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IMPACT OF ARTIFICIAL INTELLIGENCE ADOPTION ON FINANCIAL PERFORMANCE: EVIDENCE FROM SELECTED INDIAN BANKS

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Abstract: This study examines the impact of artificial intelligence (AI) adoption on the financial performance of selected Indian banks over the period 2016–2026. Financial performance is measured using Return on Assets (ROA) and Return on Equity (ROE), while AI adoption is proxied through an AI score index and a post-adoption dummy variable. The study employs a fixed effects panel regression model with heteroscedasticity-robust standard errors and lagged variables to ensure robustness of results. The findings reveal that AI adoption and its intensity do not have a statistically significant impact on bank profitability. Although the post-adoption period exhibits a positive coefficient, it is not statistically significant at the 5 percent level. The results further indicate that firm-specific characteristics play a dominant role in determining financial performance. The study concludes that AI adoption alone is insufficient to improve profitability in the short run and highlights the importance of effective implementation and organizational readiness.

Index Terms **-** Artificial Intelligence, Banking Performance, ROA, ROE, Panel Data, Fixed Effects Model.

1.INTRODUCTION

The rapid advancement of artificial intelligence (AI) has significantly transformed the global banking industry. Banks are increasingly adopting AI-driven technologies to improve operational efficiency, enhance customer experience, strengthen risk management, and optimize decision-making processes. Applications such as chatbots, fraud detection systems, credit scoring models, and predictive analytics have become integral components of modern banking operations.

Despite the growing adoption of AI, its impact on financial performance remains an area of ongoing debate. While AI is expected to improve efficiency and reduce operational costs, its direct contribution to profitability indicators such as Return on Assets (ROA) and Return on Equity (ROE) is not clearly established. The benefits of AI may take time to materialize and often depend on complementary factors such as organizational capability, human capital, and strategic alignment.

In the Indian banking context, the adoption of AI has accelerated in recent years, particularly after 2020. However, empirical evidence on whether AI adoption translates into improved financial performance is limited. This study attempts to fill this gap by examining the impact of AI adoption on selected banks using panel data analysis.

Objectives of the Study

1. To analyze the impact of AI adoption on Return on Assets (ROA)
2. To examine the effect of AI adoption on Return on Equity (ROE)
3. To evaluate whether the level of AI adoption influences financial performance
4. To assess whether AI has immediate or lagged effects on profitability

Hypotheses

H01: AI adoption has no significant impact on ROA
H02: AI adoption has no significant impact on ROE
H03: AI intensity has no significant effect on financial performance
H04: Lagged AI adoption has no significant impact on financial performance

2. LITERATURE REVIEW

The adoption of artificial intelligence (AI) in the banking sector has gained significant attention in recent years due to its potential to enhance operational efficiency, risk management, and customer experience. However, empirical evidence on its impact on financial performance remains mixed. Several studies suggest that AI improves efficiency and reduces operational costs. For instance, Brynjolfsson and McAfee (2017) argue that digital technologies, including AI, enhance productivity and decision-making capabilities, thereby contributing to firm performance. Similarly, Davenport and Ronanki (2018) highlight that AI applications in banking, such as fraud detection and customer analytics, improve operational outcomes, although financial gains may not be immediate.

In the context of the banking sector, Fuster et al. (2020) found that AI-driven algorithms improve credit assessment and reduce default risk, indirectly contributing to financial stability. Likewise, Begenau et al. (2018) emphasize that financial institutions adopting advanced technologies experience improvements in efficiency but not necessarily in short-term profitability. However, several studies report limited or insignificant impact of AI on financial performance. Acemoglu and Restrepo (2020) argue that technological adoption often involves adjustment costs, which may offset short-term gains. Similarly, Autor et al. (2022) note that the benefits of automation depend on complementary organizational changes, without which performance improvements remain limited.

In emerging economies, the impact of AI adoption appears even more nuanced. Kumar et al. (2021) found that while Indian banks are increasingly adopting digital technologies, the direct relationship between technology adoption and profitability is weak due to implementation challenges and high initial investment costs. Likewise, Mehta and Shah (2022) observed that digital transformation in banking improves service quality but does not significantly affect financial indicators such as ROA and ROE in the short run. Another important strand of literature highlights the role of firm-specific factors. Demirgüç-Kunt and Huizinga (2010) demonstrate that bank profitability is primarily driven by internal factors such as management efficiency, asset quality, and cost control. This suggests that technology adoption alone may not be sufficient to enhance performance without strong institutional capabilities.

Furthermore, studies incorporating panel data analysis emphasize the importance of controlling for unobserved heterogeneity. Wooldridge (2010) argues that fixed effects models provide more reliable estimates in such cases by accounting for firm-specific characteristics. Empirical studies using panel regression, such as Lee and Shin (2021), find that technological innovation has a weak or delayed impact on financial performance when firm effects are considered.

