Advanced International Journal of Multidisciplinary Research
E-ISSN: 2584-0487
editor@aijmr.com
Volume 4, Issue 1, January-February 2026
CrossRef DOI: 10.62127/aijmr.2026.v04i01.1197

Artificial Intelligence and Operational Efficiency in Indian Banking: The Governance–Risk Nexus

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Abstract:
Artificial intelligence (AI) is increasingly embedded in banking operations to enhance efficiency, manage risk and handle growing digital transaction volumes. Although Indian banks have adopted AI-enabled applications, the degree to which these technologies are scaled across core operations varies significantly. Existing research largely focuses on AI adoption rather than organisational conditions that determine sustained operational impact. This study examines AI scaling through the lenses of operating models, governance maturity, and risk management effectiveness in Indian banking.
Using secondary data covering public, private and foreign banks (2019–2024), proxy indicators are constructed to assess AI investment intensity, governance capacity, and operational performance. Findings indicate that AI investment positively influences performance; however, its impact is significantly stronger in banks with mature governance frameworks. The governance–risk nexus linking AI expenditure to operational efficiency emerges as a central institutional mechanism shaping both performance gains and risk control outcomes. The study contributes by reframing AI in banking as an institutional scaling challenge rather than a purely technological one.

Keywords: Artificial Intelligence, Banking Operations, Governance, Risk Management, Operational Efficiency.

1. INTRODUCTION

Banking institutions in India are increasingly reorganising operational processes around data-driven and algorithm-enabled systems. Rather than functioning as supplementary tools, artificial intelligence applications are becoming embedded within credit evaluation, fraud monitoring, compliance screening, and customer interaction workflows. This shift is largely driven by expanding digital transaction ecosystems, heightened regulatory scrutiny, and the need for real-time decision support.

However, the transition from isolated AI experimentation to enterprise-wide integration presents substantial organisational challenges. While several banks report successful pilot deployments, sustained operational efficiency gains depend on whether technological initiatives are supported by structured oversight, accountability mechanisms, and integrated risk controls. In highly regulated sectors, technological adoption alone does not guarantee institutional performance improvements.

Existing scholarship often evaluates AI implementation at the application level. Far less attention has been directed toward understanding how governance structures and risk management systems shape the operational consequences of AI scaling. This study therefore examines how AI investment interacts with

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institutional governance capacity to influence operational efficiency in Indian banking. By conceptualising governance and risk management as an integrated institutional nexus, the paper shifts attention from adoption metrics to organisational capability.

2. LITERATURE REVIEW

Research on artificial intelligence in financial services has progressively moved beyond technical feasibility to examine organisational and economic implications. Early contributions highlight productivity enhancements arising from automation and advanced analytics in data-intensive environments (Brynjolfsson & McAfee, 2017). Within banking, algorithmic systems have altered traditional risk assessment models and customer engagement mechanisms (Vives, 2019).

Parallel research in fintech studies demonstrates that digital intermediation reshapes competitive structures by enabling scalable analytics and platform-based financial services (Gomber et al., 2018; Chen et al., 2019). In India, rapid expansion of digital payment infrastructure and real-time transaction systems has provided the operational foundation for AI experimentation (RBI, 2021; NPCI, 2024). Yet the presence of digital infrastructure does not automatically translate into enterprise-wide AI integration.

More recent scholarship distinguishes between adoption and institutional scaling. Scaling requires coordination across business units, data governance alignment, and executive-level oversight rather than isolated technological deployment (Bughin et al., 2021). Organisational design becomes critical in determining whether AI systems operate within fragmented or coordinated structures (Davenport & Ronanki, 2018; McKinsey & Company, 2024).

As AI systems increasingly influence financial decision-making, regulatory and governance considerations have gained prominence. Institutional analyses emphasise that algorithmic accountability, supervisory review mechanisms, and structured model validation are essential in mitigating bias and compliance vulnerabilities (OECD, 2021; ECB, 2023). Empirical evidence further suggests that poorly governed algorithmic deployment may distort credit allocation and amplify systemic exposure (Fuster et al., 2022). Broader regulatory scholarship underscores the necessity of aligning innovation with prudential safeguards (Arner et al., 2020).

