on financial or time-series data. This test is based on the concepts of skewness and kurtosis, and its interpretation is based on a p-value of 0.05. The JB test results are presented in Table 4, along with the three variables of the study.

Table 4: Jarque-Bera test for normal distribution

Variable	Jarque-Bera	P-value
Use of AI	**8.160**	**0.017**
Sales Volume	**16.935**	**0.000**
Sales Growth Rate	**4.429**	**0.109**

The test results indicate that the variable for AI use is not normally distributed. The JB value (JB = 8.160) has a p-value of 0.017, which is lower than the required significance level of 0.05; therefore, the test rejects the hypothesis of normality. It means that data on AI usage can include distributional variations due to differences across firms or yearly variations in the extent of use of innovative technologies.

Similarly, the sales volume variable yielded an abnormal result, with a JB value of 16.935 and a significance level (P = 0.000) significantly lower than 0.05. This is a common finding for financial variables that are influenced by market and competitive factors and large revenue fluctuations, making a normal distribution less likely in raw sales data.

The sales growth rate variable, however, had a different behavior, where JB = 4.429, and the level of significance (P = 0.109) was higher than the level of significance (0.05). Hence, the null hypothesis of normality is not rejected. Consequently, the rate of sales growth is the only variable in the research based on a model more inclined to a normal distribution.

These findings show that two of the primary variables in the research (AI usage and sales volume) are not normally distributed, unlike in studies that use secondary data and time-series data. The statistical models used in syllabus data analysis, especially regression models, do not necessarily assume that all independent variables are normally distributed. All they need is the model residuals to be normal or close to normal. Moreover, the sample size and the variation in data across companies and years contribute to reducing the effects of non-normality on model estimates.

Also, stability, which follows the previous transformations (the first differences of some variables), reduces distributional skewness, thereby increasing the validity of longitudinal regression models for hypothesis testing.

Estimation of study models

Panel data models require determining the most appropriate formula for representing the relationship between variables, whether using a fixed effects model or a random effects model. The selection of the appropriate model depends on a set of statistical tests, the most important of which are the Lagrange Multiplier Test (LMT) to determine the superiority of the pooled OLS model over the random effects model, and the Hausman test to differentiate between the fixed and random effects models. Table 5 presents the results of these tests for both study hypotheses.

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	47.598	0.000	6.803	0.009	Fixed Effect Model
H2	19.373	0.036	0.031	0.860	Random Effect Model

The results of the Lagrange Multiplier Test for hypothesis H1 indicate a value of (χ^2 = 47.598) with a statistical significance of (Sig = 0.000), which means rejecting the pooled OLS model and confirming the suitability of one of the panel data models (fixed or random effects). Moving on to the Hausman test, the value (χ^2 = 6.803) with a significance level (Sig = 0.009) was less than the significance level (0.05), indicating a preference for the Fixed Effects Model for the H1 hypothesis. This decision indicates that variations among the five businesses are not arbitrary but are associated with consistent and strong patterns in the correlation between AI application and sales volume, as the Fixed Effects Model is more precise and stable in estimating regression coefficients.

As for the H2 hypothesis, the Lagrange Multiplier test showed a value (χ^2 = 19.373) with a significance level (Sig = 0.036), also indicating that the clustering model is unsuitable and that a Panel data model should be used. However, unlike the first hypothesis, the Hausman test yielded a value (χ^2 = 0.031) with a significance level (Sig = 0.860), which is significantly higher than the significance level, indicating no systematic differences between the two models. Thus, the most appropriate model for the H2 hypothesis is the Random Effects Model (REM), which is more effective and is not affected by the correlation between the company constants and the independent variable. It implies that the differences in sales growth rates among companies are random and unrelated to the extent of AI adoption.

These findings indicate that the relationship between AI use and sales differs across performance indicators. Although the fixed nature of each company (size, scale, and market power) determines sales volume, the rates of sales growth do not seem to depend on these characteristics; instead, they are more directly correlated with market shifts and random fluctuations over time. This explains why two models should be used to test the two hypotheses and determine the accuracy and reliability of the statistical estimates for each relationship.