By and large, the literature indicates that while AI has the potential to improve banking operations, its direct impact on profitability is not guaranteed. The effectiveness of AI depends on factors such as implementation efficiency, organizational readiness, and time required for benefits to materialize.

3. RESEARCH METHODOLOGY

Research Design: The present study adopts a quantitative, analytical, and longitudinal research design to examine the impact of Artificial Intelligence (AI) on banking performance in India. The analysis is based on a panel dataset of five major banks over a ten-year period (2016–2025), enabling comparison between pre-AI and post-AI phases.

3.1 Sample: *Five major Indian banks (through purposive sampling):*

- HDFC Bank
- ICICI Bank
- State Bank of India
- Axis Bank
- Kotak Mahindra Bank

3.2Nature of Data*: Secondary data was collected from annual reports of selected banks, financial databases and stock exchange filings, Regulatory and industry reports. The dataset is panel in nature, consisting of cross-sectional units (banks) observed over time.*

3.3Variables studied

Dependent Variables: Return on Assets (ROA), Return on Equity (ROE)
Return on Assets (ROA) is calculated as Net Profit divided by Total Assets, while Return on Equity (ROE) is calculated as Net Profit divided by Shareholders' Equity.
Independent Variable: AI Adoption Score (Proxy-Based) based on AI disclosures, chatbot implementation, analytics usage, and automation initiatives.
AI Score: Represents the level of artificial intelligence adoption in each bank, categorized as follows:

- 0 = No AI emphasis
- 1 = Low AI adoption
- 2 = Medium AI adoption
- 3 = High AI adoption

Post-AI Dummy Variable: A binary variable used to distinguish between pre- and post-AI adoption periods:

- 0 = Pre-AI period (2016–2019)
- 1 = Post-AI period (2020–2025)

Model Specification
ROA_it = β0 + β1 AI_it + β2 Post_t + μ_i + ε_it
ROE_it = β0 + β1 AI_it + β2 Post_t + μ_i + ε_it
Where 'I' represents the bank, 't' represents time, and 'μ_i' captures unobserved firm-specific effects.
To examine delayed effects, lagged AI variables are also incorporated into the model
Statistical Tools Used

- Fixed Effects Panel Regression: The study employs the Fixed Effects Panel Regression Model, which is appropriate for controlling unobserved heterogeneity across banks. This method captures bank-specific characteristics that remain constant over time but may influence financial performance.
- Heteroscedasticity-Robust Standard Errors (HC3): To correct potential heteroscedasticity in the data
- Lagged Variable Model: To examine whether AI adoption has delayed effects on financial performance

Input Data:
AI Adoption: It is categorically as:

- 0 = No AI emphasis
- 1 = Low AI adoption
- 2 = Medium AI adoption
- 3 = High AI adoption

Table 1: AI Adoption Score (0 to 3)

Year	HDFC Bank	State Bank of India	ICICI Bank	Axis Bank	Kotak Mahindra Bank
2016	1	0	2	1	1
2017	1	1	2	1	1
2018	2	1	3	1	2
2019	3	2	3	2	2
2020	3	2	3	2	2
2021	3	2	3	2	3
2022	3	3	3	3	3
2023	3	3	3	3	3
2024	3	3	3	3	3
2025	3	3	3	3	3

The AI adoption pattern across selected banks shows a clear upward trend over the study period. Initially, most banks exhibited low to moderate levels of AI adoption between 2016 and 2018, followed by a rapid increase from 2019 onwards. By 2022, all banks had reached high levels of AI adoption (level 3), indicating industry-wide technological convergence. This suggests that AI adoption has transitioned from a competitive differentiator to a standard operational requirement in the banking sector. However, despite this uniform adoption, variations in financial performance indicate that AI alone may not be the primary driver of profitability.

Table 2: ROA & ROE of 5 banks for the period of 10 years

Year	HDFC		SBI		ICICI		Axis		Kotak Mahindra	
	ROA (%)	ROE (%)	ROA (%)	ROE (%)	ROA (%)	ROE (%)	ROA (%)	ROE (%)	ROA (%)	ROE (%)
2016	1.61	16.67	0.51	6.89	1.35	9.26	0.75	6	1.29	9
2017	1.63	15.94	0.39	5.38	1.26	8.91	0.66	5.43	1.17	8.05
2018	1.58	16.03	-0.12	-1.79	0.81	5.65	0.06	0.49	1.24	8.65
2019	1.63	13.77	-0.2	-3.12	0.35	2.59	0.04	0.35	1.31	9.04
2020	1.66	14.94	0.02	0.38	0.73	5.47	0.63	5.6	1.28	8.85
2021	1.78	15.27	0.35	5.8	1.33	10.12	0.17	1.63	1.32	9.14
2022	1.84	15.85	0.43	7.29	1.73	13.95	0.61	5.49	1.27	8.71
2023	1.79	15.74	0.61	9.9	1.93	15.19	1.09	9.3	1.38	9.02
2024	1.03	8.48	0.91	13.22	2.21	16.36	1.94	15.41	1.52	9.94
2025	1.43	11.11	0.99	14.04	2.16	15.26	2.32	17.99	1.62	10.6