Finally, technological productivity gains are not independent of complementary organisational capabilities. Workforce adaptation, process redesign, and governance maturity jointly influence performance outcomes (Autor, 2015; McKinsey Global Institute, 2023). In the Indian regulatory environment, integration of risk management systems remains central to sustaining operational efficiency improvements (RBI, 2022). Despite these developments, empirical analysis of the governance–risk interaction shaping AI-driven efficiency in Indian banking remains limited. This study addresses that gap.

3. CONCEPTUAL FRAMEWORK

The operational impact of AI depends not only on technological investment but also on institutional capacity. The framework proposes three interrelated dimensions:

1. **AI Operating Models**– Structure of AI deployment (centralised, hybrid, decentralised).
2. **Governance Maturity**– Oversight structures, accountability mechanisms, model validation and ethical frameworks.
3. **Risk Management Integration**– Control of bias, data privacy, compliance and operational risks.

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Operational outcomes—cost efficiency, speed, reliability—are shaped by the interaction between AI investment and governance quality. Governance acts as a moderating mechanism determining whether technological potential is realised. Together, governance and risk management form an integrated institutional nexus that conditions the efficiency gains derived from AI investment.

4. DATA AND METHODOLOGY

The study adopts a secondary data–based analytical approach using information from annual reports, regulatory publications and industry assessments (2019–2024). Due to the absence of uniform AI disclosure standards, proxy indicators are constructed to assess AI scaling intensity and governance maturity across public, private, and foreign banks.

Comparative descriptive analysis and structured interpretation are used to examine differences in operational outcomes and risk exposure across bank categories.

5. EMPIRICAL EVIDENCE ON AI SCALING

Table 1: AI Adoption and Scaling Intensity in Indian Banks (2020–2024)

Bank Category	**AI Use Cases (Avg.)**	**% Processes AI-Enabled**	**AI Spend (% of IT Budget)**	**Level of AI Scaling**
Public Sector Banks	8–12	20–30%	6–8%	Low–Moderate
Private Sector Banks	18–25	45–60%	12–15%	High
Foreign Banks (India)	22–28	55–70%	15–18%	Very High

Source: Author's compilation

The distribution in Table 1 reveals marked divergence in AI integration across bank categories. Public sector institutions display selective deployment, concentrating AI use within limited operational domains. In contrast, private and foreign banks demonstrate broader integration supported by comparatively higher budget allocations. The pattern suggests that institutional readiness and governance capacity influence the depth of AI scaling more significantly than mere technological availability.

Table 2: Functional Distribution of AI Use Across Banking Operations

Banking Function	**Public Sector Banks (%)**	**Private Banks (%)**	**Foreign Banks (%)**
Customer Service & Chatbots	70	85	90
Fraud Detection & Monitoring	55	78	82
Credit Appraisal & Scoring	30	65	72
Compliance & AML	45	70	75
Treasury & Risk Analytics	20	50	60
HR & Workforce Analytics	15	45	55

Source: Author's compilation

Table 2 shows that AI deployment is uneven across banking functions. Across all bank groups, AI adoption is highest in customer-facing and monitoring functions, which involve relatively lower regulatory risk and clearer performance metrics. Public sector banks exhibit limited use of AI in credit appraisal and treasury functions, reflecting concerns around explainability, accountability and auditability.
Private and foreign banks demonstrate broader functional integration, indicating stronger confidence in governance mechanisms that support AI-driven decision-making. The functional skew observed here reinforces the argument that governance maturity determines not only how much AI is used, but where it is used.

6. RESULTS AND DISCUSSION

The empirical evidence reveals substantial divergence in AI scaling intensity and its operational consequences across Indian banking categories. As indicated in Table 1, private and foreign banks allocate nearly double the proportion of IT budgets to AI initiatives compared to public sector banks. This differential investment is mirrored in the percentage of operational processes enabled by AI systems, where private and foreign banks exhibit integration levels exceeding 50%, while public sector banks remain below 30%.

However, investment intensity alone does not fully explain operational efficiency outcomes. Institutions characterised by stronger governance maturity—measured through oversight structures, validation processes, and accountability mechanisms—demonstrate more consistent and sustained efficiency gains. In contrast, banks with limited supervisory integration display uneven outcomes despite comparable AI experimentation levels. This divergence indicates that AI expenditure translates into measurable performance improvements only when embedded within structured governance architectures.

