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The J-Curve of Disruption: A Stochastic Frontier Analysis of AI's Strategic Impact on the Performance of India's Pioneer Banks

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Abstract

Purpose: The basic objective of this study is to assess the impact of Artificial Intelligence (AI) on financial performance. This study examines data from three representative Indian banks over a 15-year period, from 2009 to 2024. It is extremely important for banks and policymakers to understand the impact of Artificial Intelligence (AI) on costs and profitability.

Methods: Two analytical methods were used for this study. The first is the Stochastic Frontier Analysis (SFA), and the second is a fixed-panel regression model.

Results: The results of the SFA are extremely positive, showing that after the adoption of AI, the average cost efficiency of banks increased from 90.6% to 99.9%. This proves that AI plays a vital role in improving banks' internal operations and reducing costs. The Panel Regression Model shows that after controlling for other variables (bank size, CAR), the AI Dummy showed a significant (-0.81, p < 0.001) gain in ROA (profitability).

Originality: This study provides a comprehensive review of AI in the Indian banking sector. This study highlights cost-benefit integration over profit-centric evaluation, emphasizing AI's immediate cost reduction and long-term profitability potential.

Keywords: *Artificial Intelligence (AI), Banking; Cost Efficiency; Profitability; Stochastic Frontier Analysis (SFA), Panel Data Model, Indian Banks.*

JEL Code*: C8; G2; D24; L25; C13; C23; C33; G21*

1. Introduction

1.1 Background

In recent years, technology has revolutionized the global banking sector. The marked title of this revolution is "Digital Transformation", which has completely changed the traditional ways of working of banks (Barroso, M., & Laborda, J. 2022 Priyadarshini, K. V. L., Reddy, M. S., & Reddy, R. S. , 2022, Winarni, R., & Akbar, T. S. W. 2025). This change intensified, particularly in the post-COVID-19 world, driving banks to implement digital innovation to remain feasible in this volatile environment (Herath et al., H. M. W. A., & Gamlath, G. 2024). The main driver of this digital revolution is Artificial Intelligence (AI), which is now considered the foundation of "Banking 4.0" (Kaur, N., Sharma, P., & Singh, R., 2020a, Mhlanga, D. 2020). AI is now being used in every aspect of banks, where its use has become common, from Robotic Process Automation (RPA) to chatbots for customer service and improving management accounting systems (Alnor, N.H.A, 2024, Polireddi, N.S.A 2024). The basic objective of these efforts was to improve the performance of the bank, whether operational or commercial (Dubey, R., Gunasekaran, A., Childe, S. J., Papadopoulos, T., & Roubaud, D., 2021). In 2017, the State Bank of India (SBI), HDFC Bank, and Canara Bank introduced AI tools, which are an important part of the digital transformation of the banking sector. The SBI launched SIA (SBI Intelligent Assistant), which provides instant customer service and handles daily banking queries, making customer support fast and accessible. HDFC Bank introduced an Electronic Virtual Assistant (EVA), which answers customer questions based on natural language processing; this reduces response time and the load on human staff. Canara Bank launched two tools Mitra (humanoid robot) and CANDI chatbot; these AI tools help to navigate branch visitors and automate routine tasks (Baruah, A. 2017, December 28). It is important for academic research to assess the effects of AI tools on efficiency and profitability. It is not just important to introduce them but also to find out whether these tools have made any measurable difference to the bank's profitability and efficiency of banks (Fethi, M. D., & Pasiouras, F. (2010). Dsouza, S., Rabbani, M. R., Hawaldar, I. T., & Jain, A. K. 2022,Wahab, A 2024, Xu, F., Kasperskaya, Y., & Sagarra, M. 2025). Continuous observation and data-driven evaluation are essential for essential policies and AI deployment for the banking sector (Kishori, B., Mahalakshmi, A. 2022).

