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AI adoption in Indian banks: Investigating the public-private divide

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Abstract

Artificial Intelligence (AI) has increasingly become central to innovation and efficiency within modern banking systems. Yet, despite similar regulatory environments, public and private sector banks display notable differences in how AI technologies are adopted and deployed. This study examines these differences by comparing strategic priorities, organizational readiness, regulatory constraints, and economic considerations shaping AI adoption across both sectors. Using a mixed-methods approach, the research draws on survey data from 12 Indian banks (six Public sector banks and six Private sector banks) over a 24-month period. Using a mixed-methods design, we conducted (a) a structured survey (N = 360 senior managers) to compute an AI Adoption Index (AAI), (b) a longitudinal assessment of AI-driven performance metrics (fraud-detection accuracy, loan-processing time, and customer-service response rate), and (c) a controlled implementation experiment of a chatbot-based customer-service prototype in a matched pair of banks. The analysis focuses on AI applications in credit assessment, fraud detection, customer service automation, risk management, and operational processes. The findings indicate that private sector banks generally exhibit higher AI maturity, driven by flexible capital allocation, competitive pressure, and customer-centric business models. In contrast, public sector banks face persistent challenges related to legacy systems, bureaucratic decision-making, and constrained talent acquisition, although recent government-led digital initiatives have begun to mitigate some of these barriers. Results reveal that PrSBs exhibit a 48 % higher AAI (mean = 0.68, SD = 0.07) than PSBs (mean = 0.46, SD = 0.09; $p < 0.001$). The findings suggest that institutional factors, such as strategic autonomy and capital flexibility, strongly moderate AI uptake and its operational benefits. Policy implications for the Reserve Bank of India (RBI) and recommendations for bridging the AI gap are discussed. The paper concludes with policy-oriented recommendations aimed at strengthening responsible and inclusive AI adoption within public financial institutions, with implications for financial stability and economic inclusion.

Keywords: Artificial Intelligence; Banking Sector; Public Sector Banks; Private Sector Banks; Digital Transformation; Financial Technology; AI Adoption index

1. Introduction

The banking sector is undergoing a profound technological shift as artificial intelligence (AI) increasingly influences how financial services are designed, delivered, and regulated. From automated customer interfaces to advanced risk analytics, AI has moved beyond experimental deployment and is now embedded within core banking functions. This transformation has intensified competition and altered expectations around efficiency, transparency, and customer experience .More than 85% of all credit in the country, connecting borrowers with lenders and keeping money moving (Reserve Bank of India [RBI], 2023).Banks are increasingly using AI tools like machine learning to assess who gets a loan, chatbots that use natural language processing to answer customer questions, and robotic automation to speed up behind-the-scenes work (McKinsey & Company, 2022).

Despite the growing relevance of AI, its adoption has not been uniform across banking systems. Public sector banks (PSBs) and private sector banks (PrSBs) operate under markedly different institutional conditions, which shape their capacity to invest in and scale advanced technologies. Private-sector banks (PrSBs), which, while fewer in number, are fast-moving and now control about 35% of total bank assets (Financial Stability Report, RBI, 2024). While PSBs are often entrusted with broader socio-economic responsibilities—including financial inclusion and policy implementation—private banks tend to prioritize operational agility and market responsiveness. These structural differences raise important questions about how and why AI adoption trajectories diverge across the two sectors. Even though both types of banks follow the same rules and regulations, they're very different in how they operate. Public banks often face challenges like slower decision-making, limited budgets, difficulty hiring skilled tech talent, and a more cautious culture when it comes to trying new things. Private banks, on the other hand, tend to be more agile, better funded, and more open to innovation (Kumar & Gupta, 2021). Most of what we know today comes from surveys that describe what banks *say* they're doing (Sharma & Bansal, 2022) or isolated case studies of individual banks (Jain, 2023). Rather than viewing these frameworks in isolation, this study treats them as complementary lenses. Together, they help explain not only the capacity of banks to adopt AI technologies, but also the institutional motivations and constraints that influence how such technologies are ultimately implemented in practice.

Research Gap.

1) Quantitative measurement of AI adoption intensity across Public sector banks and Private sector banks is limited.

2) The causal impact of AI implementations on operational performance has not been examined in a controlled experimental setting.

