

Risk Management in Banking Sector Using Artificial Intelligence and Machine Learning

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Cite as: Aditya Kumar Singh, Arth Pratap Singh, Kanishk Bhalla, & Dr. K.R. Gola. (2026). Risk Management in Banking Sector Using Artificial Intelligence and Machine Learning. Journal of Research and Innovation in Technology, Commerce and Management, Vol. 3(Issue 4), 34062–34066. <https://doi.org/10.5281/zenodo.19568155>

DOI: <https://doi.org/10.5281/zenodo.19568155>

Abstract - This study investigates the implementation of Artificial Intelligence (AI) and Machine Learning (ML) in banking risk management, focusing on credit risk, fraud detection, and regulatory compliance. Using secondary data sources, industry reports, and a GAP Analysis framework, findings reveal that most banking institutions are not fully utilizing AI for core risk functions. Even early adopters apply AI to less critical operations, missing high-impact areas like predictive credit scoring and real-time fraud prevention. The report provides recommendations for Chief Risk Officers on data infrastructure, AI governance, and workforce development.

Keywords - Risk Management, Artificial Intelligence, Machine Learning, Fraud Detection, Banking Sector, Data Governance, Digital Transformation.

Introduction

Traditional banking risk management centred on regulatory compliance, using tools like ratio analysis, asset-liability management, and static stress testing. Risk was managed in silos across credit, liquidity, and foreign exchange categories. This reactive approach proved inadequate as globalization, digital banking, and complex financial instruments intensified the speed and complexity of risk.

Modern risk management shifted toward enterprise-wide ERM systems, sophisticated VaR models, and the Three Lines of Defence (3LOD) framework. AI further transforms this landscape by enabling real-time monitoring, predictive analytics, and automation across credit risk, fraud detection, and compliance—offering speed and accuracy that traditional and modern methods cannot match.

A. Problem Statement

Traditional frameworks are inadequate against modern threats: accelerating deposit runs, digital fraud, cyberattacks, and evolving ESG regulations. Banks must transition from reactive compliance to a strategic, proactive, and technology-driven risk function that leverages AI to navigate this dynamic environment.

B. Objectives

(1) Trace the evolution of risk management from traditional to AI-based approaches. (2) Study how AI helps banks predict loan defaults, detect fraud, and automate compliance. (3) Identify how banks can implement AI safely through robust data systems, staff training, and ethical governance.

Review of Literature

Allen & Carletti (2009) showed traditional frameworks failed to prevent the 2007–08 financial crisis by ignoring systemic interconnections. Jones (2011) structured key bank risk categories and stressed integrated management. Saunders & Allen (2015) explored advanced credit risk models like CreditMetrics and KMV to improve default prediction accuracy.

Fuster et al. (2018) demonstrated that ML models outperform traditional statistical methods in predicting defaults. Jobin et al. (2019) highlighted ethical risks of AI deployment including algorithmic bias and lack of accountability. Luijten (2024) synthesized evidence showing AI improves predictive capabilities but requires careful regulatory and organizational consideration.

A. Evolution of Risk Paradigms

The 3LOD framework assigns risk ownership to front-line business units, oversight to risk/compliance functions, and independent assurance to internal audit. Basel Accords set global capital standards but rely on static, backward-looking models. These frameworks introduce structural inertia that hinders adoption of dynamic AI systems, requiring governance re-engineering—not just technology overlay.

B. AI-Based Approaches

AI enables banks to analyze vast structured and unstructured datasets in real-time, supporting predictive analytics, automated compliance reviews, and proactive fraud remediation. Unlike static models, AI continuously adapts, identifying anomalies and evolving threats with a level of precision that manual processes cannot replicate.

Research Methodology

A. Data Sources

Traditional data includes historical financial statements, credit bureau records, and loan repayment patterns. Alternative data includes digital footprints (e-commerce, app usage), behavioral signals, social media sentiment, and public/multimodal datasets. All data requires robust governance to ensure quality, compliance with FCRA, ECOA, and CCPA, and freedom from bias.

B. Data Preprocessing

Exploratory Data Analysis (EDA) examines distributions and detects outliers. Data Cleaning removes duplicates, handles missing values, and balances class imbalance (fraudulent transactions may be <0.2% of

activity). Feature Engineering computes financial ratios (e.g., debt-to-equity, current liabilities to net worth) to capture risk dimensions like profitability and leverage in interpretable, model-ready formats.

C. Model Comparison

Table 1: Comparison of AI/ML Models for Credit Risk

Model	Strengths	Weaknesses	Best Use
Logistic Regression	Transparent, explainable	Assumes linearity	Regulatory compliance
Decision Tree	Flexible, non-linear	Prone to overfitting	High-stakes prediction
SVM	Strong classification	Black-box	Complex non-linear data
Neural Networks	Detects subtle patterns	Hard to explain	Real-time fraud detection

D. Implementation Workflow

The AI risk model lifecycle: (1) Problem Definition—specify the risk to address. (2) Data Collection—gather internal, external, and alternative data. (3) Preprocessing—clean, balance, and engineer features. (4) Model Development—select algorithm based on accuracy vs. explainability trade-off. (5) Validation—test on unseen data for accuracy and generalization. (6) Deployment—integrate with core banking systems for real-time decisions. (7) Continuous Monitoring—detect model drift and retrain as needed.

