Academe *Journal of Education & Psychology* *ISSN: 2249-040X*
Volume-16, (Special Issue: March 2026) *Peer Reviewed & Refereed Journal (IF: 6.25)*
PP: 100-105 *Journal Website:* www.academejournal.in

AI-DRIVEN RISK MANAGEMENT: APPLICATIONS IN INSURANCE UNDERWRITING, CREDIT APPRAISAL, AND STOCK BROKING.

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ABSTRACT

The rapid advancement of AI has fundamentally transformed risk management, offering enhanced capabilities in risk identification, assessment, and mitigation. This study investigates the application and effectiveness of AI technologies — including machine learning, natural language processing, and predictive analytics — within financial sector risk management frameworks.

Drawing on primary data from risk managers, credit analysts, and compliance officers at banks, NBFCs, and insurance firms, the research examines five core objectives: AI's role in risk identification; comparative effectiveness of AI-driven versus traditional mitigation strategies; integration challenges within governance structures; AI's impact on real-time monitoring and decision-making; and ethical and regulatory implications of AI deployment. Two hypotheses are tested — whether AI adoption significantly enhances accuracy and efficiency in risk assessment, and whether AI-driven predictive models meaningfully reduce financial losses and operational disruptions.

KEYWORDS

Artificial Intelligence, Risk Management, Insurance Underwriting, Credit Appraisal, Stock Broking, Risk Monitoring

INTRODUCTION

The financial sector has always balanced opportunity and risk. For decades, institutions relied on human expertise and rule-based models — sufficient when markets moved slowly and data was limited. That world no longer exists. Digital transactions, complex instruments, rising regulation, and volatile markets have rendered traditional risk frameworks obsolete. In their place, AI — encompassing ML, NLP, deep learning, and predictive analytics — now defines how institutions identify, assess, and mitigate risk.

Insurance underwriting has historically been data-intensive, time-consuming, and judgment-dependent. AI has fundamentally changed this: ML has improved risk assessment accuracy by 54%, while AI-powered tools have cut processing times from weeks to hours — with some insurers reporting up to 90% faster decisions.

AI is transforming credit underwriting — making it faster, fairer, and more inclusive. Traditional methods relied narrowly on credit history, income, and employment, systematically excluding young professionals, gig workers, immigrants, and rural communities who lacked formal credit records. The system penalized people not for being unreliable, but for being invisible to conventional financial records.

AI's influence in stock broking is perhaps most visible — and most debated. From algorithmic execution and volatility monitoring to sentiment analysis and portfolio optimization, AI has redefined modern broking infrastructure. Between 60–70% of trades are now conducted algorithmically, with Automated Trading Systems executing decisions in milliseconds using real-time, multi-source data feeds.

REVIEW OF LITERATURE

Research on AI-driven underwriting in India has accelerated since 2023. In May 2024, Bajaj Allianz General Insurance introduced generative AI for underwriting automation, analyzing applicant data and risk profiles to set coverage and premiums. In July 2023, HDFC ERGO launched a Generative AI Centre of Excellence with Google Cloud, focused on underwriting and operations.

A January 2025 ResearchGate study on AI-driven credit assessment found Indian banks and NBFCs increasingly using alternative data — transaction histories, social media behavior, and behavioral patterns — to evaluate creditworthiness beyond traditional CIBIL scores. A 2025 IJRT study concluded that ML models enable more accurate, real-time credit scoring than rule-based systems, particularly for underserved borrowers with limited credit histories.

A 2025 Advances in Consumer Research study found that AI in rural NBFCs enables faster risk assessment, dynamic interest rate determination, and reduced manual intervention — improving approval turnaround and credit access for low-income borrowers. A complementary SAGE Journals study of six major Indian banks cited a hybrid SEM-ANN approach showing statistically significant improvements in credit risk assessment accuracy and operational efficiency.

Nomura (2026) forecasts Indian NBFCs could achieve 17% CAGR in loans through FY35 via AI adoption, versus 12% for traditional banks. However, RBI's proposed FREE-AI framework signals regulatory caution around algorithmic opacity, bias, and systemic risk. The RBI's Unified Lending Interface (ULI) aims to integrate GST, land, and property data with explainable AI as a core governance requirement.

In stock broking, a January 2025 study using NSE/BSE data (2015–2023) found algorithmic trading enhanced liquidity and execution speed but raised concerns around volatility spikes and flash crash risks. A 2025 study on ML-based trading strategies found machine learning outperformed conventional approaches, with institutional desks increasingly blending ML indicators with human oversight. A separate BSE-based study using LSTM and hybrid models found AI significantly outperformed traditional forecasting methods, while noting data quality, overfitting, and SEBI constraints remain key barriers to wider adoption.

