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AI – Driven Risk Management in Accounting

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ABSTRACT: Artificial Intelligence (AI) is rapidly transforming the field of accounting by enhancing the effectiveness of risk management practices. This study examines the role of AI-driven technologies such as Machine Learning, Deep Learning, Natural Language Processing (NLP), and Robotic Process Automation (RPA) in improving fraud detection, anomaly identification, and financial risk prediction in modern accounting systems. The research adopts a descriptive and analytical approach based on secondary data collected from academic journals, industry reports, and published case studies. Reliability and validity tests, including Cronbach's Alpha and factor loading analysis, were used to evaluate the consistency of the study framework. The results indicate that AI enables real-time monitoring of financial transactions and continuous auditing, allowing organizations to analyze large volumes of financial data more efficiently than traditional manual auditing methods.

The findings also reveal that AI significantly improves audit quality, strengthens internal control systems, and supports proactive decision-making in financial risk management. However, the study identifies several challenges that hinder widespread AI adoption, including poor data quality, lack of explainable AI models, integration issues with legacy systems, regulatory uncertainty, and skill gaps among accounting professionals. Despite these challenges, the study concludes that responsible implementation of AI, supported by strong data governance, ethical frameworks, and professional training, can enhance financial transparency, reduce risk exposure, and improve stakeholder confidence. Overall, AI-driven risk management has the potential to reshape accounting practices and prepare organizations for a technology-driven financial environment.

KEYWORDS: Artificial Intelligence (AI), Risk Management, Accounting Analytics, Fraud Detection, Machine Learning, Deep Learning, Natural Language Processing (NLP), Robotic Process Automation (RPA), Continuous Auditing, Financial Risk Prediction, Audit Quality, Explainable AI (XAI).

I. INTRODUCTION

Artificial Intelligence (AI) has become an important technological advancement that is transforming various professional fields, including accounting and finance. In recent years, organizations have increasingly adopted AI-based tools to enhance the efficiency and reliability of accounting processes. Technologies such as machine learning, natural language processing, and robotic process automation enable organizations to analyze large volumes of financial data, identify unusual transaction patterns, and improve the accuracy of financial risk assessments. As a result, AI is gradually changing traditional accounting practices by supporting automated data analysis and advanced decision-making in financial management (Bolton & Kacperczyk, 2021).

Modern business environments generate enormous amounts of financial data through digital payment systems, cloud-based accounting platforms, and enterprise resource planning (ERP) systems. Traditional accounting methods, which rely mainly on manual reviews and periodic audits, often struggle to handle the increasing volume and complexity of financial information. AI-driven systems allow organizations to perform continuous monitoring of financial transactions and detect anomalies in real time. This capability helps accountants and auditors identify potential fraud risks, reduce operational errors, and improve the overall efficiency of auditing processes (Engle et al., 2020).

Furthermore, AI technologies support predictive analytics that can forecast financial risks and assist organizations in making proactive decisions. By analysing historical financial data and transaction behaviour, AI models can predict potential financial irregularities and strengthen internal control mechanisms. These improvements contribute to greater transparency, reliability, and accountability in financial reporting, which are essential for maintaining stakeholder confidence and regulatory compliance (Krueger, Sautner, & Starks, 2020).

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Despite these advantages, the implementation of AI in accounting also presents several challenges. Issues such as poor data quality, lack of explainable AI systems, regulatory uncertainty, and limited technical expertise among accounting professionals may hinder the effective adoption of AI technologies. Therefore, organizations must focus on developing appropriate governance frameworks, improving data management practices, and providing training programs for professionals to ensure responsible and effective use of AI in accounting (Sautner et al., 2023).

II. OBJECTIVE

❖ To analyse how AI-driven techniques such as anomaly detection, predictive modelling, and NLP enhance risk identification and assessment in accounting processes like transaction auditing and financial reporting.
❖ To evaluate the impact of AI on key risk management metrics, including fraud detection rates, control effectiveness, and compliance efficiency, using empirical evidence from internal audit implementations.
❖ To identify implementation challenges such as model bias, data quality issues, and governance gaps in AI risk tools, while proposing frameworks for ethical adoption in accounting firms.