Measuring a bank's financial performance is a complex task. Traditionally, the Capital, Assets, Management, Earnings, Liquidity, Sensitivity (CAMELS) framework has been used to measure banks' financial health (Herath, H. M. W. A., & Gamlath, G., 2023, Boubaker, S., Ngo, T., Samitas, A., & Saeed, A. 2025) etc. However, frontier analysis techniques such as Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) are becoming increasingly popular for measuring the impact of technology (Ferrara, M., Lanza & Stillitano, G. ., 2016). SFA is particularly useful because it distinguishes 'technical inefficiency' (Hjalmarsson, L., Kumbhakar, S.C., Heshmati, A. 1996) (which is within the control of management) from 'random statistical noise' (which is out of control), allowing more accurate measurements of efficiency (Bag, S., Gupta, S., et al (2020). There is an interesting discussion in the literature regarding the financial performance of AI. Shiyyab, F. S., Alshurideh, M., & Kurdi, B., (2023) studied Jordanian banks and found a positive correlation between the disclosure of fundamental knowledge from AI and banks' Return on Assets (ROA) and Return on Equity (ROE). Similarly, Rao, P., Sharma, V., & Kumar, R., (2024) explored the positive effect of AI on Indian banks' ROE. This finding supports the idea that AI increases bank profitability through investments. However, this picture is incomplete. Several studies have addressed this issue. For example, Mushtaq, R., Rizwan, M. S., & Ahmad, G.. (2022) found, using Natural Language Processing (NLP), that better financial performance reduces negative sentiments in bank reports but does not have any significant effect on positive sentiment. This indicates that there is no general understanding of the financial performance. dual aspects of AI scope. AI is expected to increase cost efficiency, but its profitability is not immediately clear. Studies have often focused on only one aspect. The basic aim of this technology is to bridge this research gap. In this theoretical comparison, we evaluate the impact of AI on the Indian banking sector from two aspects: 1. Cost Efficiency: Stochastic frontier analysis (SFA) is used to determine how banks can better control their costs (costs) using AI. 2. Profitability: A fixed-panel regression model is used to evaluate the impact of AI on Assets (ROA). 3. Explanation of the Paradox: Explaining the difference between cost efficiency and profitability outcomes and understanding their policy implications. The basic hypothesis of this study is that a heavy initial investment in AI technology may have a negative impact on profitability in the short term, while the benefits of reducing costs become apparent soon. Understanding this 'Productivity Paradox' and J-curve theory, where efficiency increased but profitability decreased, are consistent with this study results, which was first proposed by **Erik Brynjolfsson,1993** and the Investment J-Curve' theory(Bahmani-Oskooee M Ratha, 2004). This aspect is essential for banks to prepare for economic wisdom. This argument is based on data from the State Bank of India, HDFC Bank, and Canara Bank from 2009 to 2024, which will help draw important conclusions regarding Indian trade.

2. Literature Review

Digital transformation has initiated a fundamental change in the banking sector, where technologies such as Artificial Intelligence (AI), the Internet of Things (IoT), and cloud computing play a crucial role (Barroso & Laborda, J. 2022 Priyadarshini, K. V. L., Reddy, M. S., & Reddy, R. S. , 2022, Winarni, R., & Akbar, T. S. W. 2025). This change has accelerated, especially in the post-COVID-19 world, which has obliged banks to implement digital innovations (Herath, H. M. W. A., & Gamlath, G., 2024). The central point of this digital revolution is AI, which is now considered an essential part of 'Banking 4.0' (Kaur, N., Sharma, P., & Singh, R. 2020a). Banks use AI in various operations, including automating routine tasks with Robotic Process Automation (RPA), using chatbots for customer service, and enhancing management accounting systems (Alnor, N.H.A, 2024). The primary objective of these technologies is to improve performance, whether operational or financial (Dubey, R., Gunasekaran, A., Childe, S. J., Papadopoulos, T., & Roubaud, D.,. 2021). Researchers have used various frameworks to measure the performance of banks. The capital adequacy, asset quality, management efficiency, earnings, liquidity, and sensitivity (CAMELS) framework is a traditional yet important tool for assessing the overall health of banks (Herath, H. M. W. A., & Gamlath, G.., 2023).However, to measure the effects of technology, frontier analysis techniques such as Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) are becoming more popular (Hjalmarsson, L., Kumbhakar, S.C., Heshmati, A. 1996, Ferrara, M., Lanza, G., & Stillitano, G., 2016,). SFA is particularly useful because it distinguishes 'technical inefficiency' (which is under management's control) from 'random statistical noise' (which is outside of control), allowing for a more accurate measurement of efficiency (Bag, S., Gupta, S., et al. (2020). However, there are some contradictions in the literature regarding the effects of AI on financial health. Often, research, such as the study by Shiyyab, F. S., Alshurideh, M., & Kurdi, B., (2023) conducted on banks in Jordan, found a positive relationship between the disclosure of information related to AI and banks' Return on Assets (ROA) and Return on Equity (ROE). Similarly, Rao, P., Sharma, V., & Kumar, R. (2024) discovered a positive effect of AI on the ROE of Indian banks. This finding supports the notion that AI investment enhances bank profitability. However, some studies have highlighted the complexities of this issue. Mushtaq, R., Rizwan, M. S., & Ahmad, G. , (2022) analyzed 10-K reports using Natural Language Processing (NLP) and found that better financial performance reduces negative sentiments in reports but has no significant impact on positive sentiments. This finding suggests that the relationship between financial performance and its expression is not well understood. Additionally, there is room for debate regarding the costs and immediate results of adopting AI technology (Herath, H. M. W. A., & Gamlath, G., 2024). This study attempts to address this research gap. We assessed the impact of AI on 'cost efficiency' using SFA and simultaneously examined its effects on 'profitability' (ROA) using a Fixed Panel Model. Through this dual analysis, this study presents a comprehensive picture of the financial impact of AI in the Indian banking sector.

3. Methods

This study uses a quantitative approach to assess the impact of AI on the financial performance of Indian banks. This section provides a detailed explanation of the research framework, data sources, identified variables, and the underlying models used.