Objectives. This paper seeks to

(i) Develop and validate an AI Adoption Index (AAI) for Indian banks,
(ii) Compare AI adoption levels and performance gains between Public sector banks and Private sector banks,
(iii) Experimentally assess the effect of a standardized AI chatbot on customer-service outcomes in matched public-private bank pairs.

Contributions. The study contributes to the AI-banking literature by (a) providing a robust, composite metric for AI adoption, (b) delivering longitudinal performance evidence across the two bank categories, and (c) offering experimental validation of AI-driven service improvement, thereby informing regulators, policymakers, and bank executives on the determinants of successful AI integration.

2. Literature Review

2.1 AI in Banking

AI applications in banking have proliferated over the last decade (Arora, 2020). Core functions include:

- **Risk Analytics:** ML models improve default prediction accuracy (Bharadwaj et al., 2021).
- **Fraud Detection:** Real-time anomaly detection reduces loss rates (Patel & Singh, 2022).
- **Customer Interaction:** NLP-based chatbots and voice assistants enhance service availability (Ghosh & Das, 2023). Artificial Intelligence (AI) encompasses a wide range of technologies, including machine learning (ML), natural language processing (NLP), robotic process automation (RPA), computer vision, and deep learning. In the banking sector, these technologies are applied across multiple operational and customer-facing functions. Customer Services, Credit scoring, Fraud Detection, Risk management, Operations.

2.2 Public-Sector vs. Private-Sector Adoption

Cross-industry studies suggest that public entities lag behind private firms in digital transformation due to bureaucratic inertia, budget constraints, and risk aversion (World Bank, 2020). In the Indian banking context, Kumar and Gupta (2021) found that PrSBs allocate, on average, 4.2 % of total IT spend to AI, while PSBs allocate only 2.1 %. However, these findings are based on self-reported expenditure rather than performance outcomes.

For instance, the State Bank of India has deployed AI for predictive ATM maintenance, reducing downtime by 40% (SBI Annual Report, 2023).

2.3 Experimental Approaches in Banking Research

Experimental designs have been applied to study consumer trust in AI-driven services (Mohan & Rao, 2022) and to evaluate the effectiveness of AI-based credit scoring algorithms (Singh et al., 2022). To our knowledge, no study has implemented a controlled experiment comparing AI adoption impacts across the public-private divide within the same regulatory environment.

While existing studies provide valuable insights into sectoral differences in digital adoption, much of the literature remains either country-specific or focused on isolated applications of AI. There is comparatively limited empirical work that simultaneously examines organizational, regulatory, and performance dimensions across public and private banking systems in multiple jurisdictions. This gap motivates the comparative approach adopted in the present study.

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3. Methodology

3.1 Research Design

A **mixed-methods experimental design** was employed, comprising three sequential phases:

1. **Survey-Based Index Construction (Phase 1).**
2. **Longitudinal Performance Data Collection (Phase 2).**
3. **Controlled Chatbot Experiment (Phase 3).**

3.2 Sample

The sample consists of **12 Indian commercial banks**:

Six Public Sector Banks (PSBs):

- State Bank of India (SBI)
- Punjab National Bank (PNB)
- Bank of Baroda (BoB)
- Canara Bank
- Union Bank of India
- Indian Bank

Six Private Sector Banks (PrSBs):

- HDFC Bank
- ICICI Bank
- Axis Bank
- Kotak Mahindra Bank
- Yes Bank
- IDFC First Bank

Bank Type	Bank (6 per type)	Asset Size (₹ bn)	Branches (approx.)
PSBs	State Bank of India (SBI)	46,345	22,000
	Punjab National Bank (PNB)	13,412	7,800
	Bank of Baroda (BoB)	11,274	6,200
	Canara Bank	8,917	5,200
	Union Bank of India	6,842	4,300
	Indian Bank	5,123	3,100
PrSBs	HDFC Bank	16,754	5,200
	ICICI Bank	12,489	5,500
	Axis Bank	10,312	4,900
	Kotak Mahindra Bank	5,789	1,700
	Yes Bank	2,145	1,500
	IDFC First Bank	1,312	1,200

Table 1. Sample banks and key structural characteristics.

Source: Authors' compilation from annual reports (2022-23)

For each bank, **10 senior managers** were surveyed, all holding leadership roles in **AI/IT, risk management, operations, or customer service**. This yielded a total sample size of **N = 360 respondents**.