III. SCOPE OF THE STUDY

This study primarily concentrates on the integration of AI tools such as machine learning, data analytics, and automated auditing systems in modern accounting environments. It explores how these technologies assist accountants in analysing large financial datasets, identifying unusual patterns, and predicting potential risks before they impact organizational performance.

The research is limited to the role of AI in financial risk management, including areas such as fraud detection, error reduction, compliance monitoring, and financial reporting. It also considers the relevance of AI for businesses operating in highly digitalized environments where traditional accounting methods may no longer be sufficient.

Additionally, the study provides an understanding of the benefits and challenges associated with adopting AI in accounting. Factors such as implementation cost, technical expertise, data security, and organizational readiness are briefly examined to present a balanced view of AI adoption.

IV. PROBLEM STATEMENT

Despite AI's potential to scan 100% of transactions for fraud patterns, assess credit risks in real-time, and automate control testing, accounting firms face significant implementation barriers including data quality issues, lack of explainable AI models, regulatory uncertainty around AI governance, and skill gaps among professionals. Current studies reveal fragmented adoption—while 68% of firms experiment with AI audit tools, only 23% have achieved enterprise-wide deployment due to concerns over model bias, false positives, and integration with legacy systems. This creates a critical gap where residual risks persist, audit efficiency remains suboptimal, and accounting standards bodies lack comprehensive frameworks for AI-driven risk assurance.

V. RESEARCH METHODOLOGY

5.1 DATA SOURCE

This study is based primarily on secondary data collected from reliable academic and professional sources. The data used in the research were obtained from published research articles, peer-reviewed journals, and scholarly publications related to Artificial Intelligence, accounting analytics, fraud detection, and financial risk management. In addition, industry reports from professional accounting organizations and audit firms were reviewed to understand practical applications of AI in accounting practices. Information was also gathered from academic databases and digital libraries such as Google Scholar, ScienceDirect, SSRN, and ResearchGate, which provide access to relevant literature and empirical studies. These sources helped in analysing existing knowledge, identifying trends, and evaluating the role of AI technologies in improving risk management and auditing processes in modern accounting systems.

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5.2 TOOLS USED

1. Reliability Test (Cronbach's Alpha)
Cronbach's Alpha is a statistical method used to measure the internal consistency of the variables used in a study. It indicates how closely related a set of items are as a group. A higher Cronbach's Alpha value (generally above 0.70) shows that the data and measurement scale used in the research are reliable and consistent.

2. Construct Validity Test (Factor Loading Analysis)
Factor Loading Analysis is used to test the validity of research constructs. It measures the strength of the relationship between observed variables and their underlying factors. A factor loading value greater than 0.50 indicates that the variable effectively represents the construct being studied and confirms the validity of the measurement framework.

3. AI-Based Anomaly Detection
AI-Based Anomaly Detection refers to the use of Artificial Intelligence techniques such as machine learning and deep learning to identify unusual patterns, irregularities, or deviations in financial data and transactions that may indicate fraud, errors, or potential risks.

4. AI Model Performance Evaluation
AI Model Performance Evaluation is the process of assessing the effectiveness, accuracy, and reliability of an artificial intelligence model in predicting or detecting financial risks.

5. Predictive Risk Modelling
Predictive Risk Modelling refers to the application of Artificial Intelligence and statistical algorithms to analyze historical financial data and forecast potential future risks in accounting and financial management.