3.1 Research Framework and Data

This study uses a quantitative, longitudinal 'multi-case study' design to examine the evolutionary journey of Artificial Intelligence (AI) adoption at three leading banks in India: HDFC Bank, State Bank of India (SBI), and Canara Bank. Our sample consists of panel data spanning (FY 2009-10 to 2024-25) years obtained from banks' annual reports and the Reserve Bank of India's (RBI) Database on the Indian Economy (DBIE). We accept that the sample of three banks (N=3) is small in size. Therefore, this study does not aim to create a generalizable econometric model for the Indian banking industry. Rather, our marketing objective is to offer a deep, recent analysis of the AI strategies and performance of these three 'pioneering' banks, which are market trendsetters. For this type of 'small-N(03), large-T(45)' panel data, fixed-effects models are considered the most robust method for this data structure. To assess the impact of AI, researchers used 2017 as an "event year" or "transition year." Based on this, the data were divided into two categories: 1. 'Before AI' Period: 2009 to 2016. 2. 'After AI' Period: 2018 to 2024. This "before-and-after" approach allows us to appreciate the impact of AI (Herath, H. M. W. A., & Gamlath, G.., 2023). A key challenge of this technique is measuring complex phenomena, such as AI adoption. Machine learning is already being used in the banking sector. However, our AI_Dummy (where 2017 is 0 and 1 after) captures

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not the 'invention' of AI technology, but a paradigm shifts in its 'strategic adoption.'

In academic literature, dummy variables of this type are often used to measure the magnitude of a major "event," "policy change," or "structural break." We claim that 2017 was the year when the use of AI in Indian banking moved from isolated, tactical experiments to a clear, board-level strategic imperative. There is strong evidence for this "structural break," including HDFC Bank's 'EVA' chatbot, SBI's 'YONO' platform, and Canara Bank's rapid digital transformation. Therefore, our dummy variable does not indicate that AI emerged in 2017, but rather that banks fundamentally shifted their AI-adoption strategies in 2017. We were assessing the nature of this "pre- vs. post-strategy shift." Because clear IT spending data were not available in past reports, this "event-based" approach allowed us to cut through the noise of routine expenses each year and isolate only the impact of that strategic shift on productivity.

3.2 Research Hypotheses

This research hypothesis has two fundamental objectives: to measure the impact of AI on bank cost efficiency and profitability. Additionally, researchers have formulated hypotheses to examine their impacts on specific operational metrics.

H_1: The adoption of AI leads to a positive and significant increase in banks' cost efficiency.

H_2: The adoption of AI has a negative and significant impact on banks (ROA).

H_3: There is a significant reduction in banks' non-performing assets (NPAs) after AI adoption.

H_4: After AI adoption, banks' business per employee increases significantly.

H_5: After AI adoption, banks 'Price of Labor' decreases.

3.3 Measurement of Variables

Table I provides all the variables used in this study, their calculation methods, and the literary justification for their use.

Table I: Measurement of Variables

Model	Variable Name	Calculation	Justification
SFA	Total Cost	(Operating Expenses + Interest Expenses)	The basic dependent variable of the cost efficiency model (Alnor, N.H.A, 2024).
	Advances	Total Advances	The bank's key output, which defines the cost frontier
	Investments	Total Investments	The second important output of the bank
	Price of Labor	(Personnel Expenses / No of Employee)	keeps prices under control to guarantee precise efficiency measurements.
	Price of Funds	(Interest Expenses / Total Deposits)	A proxy for the price of Funds
	Price of Capital	(Other Operating Expenses / Net Fixed Assets)	Represents the cost of using physical/ Fixed assets
	Gross NPA	(Gross Non-Performing Assets)	Used to control risk-related costs.
	All SFA variables log transformed		
Panel Model	ROA	Net Profit / Total Assets	A common and reliable measure of bank profitability (Herath, H. M. W. A., & Gamlath, G.., 2023; Mushtaq, R., Rizwan, M. S., & Ahmad, G. ., 2022).
	AI Dummy	0 for years < 2017, 1 for years > 2017	A standard 'event study' variable to measure the impact of technology adoption (Shiyyab, F. S., Alshurideh, M., & Kurdi, B., 2023).
	Total Assets	Log Transformed of Total Assets	Controls for the effect of bank size, which is estimated to affect (Rao, P., Sharma, V., & Kumar, R. 2024).
	CAR	Data from Annual Reports	An important indicator of a bank's financial stability (Herath, H. M. W. A., & Gamlath, G., 2023).
T-Tests	Gross NPA	Gross NPA Amount	A direct measure of asset quality (Herath, H. M. W. A., & Gamlath, G., 2024).

	Business per Employee	Net Profit/ Total Employees	A proxy for operational efficiency and employee productivity (Alnor, N.H.A, 2024).
	Price of Labor	Personnel Expenses / No of Employee	Reveals the impact of cost structure and human resource management.

Source: Authors compilation

3.4 Methods of Statistical Analysis

This study used several statistical methods to analyze the data.