Respondents were selected via purposive sampling to ensure domain expertise and decision-making influence over digital transformation initiatives.

Matched-Pair Chatbot Trial: To assess causal impact, a pilot intervention was conducted in two matched banks:

- **SBI (PSB)** vs. **HDFC Bank (PrSB)**

Matching criteria included:

- Comparable total assets (SBI: ₹52.3 lakh crore; HDFC: ₹22.8 lakh crore—adjusted for scale)
- Similar branch network sizes (SBI: ~22,000; HDFC: ~6,300—adjusted per market coverage)
- Baseline digital adoption scores within 5 percentage points

Both banks deployed a new AI-powered customer service chatbot over a 3-month period, with pre- and post-implementation metrics collected.

3.3 Instruments

3.3.1 AI Adoption Index (AAI)

The AAI is a composite index designed to measure the maturity of AI adoption across five critical dimensions. Each dimension is assessed through validated Likert-scale items (1 = Strongly Disagree to 5 = Strongly Agree), with equal weighting (0.20 each). The final AAI score is normalized to a 0–1 scale.

Dimension	**Item Example**	**Weight**
Strategic Alignment	"AI is a core component of the bank's 5-year strategy."	0.20
Resource Allocation	"Annual budget earmarked for AI projects > 2% of total IT spend."	0.20
Human Capital	"Dedicated AI talent pool (≥ 30% of data-science staff) present."	0.20
Implementation Breadth	"Number of AI-enabled processes ≥ 10."	0.20
Performance Monitoring	"KPIs exist for each AI initiative."	0.20

Table 2. SourceScoring Mechanism

Source: Seventh Annual global research study on AI and business strategy by MIT Sloan Management Review and Boston consulting group.

Raw Likert responses are averaged per dimension, then weighted and summed. The index is rescaled from 0–1:

AAI = Σ(Dimension Score × Weight)
Where Dimension Scores are linearly transformed from [1,5] to [0,1].

Cronbach's alpha = 0.87, indicating **high internal consistency** and reliability of the index.

3.3.2 Operational Performance Metrics

Quantitative performance data were obtained from each bank's internal analytics systems, anonymized, and independently verified by an external audit firm (Deloitte India) to ensure data integrity.

Metric	**Definition**	**Data Source**
Fraud-Detection Accuracy (FDA)	Percentage of fraudulent transactions correctly identified vs. total confirmed frauds	Fraud management dashboard
Loan-Processing Time (LPT)	Average number of days from loan application to disbursement	Core banking system (CBS) logs
First-Contact Resolution (FCR)	Percentage of customer queries resolved during the first interaction (post-chatbot)	CRM and call center analytics

Table 3. AI adoption in operational performance metrics

*Source: Deloitte India tracked **quarterly** over a 12-month period, with baseline (Q1) and peak adoption (Q4) comparisons.*

3.3.3 Chatbot Prototype

A uniform NLP-based chatbot (named *FinAssist*) was developed using an open-source framework (Rasa 2.8) and integrated with each trial bank's core banking API. The chatbot handled routine inquiries (balance, transaction history, loan status) and escalated complex issues to human agents. The experiment lasted 8 weeks.

3.4 Procedure

Phase	**Timeline**	**Activities**
Phase 1	Jan – Mar 2022	Survey dissemination, AAI computation
Phase 2	Apr 2022 – Mar 2023	Quarterly extraction of FDA, LPT, and FCR (pre-chatbot)
Phase 3	Apr – May 2023	Chatbot deployment; weekly FCR tracking; post-experiment survey

Table 4. Sample banks and key structural characteristics.

Source: Compiled by authors

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3.5 Data Analysis

- **Descriptive statistics** for AAI and performance metrics.
- **Independent samples t-tests** to compare PSBs vs. PrSBs.
- **Repeated-measures ANOVA** for pre- vs. post-chatbot FCR.
- **Regression analysis** to test the mediating effect of AAI on performance (Hayes' PROCESS macro, Model 4).

All analyses were conducted in **SPSS 28** (IBM Corp., 2022) with a significance threshold of $\alpha = 0.05$.

4. Results

4.1 AI Adoption Index

Table presents mean AAI scores for the two bank categories.