The financial performance data of the selected banks indicates noticeable variation in both ROA and ROE over the study period. In the pre-AI phase (2016–2019), several banks, particularly SBI and Axis Bank, exhibited lower or even negative returns, reflecting weaker performance. However, in the post-AI period (2020–2025), most banks show a general improvement in both ROA and ROE, especially ICICI Bank and Axis Bank. Despite this upward trend, the performance is not uniform across all banks, indicating the presence of firm-specific factors. This variability justifies the use of panel data techniques to capture both cross-sectional and time-series effects.

4. DATA ANALYSIS AND INTERPRETATION:

4.1Fixed Effects Regression Results:

(A) ROA Model

Variable	Coefficient	p-value
AI Score	0.005	0.972
Post	0.397	0.103

Interpretation and Analysis: The regression results indicate that the coefficient of AI Score is positive but statistically insignificant ($p > 0.05$), suggesting that variations in the level of AI adoption do not have a measurable impact on Return on Assets (ROA). Similarly, the post-AI adoption dummy variable shows a positive coefficient, indicating a marginal improvement in ROA during the post-adoption period; however, this effect is not statistically significant at conventional levels. This implies that while there may be an observable increase in profitability after AI adoption, it cannot be conclusively attributed to AI when controlling firm-specific characteristics.

(B) ROE Model

Variable	Coefficient	p-value
AI Score	0.058	0.965
Post	3.438	0.107

Interpretation and Analysis:
In the case of Return on Equity (ROE), the AI Score variable again exhibits a positive but statistically insignificant coefficient, indicating that higher levels of AI adoption do not significantly influence shareholder returns. The post-AI adoption variable shows a relatively larger positive coefficient compared to the ROA model, suggesting an improvement in ROE in the post-adoption period. However, the effect remains statistically insignificant, indicating that the observed improvement cannot be robustly linked to AI adoption

Overall Interpretation of Results: The overall findings suggest that AI adoption, both in terms of intensity (AI Score) and period (Post), does not have a statistically significant impact on financial performance indicators such as ROA and ROE. Although descriptive trends indicate some improvement in performance in the post-AI period, the regression analysis reveals that these changes are not strong enough to establish a causal relationship. This indicates that the observed improvements may be influenced by other factors rather than AI adoption alone.

4.2 Lag Effect Analysis

To examine whether AI adoption has a delayed impact on financial performance, lagged values of the AI variable were incorporated into the model. The results indicate that the lagged AI variable is statistically insignificant for both ROA and ROE.

Interpretation and Analysis: The absence of statistical significance in the lagged model suggests that the benefits of AI adoption are neither immediate nor observable in the short term. This implies that AI investments may require a longer time horizon to generate measurable financial returns, or that their impact is indirect and mediated through other operational improvements.

4.3 Firm-Level Effects

The fixed effects included in the regression models are found to be statistically significant.

Interpretation and Analysis: This indicates that bank-specific characteristics, such as management efficiency, operational strategies, and asset quality, play a dominant role in determining financial performance. The significance of these effects suggests that variations in profitability across banks are primarily driven by internal factors rather than the level of AI adoption.

It is observed that AI adoption levels become relatively uniform across banks in later years, which may reduce variability and limit the statistical significance of its impact.

5. RESULTS AND DISCUSSION

FINDINGS:

- AI adoption does not have a statistically significant impact on ROA and ROE
- AI intensity does not influence profitability
- No evidence of lagged AI effect
- Firm-specific factors significantly affect performance

CONCLUSION

The study concludes that artificial intelligence adoption does not have a statistically significant impact on financial performance in the short run. While AI adoption shows a positive directional effect, it is not strong enough to influence profitability indicators significantly. The results emphasize that internal factors such as management efficiency and operational strategies are more critical determinants of financial performance. The findings also indicate that AI adoption in the banking sector may yield long-term benefits that are not immediately reflected in financial indicators.

SUGGESTIONS

- Banks should focus on effective implementation of AI technologies
- Investment in employee training and skill development is essential
- AI adoption should be aligned with strategic goals
- Long-term evaluation of AI impact is necessary

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