International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

ARTIFICIAL INTELLIGENCE IN FINANCE, BANKING AND FINANCIAL TECHNOLOGY: APPLICATIONS, RISKS AND A RESPONSIBLE GOVERNANCE FRAMEWORK

Dr. Gandla Ashwini
Assistant Professor, Guru Nanak Institute of Technology
Dr. P. Chakravarthi
Director BS-MS, Vishwa Vishwani Institute Systems and Management

Abstract

Artificial intelligence (AI) is reshaping financial intermediation by enabling faster credit assessment, real-time fraud detection, personalized services, automated compliance and data-intensive investment analysis. Yet predictive gains do not necessarily translate into equitable, resilient or accountable outcomes. This critical narrative review synthesizes peer-reviewed scholarship and institutional evidence available through November 2026 to examine AI's applications across banking, finance and financial technology (fintech). A structured thematic comparison identifies four interdependent dimensions: operational value, distributive fairness, model and cyber risk, and institutional governance. Recent UK regulatory survey evidence indicates that 86% of respondent financial firms used AI in 2026, compared with 75% in the 2024 survey, although sample and measurement differences limit direct comparison. The analysis proposes a risk-tiered governance framework integrating use-case classification, explainability, independent validation, third-party oversight, human recourse and continuous monitoring. The central conclusion is that sustainable financial innovation requires AI performance to be evaluated alongside customer outcomes, contestability and systemic resilience, rather than through accuracy or cost reduction alone.

Keywords: artificial intelligence; banking; fintech; credit scoring; fraud detection; explainable AI; financial stability; AI governance

1. Introduction

AI has shifted from specialized quantitative applications to enterprise-wide systems that support lending, payments, customer interactions, surveillance and operational decisions. Machine learning identifies nonlinear relationships in financial data, whereas generative AI can summarize documents, support staff and produce conversational outputs. These capabilities offer efficiency and broader service reach but also create risks involving opaque decisions, unreliable outputs, consumer discrimination and dependence on a limited set of infrastructure providers (Financial Stability Board [FSB], 2024; Crisanto et al., 2024).

The Bank of England and Financial Conduct Authority (2026) report that 86% of their 2026 financial-sector survey respondents used AI; the corresponding headline figure was 75% in 2024. These are respondent-level estimates, not market-wide adoption rates, and survey populations and definitions differ across years. Their significance lies less in proving a causal trend than in demonstrating the material presence of AI within regulated financial services (Bank of England & Financial Conduct Authority [BoE–FCA], 2024, 2026).

This paper addresses three questions: (RQ1) Where does AI create distinctive value in financial services? (RQ2) Which technical, ethical and systemic risks accompany deployment? (RQ3) What governance architecture can align innovation with consumer protection and institutional resilience? Its contribution is an integrated, risk-tiered analytical framework linking use cases to validation evidence, accountability and measurable outcomes.

2. Methodology and Review Scope

This study adopts a critical narrative-review design rather than claiming a systematic review or reporting new primary data. Sources were purposively selected for relevance and authority: peer-reviewed research on machine-learning credit markets and credit risk; official survey evidence from UK financial regulators; international financial-stability and supervisory analyses; and recognized AI risk-management guidance. The review prioritizes published material through November 2026 and cross-checks quantitative claims against primary institutional reports. Thematic synthesis organizes the evidence by applications, benefits, risks and controls. Because the selection was not exhaustive and heterogeneous studies use different methods and jurisdictions, findings should be interpreted as analytical synthesis, not causal meta-analysis.

3. Applications of AI Across the Financial Ecosystem

3.1 Credit underwriting and financial inclusion

Machine learning can integrate transactional, behavioral and conventional credit data to estimate default probabilities and support quicker underwriting. A systematic review by Shi et al. (2022) documents the expanding range of credit-risk methods and implementation challenges. Better prediction, however, is not equivalent to fairer access. Using U.S. mortgage data, Fuster et al. (2022) show that machine-learning-based screening can produce uneven benefits across borrower groups, illustrating why lenders must assess both calibration and distributional outcomes. Where alternative data are used, consent, representativeness and lawful use must be evaluated before deployment.

3.2 Fraud detection, anti-money-laundering and payments

Anomaly detection and network models can help identify suspicious transactions, account takeovers, mule networks and emerging payment fraud. Their potential advantage lies in identifying subtle patterns across high-volume event streams, while their principal limitations include false-positive alerts, changing adversarial behavior and incomplete labels. Consequently, precision–recall trade-offs, investigator workload, latency and customer disruption should be monitored together. Financial authorities identify fraud prevention and cybersecurity among prominent AI applications (BoE–FCA, 2024).

3.3 Customer service, investment and financial operations

AI-powered assistants support service requests, document extraction, complaint triage and multilingual engagement; quantitative systems support portfolio analytics, forecasting and trading surveillance. Generative models can accelerate knowledge work but may fabricate citations, misstate product conditions or produce inconsistent recommendations. In consequential advice, validated retrieval, restricted actions and human escalation are safer than autonomous responses. As the FSB (2024) notes, widely shared models and data inputs may also contribute to correlated behavior across financial firms.

4. Benefits, Constraints and Critical Risks

The value proposition is multidimensional: operational efficiency (processing time and cost), decision support (risk discrimination and timeliness), service availability (24-hour access), and potential financial inclusion (serving overlooked customers). These expected benefits are conditional, not guaranteed. Model performance may deteriorate after economic regime shifts, while automation can accelerate errors across a larger population than manual procedures (Crisanto et al., 2024).