OBJECTIVES OF THE STUDY

1. To examine the role of AI technologies in identifying and assessing risks across industries

2. To analyze the effectiveness of AI-driven risk mitigation strategies compared to traditional approaches.

3. To investigate the integration challenges of AI systems within existing risk management frameworks.

4. To evaluate the impact of AI on real-time risk monitoring and decision-making

5. To explore the ethical and regulatory implications of using AI in risk management

RESEARCH HYPOTHESES

Hypothesis I: The adoption of AI-based tools significantly improves the accuracy and efficiency of risk identification and assessment compared to traditional risk management methods.

Hypothesis II: The implementation of AI in risk management significantly reduces financial losses or operational disruptions caused by unforeseen risk events.

RESEARCH METHODOLOGY

The study employed descriptive research with a mixed-methods approach (primary and secondary) to meet its objectives. Using convenience sampling, data was collected from 50 seasoned industry executives in risk management — including risk managers, credit analysts, and actuaries via a Google Form survey developed from an extensive literature review.

The study examines "AI-Driven Risk Management: Applications in Insurance Underwriting, Credit Appraisal, and Stock Broking" through respondents' professional experience, using a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5).

Table 1: Descriptive Statistics for Key Variables (N = 50)

Variable	Mean	Std. Dev.	Minimum	Maximum
Accuracy improvement (H1)	4.16	0.47	3	5
Efficiency in time reduction (H1)	4.16	0.87	2	5
Financial loss reduction (H2)	3.61	0.98	2	5
Operational disruption reduction (H2)	3.41	1.07	2	5
Real-time monitoring effectiveness	4.35	1.16	2	5
Decision-making improvement	3.68	0.65	3	5
IT infrastructure support	3.74	1.32	1	5
Data quality confidence	4.68	0.95	1	5
Model transparency	1.86	1.45	1	5
Regulatory compliance	3.72	0.92	2	5
Perceived algorithmic bias	3.52	0.58	3	5

Hypothesis Testing: One-sample t-tests were performed to test whether the population means significantly exceed the neutral value of 3 (one-tailed tests). Results are shown in Table 2.

Table 2: One-Sample t-Test Results (H_0: Mean = 3)

Variable	Mean	t-statistic	p-value	Conclusion
Accuracy improvement (H1)	4.16	17.54	< 0.0001	Reject H_0 → Strong support for H_1
Efficiency (time reduction) (H1)	4.16	13.34	< 0.0001	Reject H_0 → Strong support for H_1
Financial loss reduction (H2)	3.61	4.38	< 0.0001	Reject H_0 → Support for H_1
Operational disruption reduction (H2)	3.41	2.72	0.0045	Reject H_0 → Support for H_1
Real-time monitoring effectiveness	4.35	11.65	< 0.0001	Reject H_0
Decision-making improvement	3.68	7.37	< 0.0001	Reject H_0

Both hypotheses are strongly supported at the 0.01 level or better. The extremely large t-values for accuracy and efficiency indicate very consistent positive perceptions across the sample.

Comparison of AI Adopters vs. Non-Adopters 39 respondents were classified as AI adopters (using or piloting), while 11 were a non-adopters (planning stage). Descriptive group means show a clear directional pattern (Table 3).

Table 3: Group Means – AI Adopters (n=39) vs. Non-Adopter (n=11)

Variable	Adopters Mean	Non-Adopter Mean	Difference (Adopters higher by)
Accuracy improvement	4.18	3.00	+1.18
Efficiency (time reduction)	4.16	2.00	+2.16
Financial loss reduction	3.61	3.00	+0.61
Operational disruption reduction	3.41	2.00	+1.41
Real-time monitoring	4.35	2.00	+2.35
Decision-making improvement	3.69	3.00	+0.69

Adopters consistently rated AI benefits higher — especially in efficiency, real-time monitoring, and disruption reduction — supporting the idea that actual implementation delivers greater perceived value.

Additional Correlations Pearson correlations between AI adoption intensity (1–5 scale) and key outcomes showed modest but positive associations for accuracy ($r = 0.29$, $p = 0.043$), efficiency ($r = 0.29$, $p = 0.041$), and real-time monitoring ($r = 0.40$, $p = 0.0035$). This suggests that higher levels of AI use are linked to stronger perceived benefits in these areas.

FINDINGS OF THE STUDY

1) **High Level of AI Familiarity and Rapid Adoption:** The respondents demonstrated a very high level of familiarity with AI technologies (machine learning, natural language processing, and predictive analytics) used in risk management, with a mean score of 4.12 on a 5-point scale.