Descriptive Statistics: The mean, standard deviation, and minimum and maximum values of all variables were calculated to understand the basic characteristics of the data.

Table II: Descriptive Statistics of Key Variables

Variable	Mean	SD	Min	Max
ROA	1	0.76	-0.75	2.07
CAR	14.61	2.3	10.56	19.26
Total Assets	1,601,869.65	1,531,337.64	183270.77	6,179,693.94
Advances	970,176.79	897,867.35	98,883.05	3,703,970.85
Investments	413,046.83	428,463.29	57,776.90	1,671,339.66
Total Cost	0.45	0.15	0.2	0.76
Gross NPA Amount	41,272.40	50,120.52	1,694.34	223,427.46
Price of Labor	0.1	0.06	0.04	0.34
Price of Funds	0.06	0.01	0.04	0.07
Price of Capital	0.93	0.94	0.12	3.31
Business per Employee	9.84	9.09	-7.17	28.48

Source: Authors calculation

The first step in our analysis was to understand the data's underlying characteristics. Table II presents the descriptive statistics of the key variables used in this analysis, which describe the overall financial picture of our sample (SBI, HDFC Bank, and Canara Bank) from 2009 to 2024.

Profitability of Banks:

Bank profitability is measured by Return on Assets (ROA), with a mean value of 1.0%. This indicates that banks remained profitable during this period. However, the large difference between the Min (-0.75%) and Max (2.07%) values indicates that bank performance fluctuated year-on-year, with some years even ending in losses.

Capital Strength:

The average value of the Capital Adequacy Ratio (CAR) was 14.61%, which is well above the regulatory requirement (typically 8-10%). Its low Standard Deviation (2.30) indicates that all banks are generally well capitalized, which indicates their financial stability.

Scale and Operations:

The average values of Total Assets, Advances, and Investments are relatively constant, indicating the banks' overall scale. The most important result is the two standard deviations (1,531,338.0) of the Total Assets, which highlights an important aspect of this logic, including banks of different scales. This difference reflects the size distinction between small public sector banks, such as SBI, and private sector banks, such as HDFC.

Risk Profile:

The values of Gross NPA Amount also show a significant difference (Min: 1,694.34, Max: 223,427.50). This indicates that banks face serious asset quality issues across various sectors, which is a common reality for the Indian banking sector.

Efficiency and Cost Structure

Businesses per employee, a key measure of operational efficiency, averaged 9.84; however, its large variations (ranging from -7.17 to 28.48) indicate that employee productivity varied significantly across banks and time. Variables reflecting the cost structure, such as the Price of Labor (0.10) and Price of Funds (0.06), have low average values. The extremely low Standard The deviation (0.01) for the Price of Funds indicates that banks' capital costs remained relatively stable during this period.

Overall, these descriptive statistics identify a dataset consisting of three banks that are financially strong but low-performing. The high standard deviation in the variables, especially in the size and risk parameters, indicates that the use of advanced methods such as SFA and fixed-effects panel models is necessary and appropriate for our reasoning, as these models can better handle the complexities of this type of analysis.

2. Stochastic Frontier Analysis (SFA): The SFA Cost Frontier model was used to test H_1. This model was run separately for the 'before' and 'after' AI periods, and the efficiency scores were then calculated for each bank. and measure the impact of AI on banks' cost efficiency. SFA was chosen because it separates 'technical inefficiency' (which is within the control of management) from 'random statistical noise' (which is out of control), which makes the measurement of efficiency more accurate (Hjalmarsson, L., Kumbhakar, S.C., Heshmati, A., 1996; Ferrara, M., Lanza, G., & Stillitano, G. ., 2016). Researchers have developed a Cost Frontier Model that estimates the minimum possible cost (cost) that a bank should incur to produce its output (e.g., loans). This minimum cost is compensated by the bank's actual costs. Several variables were derived and used for this model.

Total Cost = f(Outputs, Input Prices) + v + u

where the Total Cost is our dependent variable, which is operating expenses plus interest expenses. u (Technical Inefficiency) and v (Random Noise), and outputs include Advances and Investments. Input Prices include the price of labor: personnel expenses/no of employees, price of funds: interest expenses/total deposits, and price of capital: other operating expenses/net fixed assets. SFA models frequently use a multiplicative Cobb-Douglas production cost function. This function is linearized using log transformation, which ensures theoretical coherence and makes it estimable through regression (Christensen et al., 1973; Berger and Mester, 1997).

3. Paired Samples T-Test: This test was used to test H_3, H_4, and H_5. The mean of the specific variables for each bank's 'before' and 'after' periods was calculated.

4. Fixed-Effects Panel Regression: This model was used to test H_2. To ensure the overall strength of the model, several diagnostic tests were performed: "In this study, to choose the appropriate model for panel data, researchers considered Fixed Effects (FE) and Random Effects (RE) models. In general, the Hausman test is used to choose between them. However, our argument includes three banks (n=3), while our model has three independent variables (AI Dummy, Log Total Assets, CAR). However, to accurately estimate the random-effects model, the number of individuals (banks) must be greater than the number of independent variables. In the present study, this condition was not satisfied. Therefore, the Random Effects model was "not estimable, " and the Hausman test could not be conducted.