Implementation

A. Phased Execution

Phase I – Pilot: Validate business case with a narrow, cloud-based pilot to minimize upfront investment.

Phase II – Infrastructure: Scale data pipelines; establish data governance for quality, security, and compliance.

Phase III – Model Validation: Rigorous iterative training, testing, and regulatory validation cycle.

Phase IV – Deployment: Integrate into production systems to support real-time, uninterrupted decision-making.

B. Model Governance

AI validation must comply with SR 11-7 and OCC 2011-12 supervisory guidance, covering: conceptual soundness (design quality, bias assessment), process verification (controlled implementation), ongoing monitoring (detecting model drift), and outcomes analysis (accuracy and stability testing). Black-box models like neural networks pose transparency challenges—especially for explaining adverse credit decisions to regulators.

Results and Discussion

A. Credit Risk Dashboard Insights

Portfolio analysis across five loan segments reveals that secured loans consistently show lower Probability of Default (PD) and Days Past Due (DPD). For example, Secured – South – Manufacturing (L001) showed PD of 50% and DPD of 15 days, while Unsecured – West – Services (L004) showed PD of 95% and DPD of 120 days, confirming that collateral significantly reduces credit risk exposure.

B. Financial Health Metrics

Key indicators tracked via AI dashboards: Revenue Growth ₹2.5 Cr (+12% QoQ), Gross Profit Margin 23%, Operating Expenses Ratio 15% (improving), Net Profit Margin 8%

(rising), Current Ratio 1.6:1 (healthy liquidity), Debt-to-Equity 1.8:1 (stable), and ROA 9% (improving). These real-time metrics enable faster, evidence-based decision-making compared to periodic manual reporting.

C. Key Risk Indicators

Table 2: Key Risk Indicators (KRIs) in the AI Era

KRI/KPI	Category	AI Relevance
RAROC	Credit/Market	More precise risk-adjusted profitability comparisons across portfolios.
Value at Risk (VaR)	Market	Dynamic, real-time VaR using large datasets instead of static models.
ALLL	Credit	Predictive analytics improves accuracy of loan loss estimates.
MTBF	Operational	Continuous AI monitoring of critical IT infrastructure.
Loan-to-Deposit Ratio	Liquidity	Real-time analytics on funding sources and market conditions.

D. ROI of AI in Risk Management

Table 3: ROI Framework for AI-Driven Risk Management

Category	Metric
Loss Avoidance	Up to 50% reduction in fraud losses reported by early AI adopters.
Operational Efficiency	Loan processing time reduced from days to minutes via AI underwriting.
Revenue Generation	Expanded lending to previously un-scoreable populations.
Compliance Savings	Reduced manual regulatory reporting and audit failure costs.
Competitive Advantage	Faster product launches; personalized, data-driven customer services.

E. Key Findings

(1) Most banks—especially public sector—have not integrated AI into core risk

functions; adoption is concentrated in private sector digital leaders. (2) AI fraud detection systems like Stripe's Radar (scanning 1,000+ transaction features in 100ms) have delivered up to 50% reduction in fraud losses. (3) A fundamental trade-off exists between predictive accuracy (neural networks, SVMs) and regulatory explainability (logistic regression). (4) Traditional governance frameworks (3LOD, Basel) create structural inertia that impedes dynamic AI deployment.

Conclusion

The banking sector must treat AI not as a supplementary tool but as a core strategic capability. This study confirms that AI in risk management delivers measurable benefits—fraud loss reduction, faster credit decisions, and improved compliance—but only when accompanied by robust data infrastructure, AI-specific governance, and cross-functional talent. Banks investing in these three pillars today will achieve lasting financial resilience and competitive advantage.

Recommendations

- (1) Data First:** Build clean, integrated data systems with strong governance before scaling AI.
- (2) AI Governance Playbook:** Map, classify, and assign ownership for every AI model with embedded lifecycle controls.
- (3) Workforce Development:** Upskill risk professionals in AI literacy; build cross-functional teams bridging finance and data science.
- (4) Strategic Pilots:** Start small with high-value use cases to demonstrate ROI and build stakeholder confidence.
- (5) AI as Strategy:** Position AI risk management as a long-term competitive differentiator, not just a compliance cost.

Limitations and Future Scope

Limitations: (1) Relies entirely on secondary data—no primary surveys or interviews. (2) Findings are biased toward advanced banking markets (US, Europe) and may not apply to India or other emerging economies. (3) Rapidly evolving AI tools may supersede current references. (4) Analysis limited to credit, fraud, and compliance risks; excludes liquidity, market, and ESG dimensions.

Future scope: (1) Primary research with CROs and data science teams. (2) AI risk management in Indian banking, including RBI-Basel III interactions. (3) Explainable AI (XAI) using SHAP and LIME for credit and fraud models. (4) Longitudinal studies on model drift across economic cycles. (5) AI for ESG and climate risk assessment in loan portfolios.

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