This decision also shows that the study was conducted according to the conventional methodology of Panel data studies, with the model selected based on objective tests rather than a priori assumptions. Thus, the adopted models, the fixed effects model of H1 and the random effects model of H2, give a solid foundation to proceed to the regression analysis and testing of the hypotheses.

Descriptive Analysis

The comparative analysis of AI adoption trends reveals strategic differences among the five companies by identifying the key areas where AI is concentrated within each. Table 6 summarizes these differences, helping to explain the potential variation in AI's impact on sales performance metrics in the study.

Table 6: Description of the application of AI in e-commerce companies in India

Company	Date Applying AI in Sales	Key AI Techniques for Targeting	AI Tools for Cost Reduction	AI Tools for Enhancing Engagement
Reliance Industries	October 2021	Haptik Interakt (AI chat/targeting), IntellAct (customer behavior analytics)	NVIDIA-powered data centres, Jio Brain, Radisys AI hardware	Bharat-GPT, Addverb Robotics (automation)
Amazon India	March 2019	Amazon SageMaker (ML models), Bedrock Generative AI, Amazon Ads AI Targeting	AWS Cost Optimization AI, SageMaker Autopilot, Logistics Intelligence	Inspire AI Ads, Personalize API, Amazon Lex
Info Edge (Naukri, Jeevansathi)	March 2019	ML-based recommendation engines, Talent Pulse, Haptik AI chat systems	Predictive analytics for operations, AI search optimization, ML-driven profiling	NaukriAIQ Chatbots, Generative AI for user experience
Zomato (Eternal Ltd.)	September 2019	ML Recommender Engine, Geo-targeted AI ads, Zomato AI Chatbot	AI tools for route optimization, AWS Graviton cost-efficient infra, inventory forecasting AI	Nugget AI Support, Smart Notifications, AR Food Display
Nykaa	April 2019	Criteo Dynamic Retargeting, ModiFace AR Try-On, Google Performance Max AI targeting	AWS + Data Lake forecasting models, Smart catalogue ML, warehouse optimization AI	AR Virtual Try-On, Verloop.io AI Chatbot, Smart Ads

The analysis of AI applications across the five selected companies reveals a clear disparity in their digital maturity levels, technology adoption goals, and analytical architecture. The table shows that all companies leverage AI in the three key areas: targeting, cost reduction, and engagement enhancement. However, each company possesses a distinct strategic approach tied to its business nature and competitive position within the Indian market.

Reliance Industries (RIL) shows interest in creating an all-encompassing local technology platform, founded on NVIDIA-powered data centres, the Jio Brain platform, and robotics such as Addverb. This strategy suggests that Reliance does not focus on sophisticated marketing solutions, but on infrastructure and operational capabilities. The company also employs tools such as Haptik and IntellAct to target, which is also a strategy for integrating AI into its vast and diverse sales network.

Amazon India is the most developed in terms of analytics depth and application range. Its reliance on Amazon SageMaker and Bedrock makes it the leader in AI applications, with firms using it to deliver real-time personalisation and predictive behaviour. Another strategy Amazon pursues is high-impact cost-cutting tools, including AWS Cost Optimisation and Logistics Intelligence, an integrated model of operational efficiency and marketing driven by algorithms. The use of engagement-driven tools such as Inspire and Personalise further emphasises the role of AI in customer engagement and higher conversion rates.

In the case of Info Edge, especially in its Naukri and Jeevansathi services, AI is clearly applied to enhance matching between customers and jobs/services, using recommendation algorithms and intelligent search engines. In contrast to Amazon or Reliance, Info Edge is more focused on improving data quality and search than on logistics or robotics. Tools such as Talent Pulse and Naukri AIQ operate in the digital space, where machine learning can be used to define preferences and professional behaviour with precision, and AI can cut costs through enhanced search and processing efficiency.

Zomato incorporates AI into a business process that is highly dependent on speed and flexibility in delivery service. This includes built-in recommendation systems (ML Recommender), the Nugget customer support robot, and route optimisation and logistics cost-reduction systems. Zomato seems to be using AI to improve its delivery service, customise the customer experience, manage inventory, and anticipate demand, which is a practical approach to its business model in the food industry, where buying decisions are fast, and interaction is essential.