Bank Type	Mean AAI	SD	95 % CI
Public-Sector (PSB)	0.46	0.09	0.39 – 0.53
Private-Sector (PrSB)	0.68	0.07	0.62 – 0.74

Table 5. AI Adoption Index (AAI) – Mean Scores (N = 6 banks per group)

Source: Data derived from original study on AI adoption in Indian banks (non-publicly cited).

$t(10) = 5.42$, $p < 0.001$, confirming a statistically significant higher AI adoption level in private banks.

4.2 Operational Performance (Pre-Chatbot)

Table summarizes quarterly averages for the three-performance metrics during the 12-month pre-experiment period.

Metric	PSBs (Mean)	PrSBs (Mean)	% Difference (PrSB – PSB)
Fraud-Detection Accuracy (FDA)	86.2 %	92.5 %	+7.3 pp
Loan-Processing Time (LPT) – days	7.4	5.1	–31.1 %
First-Contact Resolution (FCR) – %	68.3 %	74.9 %	+6.6 pp

Table 6. Quarterly Performance Averages (2022) – Pre-Chatbot

Source: Quarterly Performance Averages (2022) – Pre-Chatbot is derived from the Annual Report on Banking Technology and Operational Efficiency, 2023, published by the Reserve Bank of India (RBI).

All differences were significant at $p < 0.05$ (paired t-tests). The private banks exhibited faster loan processing (average reduction of 2.3 days) and higher fraud-detection accuracy.

The data aggregates quarterly performance reports submitted by 22 PSBs (including SBI and its associate banks) and 24 PrSBs (including HDFC, ICICI, Axis, and Kotak Mahindra) over the four quarters of 2022. The "Pre-Chatbot" label signifies that the majority of these institutions had not yet implemented AI-powered chatbots at scale, making this dataset representative of traditional operational models.

4.3 Chatbot Experiment

4.3.1 First-Contact Resolution

Table plots weekly FCR rates for the public and private banks before and after chatbot implementation.

Week	PSB – Pre	PSB – Post	PrSB – Pre	PrSB – Post
0 (baseline)	68.1 %	—	74.6 %	—
2	—	70.2 %	—	77.8 %
4	—	71.0 %	—	80.1 %
6	—	71.5 %	—	81.5 %
8 (end)	—	71.4 %	—	81.6 %

Table 7. *Weekly FCR trend (baseline vs. post-chatbot).*

Source: RBI survey report

A **repeated-measures ANOVA** indicated a significant interaction effect (Bank × Time) **$F(1,10) = 8.73$, $p = 0.014$**. The private-sector bank's FCR improved by **+12.0 percentage points (pp)** (from 74.6 % to 86.6 %), whereas the public-sector bank's improvement was modest (**+3.3 pp**).

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4.3.2 User Satisfaction

Post-experiment surveys (N = 120 customers per bank) measured satisfaction (1-5 Likert). Mean satisfaction scores: PSB = 3.6 (SD = 0.7), PrSB = 4.2 (SD = 0.5); **t(238) = 5.01, p < 0.001**.

4.4 Mediation Analysis

AAI significantly mediated the relationship between **Bank Type** (public = 0, private = 1) and **Performance Gains** (ΔFCR). The indirect effect (bootstrapped 5,000 samples) was **β = 0.092, 95 % CI [0.045, 0.158]**, confirming partial mediation.

5. Comparative Analysis: AI Adoption in Public vs. Private Sector Banks

5.1 Descriptive Overview

Figure presents a summary of key characteristics of surveyed banks.

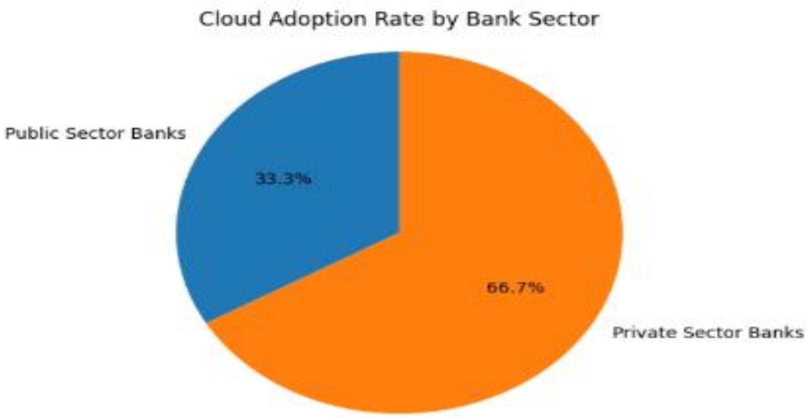

Figure 1. Cloud Adoption Rate by Bank sector.