Given this statistical limitation, researchers have selected this model on a theoretical basis. The choice of Fixed Effects model is more appropriate because The Fixed Effects model controls for all these hidden populations, which allows researchers to say with greater confidence that the change researchers observed in ROA was due to the variables in our model. Nature of the Sample: Our research aimed to assess the effectiveness of AI among these three specialist banks (SBI, HDFC, and Canara) and not to generalize the results to the population of all Indian banks. When the focus of the research is on specialist individuals, a fixed-effects model is generally preferred.

Hence, there were compulsions, and on theoretical grounds, the researchers concluded that the Fixed Effects model was the most robust and appropriate for this study. "Panel Regression Model: This model measures the effect on profitability (ROA). A fixed-effects model was used to control for each bank's internal characteristics. Its formula as:

$$\mathbf{ROA_{it} = \beta_0 + \beta_1(AI\ Dummy_{it}) + \beta_2(Log\ Total\ Assets_{it}) + \beta_3(CAR_{it}) + \alpha_i + \varepsilon_{it}}$$

where β_0 (The Intercept), β_1, β_2, and β_3 (The Coefficients or "Slopes"), α_i (The Fixed Effect), and ε_{it} (The Idiosyncratic Error Term) are ROA is a dependent variable. The AI Dummy is an important independent variable, which is '1' for the AI period and '0' for the previous period. Log of Total Assets

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The size of the bank and CAR reveal the strength of its capital.

Multicollinearity Test Variance Inflation Factor (VIF): This test checks whether the independent variables are highly correlated with each other. **Breusch–Pagan (homoscedasticity)**Test: To check whether the variance in the errors is constant. Serial Correlation Test (Wooldridge): To check whether the error terms were correlated. Hausman Test: A test was performed to distinguish between fixed and random effects. However, because of our small sample size (n=3), this test could not be performed; hence, the fixed-effects model was selected based on theoretical grounds. All analyses were performed using R statistical software (version 4.x).

4. Results

4.1 Hypothesis 1: Impact of AI on Cost Efficiency

• **Hypothesis Statement (H_1):** The adoption of AI positively and significantly increases banks' cost efficiency.

To test this hypothesis **(H_1),** researchers used Stochastic Frontier Analysis (SFA). The SFA model measures a bank's cost efficiency as a score between zero and one, where one represents 100% efficiency. Researchers conducted this analysis over two periods: first for the major period and then for the independent period for each bank. The results are presented in Table III.

Table III: Summary of SFA Analysis

Period	Mean Cost Efficiency
Before AI (Dummy=0)	0.9059(90.6%)
After AI (Dummy=1)	0.9998(99.98%)

Source: Authors calculation

The results in Table III clearly show that after AI adoption, banks' average cost efficiency increased significantly. Before the introduction of AI, banks were 90.6% efficient in terms of their costs, meaning they had the potential to reduce their costs by a maximum of 9.4%. In the post-AI period, the efficiency increased to 99.98%, which was almost perfect. This result provides clear evidence that AI plays a significant role in reducing operational costs.

To delve deeper into the overall results, the researchers measured the efficiency improvements for each bank separately. This analysis reveals the extent to which each bank benefits from AI. Table IV presents these results.

Table IV: Bank-Wise SFA Cost Efficiency Comparison

Bank	Mean Efficiency Before	Mean Efficiency After	Improvement (%)
Canara Bank	0.898	1	10.1
HDFC Bank Ltd.	0.905	1	9.48
State Bank of India	0.914	1	8.53

Source: Authors calculation

The results in Table IV closely mirror those of our earlier study. This shows that all three banks achieved approximately 100% cost efficiency after AI adoption. Interestingly, Canara Bank, which had the lowest 'before-AI' efficiency (89.8%), showed the highest improvement of 10.13%. In contrast, the State Bank of India, which was already the most efficient (91.4%), showed an improvement of 8.53%. Both the overall and bank-wise SFA results show a significant increase in cost efficiency after AI adoption. Therefore, based on these results, we accept Hypothesis 1 (H_1).

4.2 Hypothesis 2: Impact of AI on Profitability

Hypothesis Statement (H_2): The adoption of artificial intelligence (AI) has a negative and significant impact on bank profitability (measured by ROA).

To test this hypothesis, the researchers used a Fixed-Effects Panel Regression Model. This model measures the effect of the AI Dummy on ROA while controlling for bank size (Log Total Assets) and capital strength (CAR). To ensure the robustness of the model, researchers also performed all the

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necessary diagnostic tests (such as VIF and **Breusch–Pagan (homoscedasticity)**), the results of which are presented in Table V.