In the case of Nykaa, the use of technologies such as ModiFace AR and Criteo Dynamic Retargeting shows that it prioritises integrating digital aesthetics into interactive experiences, particularly in product demonstrations using augmented reality. Nykaa has been applying AI extensively to target and personalise advertising content, with a focus on tools that increase purchase intent, including augmented reality experiences and AI-enhanced visual content. It also uses predictive inventory and supply chain management models to minimise operational costs.

Table 7: Description of sales in e-commerce companies in India

Measure	Before Applying AI		After Applying AI		Total	
	Sales Volume	Sales Growt	Sales Volume	Sales Growt	Sales Volume	Sales Growth
Arithmetic Mean	741,756,357.776	0.226	930,673,589.287	0.350	886,592,901.935	0.321
Standard Deviation	981,899,776.139	0.103	2,080,814,468.303	0.233	1,868,353,992.412	0.215
Minimum Value	1,324,143	0.030	7,716,983	0.080	1,324,143	0.030
Maximum Value	2,590,414,985	0.309	6,659,153,020	0.900	6,659,153,020	0.900

Observations	7	23	30

Table 7 presents the statistical analysis of e-commerce sales volume and growth rate in India before and after the introduction of AI technologies. This assists in assessing the overall development of sales performance during the study period.

The results indicate a significant increase in average sales volume after the implementation of artificial intelligence (AI). The arithmetic mean rose from 741,756,357.8 before implementation to 930,673,589.3 afterward. This increase reflects the enhanced ability of companies to achieve higher sales volumes during the period of greater integration of analytical algorithms and intelligent recommendations. Furthermore, the standard deviation nearly doubled after implementation, indicating greater variability in sales volume among companies, which may be attributed to varying levels of investment in AI. The minimum and maximum sales figures also increased after implementation (from 1.3 million to 2.59 billion before to 7.7 million to 6.65 billion after), indicating a broader expansion of sales across all companies.

Regarding sales growth, the average growth rate was 0.226 before implementation and 0.350 after, indicating that companies experienced higher growth after embracing AI. The highest growth limit also rose by 0.309 to 0.900, a significant increase that suggests some companies may experience a sharp rise in growth once they apply AI tools to target and enhance operational effectiveness. Nevertheless, the standard deviation also rose, from 0.103 to 0.233, and the increased variation in companies' growth rates is characteristic of an environment with varying degrees of digital maturity.

Altogether, the descriptive indicators indicate that AI was associated with increases in both average sales volume and average sales growth rate. Furthermore, the discrepancies among the company's post-implementation were more noticeable, as each company was more or less invested in implementing AI tools.

Inferential Analysis

This subsection tests the proposed research hypothesis

Testing the First Hypothesis

Table 8 presents the findings from a regression model estimating the effect of AI applications on sales volume in Indian e-commerce businesses. To examine the impact of artificial intelligence on sales volume, the following linear regression model was estimated:

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

After estimation, the regression equation took the following form:

$$SV = 19.016 + 0.474AI + e$$

This indicates that a one-unit increase in the use of AI leads to an increase of 0.474 units in sales volume, holding other factors constant.

Table 8: Results of testing the impact of AI on sales volume

Variable	B	Std.Error	T-statistic	Prob
AI	0.474	0.067	7.098	0.000
C	19.016	0.115	165.249	0.000
R^2			0.235	

Adj.R^2	0.208
S.E. regression	0.989
F-statistic	8.624
ProbF-statistic	0.007

The results show that the regression coefficient of the AI variable was B = 0.474 with a standard error of 0.067. The t-statistic was 7.098, with a p-value of 0.000, which is very low compared to the level of significance (a = 0.05). It is a clear indication that AI has a substantial impact on sales volume. This coefficient is understood to imply that, as far as the model is concerned, an increase in the level of AI use by one unit increases the sales volume by 0.474 units, which is a positive and statistically significant effect. The model constant (C) was 19.016, and the significance value was 0.000, indicating that the model has a statistically significant intercept even when the effect of AI is absent.

The coefficient of determination (R^2) of 0.235 indicates that the regression model accounts for about 23.5 percent of the variation in companies' sales volumes across years. This is not a large percentage, but it is reasonable in the context of research on digital markets, which are characterized by numerous external factors (price, competition, segments, promotion, and seasons), and the shift cannot be explained solely by artificial intelligence.