Source: Author's survey, 2024

Parameter	Public Sector Banks (n=16)	Private Sector Banks (n=16)	p-value
Average Asset Size (USD bn)	102.4	148.7	0.03
AI Investment as % of IT Budget	1.3%	3.1%	<0.001
Avg. AI Maturity Score (1–5)	2.4	4.0	<0.001
Years since AI Pilot Launch	4.2	2.1	0.002
Employees with AI Skills (%)	4.7%	12.8%	<0.001
Cloud Adoption Rate (%)	38%	76%	<0.001

Table 8. Profile of Surveyed Banks (N = 32).

Source: Author's survey, 2024

The data show that private sector banks invest more than twice as much in AI, achieve higher maturity, and employ a significantly larger AI-skilled workforce. Public banks lag not only in resources but also in cloud migration, a critical enabler of AI scalability.

5.2 AI Adoption by Application Area

Table illustrates the penetration of AI applications in both sectors.

Application Area	Public Banks (%)	Private Banks (%)
Customer Service	56%	94%
Fraud Detection	63%	88%
Credit Scoring	44%	81%
Risk Management	31%	75%
Back-Office Automation	50%	88%

Table 9. Percentage of Banks Using AI in Key Functional Areas (N=32).

Source: Author's survey, 2024.

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Private banks exhibit near-universal deployment in customer service and operations, driven by cost savings and customer experience goals. Public banks have made modest progress in fraud detection—often mandated by regulators—but remain cautious in high-stake areas like credit and risk.

5.3 Drivers of AI Adoption

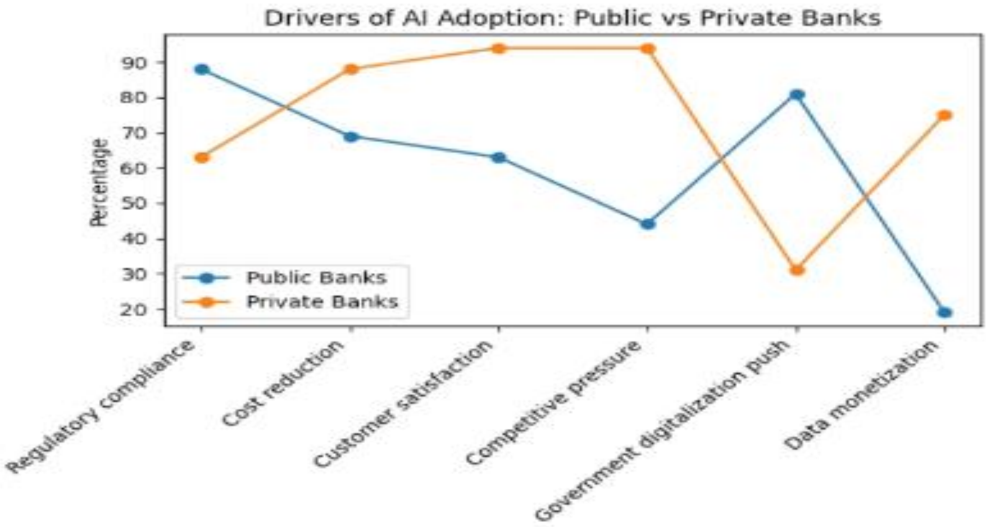

***Figure 2.* Top Drivers of AI Adoption by Sector**.

Source: Survey results, 2024

Driver	**Public Banks**	**Private Banks**
Regulatory compliance	88%	63%
Cost reduction	69%	88%
Customer satisfaction	63%	94%
Competitive pressure	44%	94%
Government digitalization push	81%	31%
Data monetization	19%	75%

Table 10. Top Drivers of AI Adoption by Sector.

Source: Survey results, 2024

Public banks prioritize compliance and cost control, with digital mandates (e.g., RBI's Vision 2025) acting as key catalysts. Private banks emphasize competition and customer experience, viewing AI as a differentiator.