Table - V : Diagnostic Tests for Panel Model

Test	**Statistic**	**df**	**p-value**	**Decision**	**Interpretation**
Breusch–Pagan (Homoscedasticity)	BP = 4.1778	3	0.0625	Accept H_0	**Homoscedasticity** is present
Wooldridge / BG (Serial Correlation)	$\chi^2 = 20.944$	15	0.1386	Accept H_0	No serial correlation
Hausman Test	—	—	—	Not estimable	Fixed Effects model chosen (few banks)
Testing Correlation and Multicollinearity					
Variables	**ROA numeric**	**AI Dummy**	**Log Total Assets**	**CAR numeric**	**VIF**
ROA numeric	1.000	-0.135 (0.376)	-0.150 (0.325)	0.786 (0.000**)	—
AI Dummy	-0.135 (0.376)	1.000	0.644 (0.000**)	0.277 (0.065*)	1.95
Log Total Assets	-0.150 (0.325)	0.644 (0.000**)	1.000	0.013 (0.935)	1.80
CAR numeric	0.786 (0.000**)	0.277 (0.065*)	0.013 (0.935)	1.000	1.14

Source: Authors calculation

Note: P-values are given in Parenthesis . ** $p < 0.01$ (highly significant), * $p < 0.1$ (moderately significant),

To ensure the statistical robustness and reliability of the Fixed-Effects Panel Model results, several basic diagnostic tests were performed. First, the Variance Inflation Factor (VIF) was used to check for multicollinearity. All VIF values were less than 2, indicating that multicollinearity was not a significant concern. The correlation analysis showed that ROA had a strong positive correlation with CAR ($r = 0.786$, $p < 0.01$), suggesting that capital adequacy is a key driver of profitability. The AI Dummy has a negative but insignificant association ($r = -0.135$, $p = 0.376$) with ROA, which provides an initial indication that AI adoption does not directly improve profitability of banks. The log of Total Assets had a strong positive association ($r = 0.644$, $p < 0.01$) with the AI Dummy, implying that AI is adopted in larger banks. The VIF values are all less than two (AI Dummy = 1.95, Log of Total Assets = 1.80, CAR = 1.14). The Breusch-Pagan test was used to test for heteroscedasticity (thick weighted variance). The p-value of this test was 0.0625, which was less than 0.05. Therefore, the researchers failed to reject the null hypothesis (that homoscedasticity is present), thus demonstrating that heteroscedasticity is not a significant issue. The Wooldridge test was used to test for serial correlation, with a p-value of 0.1386, which was less than 0.05. However, the researchers concluded that the serial correlation in the error terms of our model was not significant. Finally, an attempt was made to perform a Hausman test to distinguish between the Fixed Effects and Random Effects models; however, this test was deemed "Not Estimable" because of the presence of only three banks in our sample. Given this constraint, researchers selected a model based on theoretical grounds because every bank in the banking sector has its own unique, unchanging characteristics (unobserved heterogeneity), and the choice of a fixed-effects model is most appropriate for this rationale to control for these. Overall, the results of these diagnostic tests confirm that the fixed-effects model used by the researchers was robust and met its underlying parameters, which increased the reliability of the study results.

4.2.1 Results of Panel Regression Model

Researchers used the Fixed-Effects Panel Model to measure the effect of AI on bank profitability (ROA). The results of this model are presented in Table VI.

Table-VI. Panel Regression Results for ROA

Variable	Estimate	Std. Error	t-value	p-value	Significance
AI Dummy	-0.8071	0.2012	-4.0112	0.0002648	***
Log Total Assets	0.2941	0.1407	2.0909	0.0430982	*
CAR	0.1937	0.0415	4.6630	0.00003605	***
Model Fit Statistics:					
R-Squared	0.4590				
Adj. R-Squared	0.3896				
p-value	2.22e-05				
F-statistic:	11.0269				
Panel Type	**Fixed**				
Observation	(n = 3, T = 15, N = 45)				

Source: Authors calculation

The results of the panel regression in Table VI(within the model) show that the coefficient of AI Dummy is negative (-0.8071) and highly significant ($p < 0.001$). This means that the short-term impact of AI adoption could negatively affect profitability, perhaps because of implementation costs, training expenses, or transition inefficiencies. However, the Log of Total Assets has a positive and significant effect ($\beta = 0.2941$, $p < 0.05$), indicating that large banks have a higher ROA, which could be due to economies of scale or better diversification. The positive and highly significant coefficient of CAR ($\beta = 0.1937$, $p < 0.001$) confirms that higher capital adequacy strengthens banks' profitability. $R^2 \approx 0.46$, indicating that the model explains approximately 46% of the variation in the dependent variable ROA. The significant p-value of the F-statistic (2.22e-05) confirmed that the overall model was statistically significant. The results of the panel model clearly show that the AI Dummy has a negative and highly statistically significant effect on ROA. Therefore, based on these results, we accept Hypothesis 2 (H_2).

4.3 Hypotheses 3,4,5

H_3: There is a significant reduction in banks' non-performing assets (NPAs) after AI adoption.

H_4: After AI adoption, banks' business per employee increases significantly.

H_5: After AI adoption, banks 'Price of Labor' decreases.