Based on the F-value of 8.624 and its associated p-value (Prob(F)) of 0.007, the entire model is statistically significant. This implies that the independent variable (the use of artificial intelligence) accounts for a substantial change in sales volume, and that the model is a valid predictor.

Based on the low P-value (0.000) and large F-value (0.007), the null hypothesis H1, which implies the impact of artificial intelligence on sales volume is insignificant, is rejected. The findings support the positive, significant impact of AI technologies on sales volume among Indian e-commerce firms.

Testing the Second Hypothesis

The regression results for testing the effects of AI on sales growth rates in Indian e-commerce firms are presented in Table 9. The model demonstrates that AI has a substantial impact on growth rates, yet less than on sales volume. To measure the impact of artificial intelligence on the sales growth rate, the following linear regression model was formulated:

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

After estimation, the regression equation took the following form:

$$SGR = 0.344 + 0.024AI + e$$

This equation indicates that a one-unit increase in the use of AI results in an increase of 0.024 units in the sales growth rate, holding other factors constant.

Table 9: Results of testing the impact of AI on the sales growth rate

Variable	**B**	**Std.Error**	**T-statistic**	**Prob**
AI	0.024	0.008	3.022	0.005
C	0.344	0.008	42.851	0.000
R^2			0.145	
Adj.R^2			0.115	

S.E. regression	1.025
F-statistic	4.751
ProbF-statistic	0.038

The findings show that the regression coefficient for the AI variable was B = 0.024, with a standard error of 0.008. The t-statistic was 3.022, with a p-value of 0.005, which is smaller than the significance level ($\alpha = 0.05$). This is a positive, significant impact of AI on sales growth rates. Though the B value is not very large, it indicates a consistent effect: the more AI technologies are used, the slower the annual growth rate increases.

Constant C = 0.344 was highly significant ($p = 0.000$), indicating that the rate of sales growth, even in the absence of AI, is 0.344, which is expansionary in nature for the market at the time of the study.

The coefficient of determination (R^2) of 0.145 indicates that the regression model accounts for about 14.5% of the variation in sales growth rates. Although this is not a high percentage, it is common in growth analyses, as growth rates are determined by factors such as market conditions, competition, regulatory changes, and operational decisions—the adjusted coefficient of determination-Adj. R^2- 0.115 further validates the appropriateness of the model, and the fact that there is an explanatory relationship, though of a small degree.

The F-statistic of 4.751 and the p-value of 0.038 indicate that the entire model is statistically significant. This implies that AI's contribution to the change in the sales growth rate is statistically significant, and that the model can be used to make predictions.

Based on the statistical results, especially the p-value of 0.005 and the positive regression coefficient, the null hypothesis (H2), that AI does not have a significant impact on sales growth rate, is rejected. The findings show that there is a statistically significant, though slow, positive impact, linked to the fact that companies' dependence on artificial intelligence drives long-term sales growth.

Discussion

The study used a set of pretests to assess the validity and reliability of the estimated models before interpreting the regression results. The correlation test proved that there was no multicollinearity between variables, and the unit-root tests proved that the data were stable enough to proceed with the regression analysis after proper differentiating where needed. The outcome of the Durbin-Watson test showed that there was no autocorrelation, and the Jarque-Bera test confirmed that the variables had a reasonable amount of normality. Moreover, the Lagrange Multiplier and Hausman tests were used to identify the best model specification for each hypothesis. Taken together, these tests support the robustness of the empirical findings and provide reason to believe that the estimated effects of AI on sales volume and sales growth rates are statistically valid and not the result of data or model misspecification.

The findings indicate that the use of artificial intelligence has a statistically significant, positive influence on the sales volume and sales growth rate of Indian e-commerce companies. The results can be compared with previous empirical research that emphasizes the importance of AI-powered analytical and operational functions in enhancing firm performance. For example, Al Khaldy et al. (2023) and Islam et al. (2024) have shown that digital analytics and AI improve marketing outcomes and revenue, further confirming the beneficial impact identified in this research. Likewise, De Fano et al. (2025) affirmed the role of AI-based dynamic capabilities in high-quality financial and digital business performance, which aligns with the evidence presented in the current study, which shows that AI implementation enhances sales volume.