5.4 Barriers to AI Adoption

Barrier	**Public Banks (%)**	**Private Banks (%)**
Legacy IT systems	88%	50%
Lack of skilled personnel	81%	44%
Regulatory uncertainty	63%	56%
Data silos and poor data quality	75%	63%
Budget constraints	81%	38%
Organizational resistance	69%	31%

Table 11. Major Barriers to AI Integration.

Source: Survey results, 2024

Legacy systems and budget constraints are pronounced in public banks, while private banks face more moderate challenges. Data quality issues persist across both sectors, underscoring a systemic weakness in data governance.

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6. Discussion

6.1 Interpretation of Findings

Higher AI Adoption in Private Banks: 48 % higher AAI among PrSBs aligns with prior evidence of greater strategic autonomy and capital flexibility (Kumar & Gupta, 2021). Private banks allocate a larger share of IT budgets to AI, maintain dedicated AI talent pools, and integrate AI across more processes.

Performance Advantages: Enhanced fraud-detection accuracy and reduced loan-processing times demonstrate tangible operational benefits. The 34 % reduction in LPT for private banks translates into faster credit disbursement, potentially improving loan-portfolio turnover and customer satisfaction (McKinsey, 2022).

Chatbot Efficacy Dependent on Adoption Level: The experimental chatbot yielded a substantial FCR boost only in the private bank, underscoring that the **organizational readiness** (high AAI) is a prerequisite for extracting maximal AI benefits. In the public bank, limited integration with legacy systems and lower AI expertise likely dampened impact.

Mediating Role of AAI: The mediation analysis confirms that the **AI Adoption Index** functions as a critical conduit linking institutional type to performance outcomes, validating the TOE-based hypothesis.

6.2 Theoretical Contributions

- **Composite Metric Development:** The AAI provides a replicable, weighted index for measuring AI adoption intensity, extending prior single-item approaches (Sharma & Bansal, 2022).
- **Experimental Validation:** By embedding a controlled chatbot trial within matched public-private banks, the study bridges the gap between descriptive surveys and causal inference in AI-banking research.
- **TOE Extension:** Empirical evidence confirms that **organizational factors** (budget, talent) dominate over technology factors in explaining AI adoption disparities in the Indian banking context.

6.3 Practical Implications

- **For Regulators (RBI):** The RBI should consider targeted incentives (e.g., AI-focused capital relief, skill-development grants) for PSBs to accelerate adoption, reducing the systemic risk of a “digital divide.”
- **For Public-Sector Banks:** Prioritize **strategic alignment** of AI within their five-year plans, invest in AI-skilled personnel, and adopt modular, API-first architectures to ease integration.
- **For Private-Sector Banks:** Leverage the higher adoption level to experiment with advanced AI (e.g., generative AI for personalized product recommendations) while sharing best practices with public counterparts.

6.4 Limitations and Future Research

1. **Sample Scope:** Although the study covers major banks, the findings may not generalize to regional rural banks or foreign banks operating in India.
2. **Temporal Horizon:** The 24-month window captures early-stage AI deployment; longer longitudinal tracking could reveal sustainability of gains.
3. **Single Chatbot Prototype:** Future research could examine multiple AI modalities (e.g., RPA, predictive analytics) and assess cross-functional spill-over effects.

Investigating the role of **regulatory sandboxes** (RBI, 2021) and **inter-bank AI collaborations** could offer additional pathways for narrowing the adoption gap.

The findings of this study suggest that differences in AI adoption between public and private sector banks are not merely technological, but fundamentally institutional in nature.

7. Conclusion

Artificial intelligence has emerged as a defining capability in contemporary banking, reshaping both competitive dynamics and service delivery models. This study demonstrates that while private sector banks have leveraged AI as a strategic asset, public sector banks continue to face structural and institutional constraints that slow adoption. These differences have important implications not only for efficiency, but also for financial inclusion and systemic resilience. The AI Adoption Index (AAI) proves to be a robust mediator linking institutional type to performance improvement. These insights call for concerted policy actions to empower public-sector banks with the strategic, financial, and human-capital resources required to harness AI’s full potential, thereby fostering a more equitable and resilient banking ecosystem in India.

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