To test these Hypothesis 3,4,5, used a paired sample t-test was used. Using this test, and compared each bank's average 'Gross NPA amount,' 'Business per Employee,' 'Price of Labor.'

The detailed T-test results are presented in Table VII.

Table VII: Paired Samples T-Test Results -

Hypothesis	Variable	Mean Difference	t-statistic	p-value	Faisla (Decision on H_0)	Interpretation
H_3	Gross NPA Amount	-47,455.70	-2.075	0.913	Accept	There is no significant difference in the NPA after AI
H_4	Business per Employee	-8.352	-4.448	0.024	Reject	Productivity increased after AI
H_5	Price of Labor	-0.077	-2.715	0.943	Accept	There is no significant change in labor cost after AI

Source: Authors calculation

To understand the specific operational basis of AI in this argument in greater depth, Table VII presents three additional hypotheses using a paired-sample t-test. These tests assessed the statistical significance of the changes in the mean of specific variables between the 'Before AI' and AI' periods. The most important aspect of the results relates to Hypothesis H_4. The data show a statistically significant increase in 'Business per Employee,' with a p-value of 0.024, which is less than 0.05. This means that there was a measurable improvement in the operational productivity of each employee after AI adoption; therefore, researchers accept Hypothesis H_2. In contrast, the results for both hypotheses were not significant. According to Hypothesis H_1, no significant difference was observed between the 'before' and 'after' periods in the 'Gross NPA Amount,' as the p-value was 0.913. Similarly, in the test of Hypothesis H_3, the p-value for the Price of Labor' was 0.943, which indicates that there was no significant change in the average cost per employee. Hence, Researchers reject H_3 and H_5. Overall, these T-test results paint a positive picture: AI immediately improved operational productivity (H_4), but it had no immediate impact on asset quality (H_3) or asset costs (H_5). This suggests that the benefits of AI are most likely to manifest first in terms of efficiency, whereas its impact on risk management and cost structures may take longer to manifest.

5. Discussion

The results of this study present a refined and in-depth view of AI's role in the Indian banking sector. Our findings reveal an interesting paradox that advances the debate in the literature.

5.1 Increase in Cost Efficiency: Results of SFA analysis clearly demonstrate that after adopting AI, the average cost efficiency of banks increased from 90.6% to 99.9%. This result substantiates the claim that AI-driven automation and better data analysis lead to a noticeable reduction in operational costs (Alnor et al., 2024). Routine tasks are automated through AI, fraud detection is improved, and resource allocation becomes more effective, all of which contribute to lower costs (Dubey, R., Gunasekaran, A., Childe, S. J., Papadopoulos, T., & Roubaud, D.,., 2021). This result also highlights the general utility of SFA, which serves as an effective tool for measuring the impact of technology on cost management (Hjalmarsson, L., Kumbhakar, S.C., Heshmati, A. 1996, Ferrara, M., Lanza, G., & Stillitano, G. ., (2016).

5.2 Negative Impact on Profitability: The Paradox of the Panel Model Contrary to the positive results from SFA, our Fixed-Effects Panel Regression Model showed that the AI Dummy has a negative and statistically significant effect on ROA (estimate = -0.81, $p < 0.001$). This result is surprising at first glance and contradicts some positive results presented in the literature, such as the works of Shiyyab, F. S., Alshurideh, M., & Kurdi, B. (2023) and Rao, P., Sharma, V., & Kumar, R. (2024).

To explain this clear contradiction, Researchers presented the 'Productivity Paradox' where efficiency increased but profitability decreased, are consistent with our results, first proposed by **Erik Brynjolfsson,1993** and 'Investment J-Curve' theory(Bahmani-Oskooee, M., Ratha, A,2004) in relation to IT. According to this view, the benefits of heavy capitalism in technology are not immediately visible in economic analyses.". Adopting AI technology is not only about purchasing software; it is a wide investment that includes new hardware, building data infrastructure, extensive training of employees, and the adoption of new business models (Herath, H. M. W. A., & Gamlath, G., 2024). These factors require significant initial capital investments and constant operational expenditures. Such financial obligations immediately impact the bank's balance sheet, resulting in adverse effects on short-term profitability metrics, such as Return on Assets (ROA).

Consequently, our panel model captures the immediate and short-term effects of this investment, whereas our SFA model measures the operational improvements that begin immediately because of these investments. This dual result is a significant experience for banking executives: the benefits of AI may manifest as immediate cost reductions, but time and patience are required for profits to increase further.

5.3 Effects of Other Factors: Our panel model also confirms that bank size (Log Total Assets) and capital strength (CAR) have a positive and significant impact on ROA. This aligns with the common principles in banking literature (Herath, H. M. W. A., & Gamlath, G.., 2023). This indicates that larger and financially stronger banks perform better than smaller banks.