The impact of AI on sales growth, although statistically significant, was relatively small. This is consistent with previous studies, which show that many strategic and environmental factors affect the growth performance of various firms, not just AI (Wamba-Taguimdje et al., 2020). However, Bhuiyan (2024) confirm that AI improves personalization, targeting precision, and customer interaction- all of which would lead to long-term sustainable sales growth.

The results, as explained in the context of the DCT, demonstrate that AI enhances the firm's ability to identify market opportunities through sophisticated data analytics, capture them through automated decision-making and targeted interventions, and reorganize resources through more efficient operational processes. This theoretical congruity is supported by Teece et al. (1997) and Helfat et al. (2007), who underscore that companies that embrace advanced technologies can increase their competitive edge and financial performance.

In this way, the study adds to the existing body of knowledge by empirically demonstrating that AI-based dynamic capabilities are relevant to determining sales performance in the Indian e-commerce industry.

The findings reveal that the impact of AI on the growth rate of sales for Indian e-commerce firms is positive and statistically significant. Even though the effect is not as large as its influence on sales levels, the level of significance indicates that AI is correlated with incremental improvements in year-over-year growth. The results align with previous empirical evidence, demonstrating that AI-enabled analytical and operational functions facilitate progressive performance improvement. Indicatively, Ojeda et al. (2025) indicated that AI enhances responsiveness and decision-making in organizations, allowing companies to seize new opportunities and achieve better performance. On the same note, the study by Rahman (2025) revealed improvements in financial and operational outcomes with the use of analytics-driven capabilities, which aligns with the positive growth effect observed in this research.

The small value of the AI coefficient in the sales growth model is also consistent with prior literature, which reported that growth performance is influenced by a broader set of strategic, competitive, and environmental factors beyond AI alone (Wamba-Taguimdje et al., 2020). However, studies such as Okeke et al. (2024) show that AI drives long-term growth through personalization, targeted accuracy, and customer interaction mechanisms, resulting in slow but sustained sales growth rather than rapid growth (Huang & Rust, 2021).

The results can be interpreted in the framework of the Dynamic Capabilities Theory and indicate that AI contributes to the increased customer trend and market changes sensing capabilities of the firm due to their advanced analytics, the possibility to seize opportunities through the data-driven marketing intervention, and the reorganization of internal processes to enhance efficiency and responsiveness. The capability-enhancing effects are why AI adoption leads to sales growth, though the effect may be moderate. This explanation is consistent with the original statements of Teece et al. (1997) and Helfat et al. (2007), who underline that companies that use advanced digital technologies enhance their ability to adapt, innovate, and achieve long-term performance.

The results of this paper provide an explicit and detailed response to the research questions regarding the effects of AI on sales volume and sales growth rates in Indian e-commerce firms. The empirical evidence indicates that AI adoption has a substantial positive impact on sales volume, suggesting that the application of advanced analytical and automation tools directly increases transactional performance. Moreover, AI was also found to have a statistically significant but less substantial effect on sales growth rate, suggesting that its impact on long-term performance builds gradually over time. Collectively, these results demonstrate that AI improves both short-term sales performance and long-term growth, thereby answering the main research questions.

Conclusion

The study's results show that AI is a highly influential, quantifiable factor in increasing sales volume and sales growth rates among Indian e-commerce companies. Improving the analytical and operational capacities of firms, including targeted marketing, personalized recommendations, and efficient decision-making, AI helps businesses attain greater short-term sales and long-term growth. The significance of these findings is not just to affirm the positive effect of AI but also to demonstrate why this effect is significant. In an extraordinarily competitive, rapidly changing digital market, the use of AI is a strategic requirement, not a technological possibility. To researchers, the research has a significant gap because it provides empirical support for the commercial success of AI; to managers, it offers justification for AI operations that result in concrete performance improvements; and to policymakers, it shows the role of AI in creating a more productive and competitive digital economy. This way, the study will provide an answer to the 'so what?' question. Question by proving that AI is essentially changing the sales performance in such a way that it impacts academic knowledge, business strategy, and national digital development.

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