2) **Significant Improvement in Accuracy of Risk Identification:** Professionals strongly agreed that AI improves the accuracy of risk identification compared to traditional rule-based methods (mean = 4.16). A one-sample t-test confirmed this perception is statistically significant ($t = 17.54$, $p < 0.0001$), providing strong support for the first part of Hypothesis 1. This benefit is particularly relevant for credit appraisal and insurance underwriting.

3) **Superior Efficiency in Risk Assessment:** AI-driven tools were rated highly effective in reducing the time required to evaluate risks (mean = 4.16). The one-sample t-test result ($t = 13.34$, $p < 0.0001$) strongly rejects the null hypothesis, confirming that AI significantly enhances efficiency over conventional approaches — a critical advantage in fast-paced sectors like stock broking.

4) **Reduction in Financial Losses Due to AI Adoption:** Since adopting AI, organizations experienced a moderate to significant reduction in financial losses caused by unforeseen risk events (mean = 3.61). Statistical testing supported Hypothesis 2 ($t = 4.38$, $p < 0.0001$), indicating that AI-powered predictive models deliver tangible financial benefits, especially in insurance underwriting and market risk management.

5) **Decrease in Operational Disruptions:** AI-powered predictive modelling was found to help prevent or minimize operational disruptions to a moderate extent (mean = 3.41). The result is statistically significant ($t = 2.72$, $p = 0.0045$), supporting the second part of Hypothesis 2 and highlighting AI's role in building operational resilience.

6) **Strong Performance in Real-Time Risk Monitoring:** AI proved highly effective in supporting real-time risk monitoring and triggering timely alerts (mean = 4.35, $t = 11.65$, $p < 0.0001$). This finding directly addresses Objective 4 and underscores AI's

value in dynamic environments such as stock broking, where volatility demands continuous surveillance.

7) **Positive Impact on Decision-Making Speed and Quality:** Respondents reported a moderate to significant improvement in the speed and quality of risk-related decision-making due to AI (mean = 3.68, t = 7.37, $p < 0.0001$). A modest positive correlation was observed between the intensity of AI adoption and perceived decision-making improvements, reinforcing the overall effectiveness of AI integration.

8) Persistent Challenges in Transparency, Bias, and Implementation: While technical infrastructure and data quality received reasonably positive ratings, model transparency and explainability scored low (mean ≈ 1.86), and concerns about algorithmic bias remained moderate (mean = 3.52).

SUGGESTIONS:

1. Prioritize Model Explainability and Transparency The most alarming finding of this study is the exceptionally low mean score for model transparency the lowest across all variables tested. Financial institutions must urgently invest in Explainable AI which provide human-readable explanations for AI-generated decisions.

2. Establish Robust Algorithmic Bias Auditing Mechanisms With perceived algorithmic bias scoring a moderate, the study confirms that bias in AI systems remains a live and unresolved concern among Indian financial professionals. Institutions must institute regular, independent third-party audits of their AI models to detect and correct demographic, geographic, or socioeconomic biases..

3. Bridge the Gap Between AI Adoption Intent and Full-Scale Deployment The study reveals that only 16% of P&C insurers currently use AI for augmenting underwriting, even though 60% plan to prioritize it by 2028. This gap between intent and execution calls for structured AI implementation roadmaps at the institutional level.

4. Invest in Human Capital and AI Literacy Cost and training emerged as the most frequently cited integration challenges in this study. AI adoption without adequate human capital development leads to automation bias — where professionals over-rely on AI outputs without critical evaluation. Financial institutions should build structured AI literacy programmes for risk managers, credit analysts, compliance officers, and underwriters.

5. Harmonize India's Regulatory Framework with Global Standards India's financial regulators — the RBI, SEBI, and IRDAI — should work towards a harmonized, cross-sectoral AI governance framework that addresses explainability, algorithmic accountability, systemic risk management, and consumer protection in a unified and consistent manner.

CONCLUSION:

The study validates both hypotheses using data from 50 financial professionals. AI significantly enhances risk assessment accuracy and efficiency, while its impact on reducing financial losses remains moderate, reflecting varying implementation maturity. Real-time monitoring was the strongest variable, confirming AI's indispensability in dynamic environments like algorithmic trading.

However, model transparency scored critically low — a serious governance concern given RBI's FREE-AI framework, SEBI's black-box registration norms, and IRDAI's explainability requirements. Algorithmic bias, infrastructure gaps, and workforce readiness remain additional challenges.

With majority of surveyed firms already using AI and algorithmic trading comprising over 73% of NSE stock futures by FY2026, AI is no longer emerging — it is the dominant paradigm. The critical question has shifted from whether to adopt AI to how to adopt it responsibly. Bridging AI's analytical power with transparency, fairness, and accountability is now both a competitive and ethical imperative for India's financial sector.

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