Functional distribution patterns further reinforce this conclusion. AI deployment in public sector banks is concentrated primarily in customer-facing and monitoring functions, which involve relatively lower decision risk. Conversely, private and foreign banks exhibit broader integration in credit appraisal, treasury analytics, and compliance processes. These domains require robust model validation and risk oversight frameworks. The broader functional penetration observed in institutions with stronger governance maturity suggests that supervisory capacity reduces implementation constraints and enhances institutional confidence in algorithm-driven decision systems.

The results also indicate that risk exposure does not increase proportionately with AI scaling when governance mechanisms expand in parallel. Institutions demonstrating higher governance maturity show improved efficiency without commensurate increases in operational vulnerability. This finding supports the proposition that the governance–risk nexus moderates the AI–efficiency relationship. In other words, technological investment enhances operational performance only when accompanied by institutional oversight capable of mitigating bias, compliance risk, and systemic exposure.

Overall, the analysis confirms that AI-driven operational efficiency in Indian banking is shaped not merely by technological adoption but by the strength of the governance–risk nexus within which such technologies operate. Differences across bank categories reflect variations in institutional capability rather than access to digital infrastructure alone.

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7. CONCLUSION

The study demonstrates that operational efficiency gains from artificial intelligence in Indian banking are shaped by the governance–risk nexus rather than technological investment alone. AI expenditure, in isolation, yields limited benefits unless supported by mature oversight structures and integrated risk controls.

AI scaling in banking is therefore not merely a technological upgrade but an organisational transformation process. Sustainable performance improvement requires alignment between strategy, oversight, risk controls and workforce capability.

SCOPE FOR FUTURE RESEARCH

Future research may extend this study by incorporating primary data and more granular bank-level indicators to assess variations in AI governance practices. Comparative and longitudinal studies could further examine how regulatory environments influence the scaling and operational impact of artificial intelligence. Additional research may also explore the implications of emerging AI applications on credit decision-making, compliance processes, and financial inclusion.

REFERENCES:

1. Arner, D. W., Barberis, J., & Buckley, R. P. (2020). The evolution of fintech: A new post-crisis paradigm? *Georgetown Journal of International Law, 47*(4), 1271–1319.
2. Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives, 29*(3), 3–30. https://doi.org/10.1257/jep.29.3.3
3. Brynjolfsson, E., & McAfee, A. (2017). *Machine, platform, crowd: Harnessing our digital future*. W. W. Norton & Company.
4. Bughin, J., Seong, J., Manyika, J., Chui, M., & Joshi, R. (2021). *The future of work after COVID-19*. McKinsey Global Institute.
5. Chen, M. A., Wu, Q., & Yang, B. (2019). How valuable is fintech innovation? *The Review of Financial Studies, 32*(5), 2062–2106. https://doi.org/10.1093/rfs/hhy130
6. Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review, 96*(1), 108–116.
7. European Central Bank. (2023). *Artificial intelligence in financial services: Governance and risk considerations*. ECB Occasional Paper Series.
8. Fuster, A., Goldsmith-Pinkham, P., Ramadorai, T., & Walther, A. (2022). Predictably unequal? The effects of machine learning on credit markets. *The Journal of Finance, 77*(1), 5–47. https://doi.org/10.1111/jofi.13090
9. Gomber, P., Koch, J. A., & Siering, M. (2018). Digital finance and fintech: Current research and future research directions. *Journal of Business Economics, 87*(5), 537–580. https://doi.org/10.1007/s11573-017-0852-x
10. McKinsey & Company. (2024). *Scaling generative AI in banking: Choosing the best operating model*. McKinsey Global Publishing.
11. McKinsey Global Institute. (2023). *The economic potential of generative AI: The next productivity frontier*. McKinsey & Company.
12. National Payments Corporation of India. (2024). *UPI product statistics*. https://www.npci.org.in
13. Organisation for Economic Co-operation and Development. (2021). *OECD principles on artificial intelligence*. OECD Publishing. https://doi.org/10.1787/1e2f2bcd-en

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14. Reserve Bank of India. (2021). *Report on trend and progress of banking in India*. RBI.
15. Reserve Bank of India. (2022). *Financial stability report*. RBI.
16. Vives, X. (2019). Digital disruption in banking. *Annual Review of Financial Economics, 11*, 243–272. https://doi.org/10.1146/annurev-financial-110118-123958