5.4.Research Contribution:

This is one of the first studies to quantitatively estimate the cost efficiency and profitability of AI adoption in India. Using SFA and Panel Regression together, researchers have presented a more complete and detailed analysis of the cost efficiency of AI. These results help bank managers and policymakers understand that the use of AI is a practical strategy for the long term and that one should not be alarmed by its immediate results. Instead, the improvement in cost efficiency should be seen because of this increasing success of the banks

6. Conclusion

In the past few years, technology has created a revolution in the global banking industry, whose distinctive title is "Digital Transformation." The main driver of this revolution is Artificial Intelligence (AI), which is now considered the foundation of "Banking 4.0." After 2017, Indian banks began investing in AI technology on a large scale. Although banks are believed to benefit from AI, the nature of this benefit remains unclear. Does AI directly increase profits, or does its real benefit lie in reducing costs? The basic issue of this theoretical comparison is the effect on the 'cost efficiency' and 'profitability' of Indian banks after the adoption of AI. Finding an explanation for the obvious difference between the two is the main focus of this theoretical comparison.

This study adopted an individual (quantitative) and longitudinal approach, for which data from the State Bank of India, HDFC Bank, and Canara Bank from 2009 to 2024 were obtained from their annual reports and the RBI database. The year of change was 2017, and the data were divided into two parts: 'Before AI' (2009-2016) and 'After AI' (2018-2024). Two models were used to measure revenue performance. First, Stochastic Frontier Analysis (SFA), which measures cost dynamics and separates 'technical inefficiency' from 'random noise.' Second, we use the Fixed-Effects Balanced Panel Regression Model, which measures the effect of AI on Assets (ROA) while controlling for each bank's individual characteristics (fixed effects). In this model, the AI Dummy is used as the key independent variable, while the Log of Total Assets and Capital Adequacy Ratio (CAR) are included as control variables.

The results of the aggregated analysis were interesting and are discussed below. Descriptive statistics reveal that our sample includes banks of different sizes, with an average ROA of 1.0%. The results of the ((SFA) were extremely positive. In general, after the adoption of AI, banks' average cost efficiency improved from 90.6% to 99.9%. The bank-wise results revealed that Canara Bank showed the highest improvement (10.13%), followed by SBI (8.53%) and HDFC Bank (9.48%). However, the results of the Panel Regression Model reveal a different story. The model is significant overall (F-statistic p-value = 2.22e-05) and explains 39% of the change in ROA (Adj.. R-Squared = 0.3896). However, the coefficient of the AI Dummy was negative (-0.81) and extremely significant ($p < 0.001$), which means that after controlling for income, there was a significant decrease in ROA during the AI period. In addition, bank size and CAR have important and significant effects on ROA.

The results of this study produce an obvious paradox: our results, where efficiency increased but profitability decreased, are consistent with the 'Productivity Paradox,' first proposed by Martja Brynjolfsson (1993) in relation to IT. According to this view, the benefits of heavy capitalism in technology are not immediately visible in economic analyses. Another explanation for this reaction can be seen through the lens of 'The J-Curve of Investment.' The huge initiatives made in AI technology initially hindered profit indicators, such as ROA. However, this leverage also leads to immediate operational improvements, as our SFA results show. Thus, AI is a long-term investment, whose benefits of reducing costs become apparent immediately, whereas the benefits of increasing profits become apparent over time. A bank-wise analysis also shows that technology gives public sector banks an equal footing to the private sector. These results suggest that bank managers should not be alarmed by the immediate results of AI but should view it as a strategic investment.

This study concludes that AI has had a profound and dual impact on the performance of Indian banks. AI initially took its cost efficiency to the highest level, but the initial results of this analysis may be negated by profitability.

As in any theoretical framework, this theory is subject to certain limitations that warrant further refinement in future studies. First, the sample size employed in this study was relatively small (n=3, 15*3=45). Although these banks are representative of the Indian banking sector, the generalizability of the findings can be enhanced by incorporating a larger number. Second, the study utilizes the variable 'AI Dummy,' which merely indicates the commencement of the AI era without accounting for the extent of investment each bank has made in AI. Access to direct investment data is likely to yield more robust results in the future. Furthermore, the period designated as 'after the AI era' is still ongoing, suggesting that the positive effects associated with the '-curve may not have fully materialized by the end of our study period.

Future research should encompass a broader range of banks to enhance the significance of these findings. The evaluation of artificial intelligence (AI) can be based on metrics such as customer satisfaction, price productivity or deficiencies in fraud detection. It is crucial to periodically update these data to determine the timeframe in which the profit segment of the J-curve emerges. Subsequent studies should aim to ascertain the actual investment in AI as reported in banks' annual reports, facilitating more accurate estimations from the 'AI Dummy.' Future research could address the following questions: What is the impact of AI on banking pricing strategies? At what point does the initially negative effect on assets (ROA) transition to a positive outcome over time?

Statements and Declarations

Ethical Compliance: All procedures performed in studies involving human participants were in accordance with ethical standards.

Data Access Statement: Research data supporting this publication are available from the DBIE and Annual Reports of Respective Banks

Conflict of Interest: The authors declare no conflicts of interest.

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