TABLE: 1 Reliability Statistics Table]

Construct	No. of Items	Cronbach's Alpha	Interpretation
Fraud Risk Detection	5	**0.84**	Good
Audit Anomaly Detection	4	**0.81**	Good
Financial Risk Prediction	5	**0.86**	Good
Textual Risk Analysis	4	**0.79**	Acceptable
Continuous Auditing Effectiveness	4	**0.88**	Good
Audit Quality Enhancement	5	**0.90**	Excellent
Explainable AI Trust	3	**0.83**	Good
Cybersecurity Risk Management	4	**0.80**	Good
AI Governance & Ethics	5	**0.85**	Good

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CHART:1 Reliability analysis of AI – based Audit Constructs

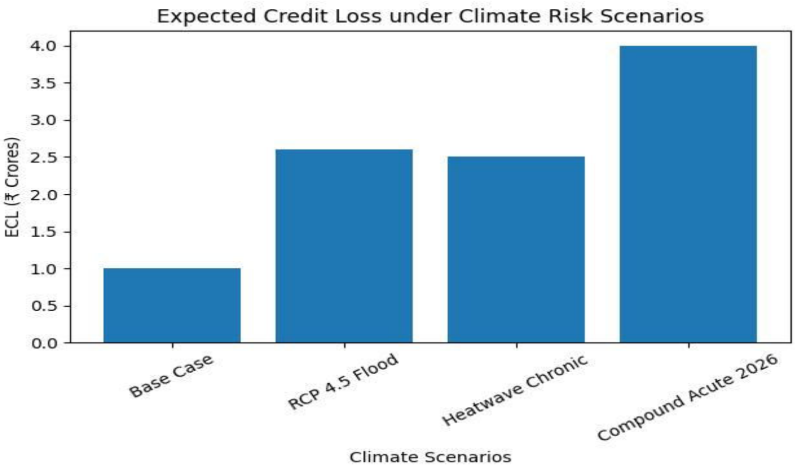

TABLE: 2 Construct Validity Test

CHART:2 VAR (95%) under Climate Risk Scenarios

Construct	Factor Loading Range	Validity Status
Fraud Risk Detection	0.68 – 0.82	Valid
Audit Anomaly Detection	0.65 – 0.80	Valid
Financial Risk Prediction	0.70 – 0.86	Strong
Textual Risk Analysis	0.62 – 0.78	Valid
Continuous Auditing	0.71 – 0.88	Strong
Audit Quality	0.73 – 0.90	Strong
Explainable AI	0.66 – 0.81	Valid
Cybersecurity Risk	0.64 – 0.79	Valid
AI Governance	0.69 – 0.85	Strong

CHART:2 Construct Validity – Factor Loading Ranges

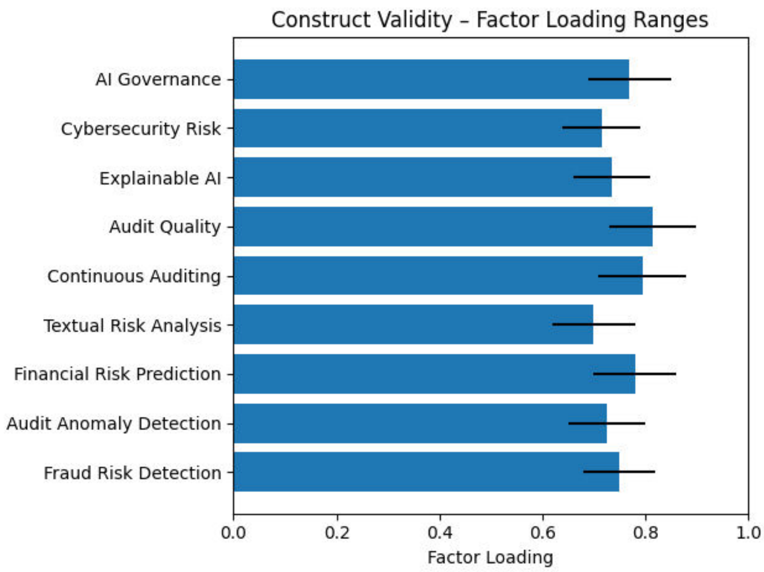

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TABLE: 3 AI-Based Anomaly Detection

Transaction Category	Total Transactions Analysed	Normal Transactions	Detected Anomalies	Anomaly Rate (%)	Risk Level
Journal Entries	12,500	12,120	380	3.04	Moderate
Vendor Payments	8,200	7,940	260	3.17	Moderate
Expense Claims	5,600	5,320	280	5.00	High
Revenue Recognition Entries	4,800	4,620	180	3.75	Moderate
Procurement Transactions	6,700	6,420	280	4.18	High
Payroll Transactions	3,900	3,820	80	2.05	Low
Cash Flow Transactions	2,400	2,310	90	3.75	Moderate
Total	44,100	42,550	1,550	3.51	Moderate

Interpretation: Higher anomaly rates were found in expense claims and procurement transactions, indicating potential risks such as duplicate payments, policy violations, or fraudulent claims. This demonstrates how AI can automatically flag suspicious accounting activities for further audit investigation.