Four risk clusters recur. First, data and algorithmic risk includes historical bias, proxy discrimination, privacy breaches, inadequate data provenance and weak explanations. Second, model risk encompasses concept drift, overfitting, poor

calibration, hallucination and insufficient independent validation. Third, operational and cyber risk concerns prompt injection, data leakage, adversarial manipulation, availability failures and ineffective incident response. Fourth, systemic risk arises from concentration among cloud/model providers and potentially correlated decision-making and market strategies (FSB, 2024).

The interaction of these risks is especially important. A model may perform well on historical default predictions but disadvantage a protected group, rely on a single external provider and remain difficult to challenge. A single accuracy metric cannot reveal these interlocking failures. Evaluations must therefore include robustness under stress, subgroup outcomes, contestability and dependency risk (Fuster et al., 2022; National Institute of Standards and Technology [NIST], 2023).

5. A Risk-Tiered Responsible AI Governance Framework

Drawing on NIST's govern–map–measure–manage approach and sector-specific supervisory concerns, the following framework is proposed as a practical synthesis rather than an empirically validated intervention (NIST, 2023; Crisanto et al., 2024).

Governance stage	Required control	Illustrative evidence / KPI
1. Classify	Register model owner, purpose, affected customers and materiality	AI inventory; impact assessment; approval tier
2. Validate	Test data quality, calibration, subgroup fairness and stress resilience	Back-testing; drift/fairness reports; challenge log
3. Control	Apply least privilege, vendor due diligence and human oversight	Access reviews; third-party exit plan; override records
4. Monitor	Track errors, complaints, security events and outcomes	False positives; complaints; incidents; retraining triggers
5. Remediate	Provide explanations, appeals, rollback and incident learning	Appeal resolution time; remediation closure evidence

For high-impact lending and customer-facing decisions, independent validation should precede production release and recur after major data or model changes. Governance boards should review both risk-adjusted business value and customer impact. Human-in-the-loop processes must be meaningful: reviewers require authority, understandable evidence and sufficient time to overturn erroneous decisions. Vendor contracts should define monitoring access, data handling, audit rights and contingency provisions (FSB, 2024; NIST, 2023).

6. Discussion and Implications

The evidence suggests three overarching insights. First, adoption is becoming widespread, but mere deployment counts provide limited information about value creation. The 2026 UK survey reports that generative AI accounts for a substantial share of reported AI systems; nevertheless, disclosure of deployment scope, materiality and measurable outcomes remains essential (BoE–FCA, 2026). Second, predictive improvement and social welfare can diverge: credit scoring should be evaluated using both discrimination metrics and fair access or treatment indicators (Fuster et al., 2022). Third, firm-level governance and system-wide resilience are linked through shared infrastructure, models and providers (FSB, 2024).

For banks, the immediate priority is integrated model-risk and operational-risk governance, including lifecycle inventories, validation and incident readiness. For fintech firms, proportionate controls should be embedded early to avoid scaling unexamined biases or insecure architectures. For regulators, supervisory technology, incident reporting, third-party

concentration mapping and cross-border coordination warrant attention. For researchers, future work should test governance controls longitudinally across jurisdictions and examine causal impacts on default losses, false fraud alerts, financial inclusion and consumer complaints.

7. Conclusion

AI can improve the speed, reach and analytical capacity of financial services, yet its benefits depend on the quality of data, governance and accountability surrounding deployment. This review offers a five-stage, risk-tiered control framework to align business value with explainability, fairness, operational security and financial stability. The framework is conceptual and requires empirical testing. Responsible adoption should therefore be assessed through validated performance, equitable customer outcomes, effective redress and resilience—not technological novelty alone.

Declarations

Funding: No external funding reported for preparation of this manuscript. Conflict of interest: None declared. Data availability: No primary dataset was created or analyzed. Ethics approval: Not applicable to this literature-based review. Author contribution: Single-author conceptualization, synthesis and drafting; confirm before submission. Use of generative AI: AI-assisted drafting and editorial support were used; the named author must verify all claims, citations and the target journal's disclosure policy before submission.

References

Bank of England & Financial Conduct Authority. (2024). Artificial intelligence in UK financial services—2024. https://www.bankofengland.co.uk/report/2024/artificial-intelligence-in-uk-financial-services-2024

Bank of England & Financial Conduct Authority. (2026). Artificial intelligence in UK financial services—2026. https://www.bankofengland.co.uk/report/2026/artificial-intelligence-in-uk-financial-services-2026

Crisanto, J. C., Leuterio, C. B., Prenio, J., & Yong, J. (2024). Regulating AI in the financial sector: Recent developments and main challenges (FSI Insights No. 63). Bank for International Settlements. https://www.bis.org/publications/fsi-insight-63-regulating-ai-financial-sector-recent-developments-and-main-challenges

Financial Stability Board. (2024). The financial stability implications of artificial intelligence. https://www.fsb.org/2024/11/the-financial-stability-implications-of-artificial-intelligence/

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

National Institute of Standards and Technology. (2023). Artificial intelligence risk management framework (AI RMF 1.0) (NIST AI 100-1). https://doi.org/10.6028/NIST.AI.100-1

Shi, S., Tse, R., Luo, W., D'Addona, S., & Pau, G. (2022). Machine learning-driven credit risk: A systemic review. Neural Computing and Applications, 34, 14327–14339. https://doi.org/10.1007/s00521-022-07472-2