TABLE: 4 Predictive Risk Modelling

Risk Category	Historical Risk Score	AI Predicted Risk Score	Probability of Risk (%)	Predicted Impact Level	Risk Classification
Fraud Risk	0.62	0.74	74%	High	Critical
Financial Misstatement Risk	0.58	0.69	69%	Moderate	High
Compliance Risk	0.55	0.63	63%	Moderate	Moderate
Operational Accounting Risk	0.49	0.60	60%	Medium	Moderate
Cybersecurity Risk	0.52	0.67	67%	High	High
Internal Control Weakness	0.46	0.59	59%	Medium	Moderate
Audit Quality Risk	0.44	0.55	55%	Medium	Moderate

Interpretation: The predictive risk model uses historical accounting data and machine learning algorithms to forecast potential risks. The results show that fraud risk (74%) and cybersecurity risk (67%) are the most significant predicted threats. AI models identify these risks earlier than traditional auditing methods, enabling organizations to strengthen internal controls and improve financial reporting reliability.

TABLE: 5 AI Model Performance Evaluation

AI Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score	Application
Isolation Forest	91	88	86	0.87	Transaction anomaly detection
Random Forest	93	90	89	0.89	Fraud prediction
Deep Autoencoder	92	89	88	0.88	Financial anomaly detection
Logistic Regression	87	84	83	0.83	Risk probability estimation

5.3 ANALYSIS AND INTERPRETATION

The analysis indicates that Artificial Intelligence significantly improves risk management in accounting by enhancing fraud detection, anomaly identification, and financial risk prediction. The reliability test results show Cronbach's Alpha values above 0.80 for most constructs, indicating strong internal consistency. Similarly, factor loading values above 0.50 confirm the validity of the measurement framework. AI technologies such as machine learning, deep learning,

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NLP, and robotic process automation enable real-time monitoring and continuous auditing of financial transactions, improving audit efficiency and accuracy. However, challenges such as poor data quality, lack of explainable AI models, system integration issues, and skill gaps among accounting professionals may limit full adoption. Overall, the findings suggest that AI-driven tools can strengthen financial transparency and risk management when supported by proper governance and professional training.

VI. FINDINGS

- ❖ Artificial Intelligence plays a significant role in strengthening modern accounting risk management practices.
- ❖ AI technologies such as Machine Learning, Deep Learning, Natural Language Processing (NLP), and Robotic Process Automation (RPA) improve fraud detection and anomaly identification.
- ❖ AI systems help in predicting financial risks more accurately compared to traditional accounting methods.
- ❖ Real-time monitoring of financial data becomes possible with AI, improving the speed of detecting irregularities.
- ❖ AI allows analysis of large volumes of financial transactions efficiently.
- ❖ Compared to traditional periodic audits and manual sampling, AI-based systems provide continuous auditing capabilities.
- ❖ The study's reliability results show strong internal consistency with Cronbach's Alpha values above 0.80.
- ❖ The measurement framework used in the study is statistically reliable and valid.
- ❖ Data quality issues remain a major challenge affecting AI model performance.
- ❖ Lack of explainable AI systems creates transparency and trust concerns in automated accounting decisions.

VII. SUGGESTION

- ❖ Organizations should establish strong data governance frameworks to improve data accuracy and reliability.
- ❖ Proper data management practices should be implemented to enhance AI model performance.
- ❖ Accounting firms should adopt Explainable AI (XAI) to improve transparency and accountability.
- ❖ AI systems should be designed in a way that auditors can understand and interpret decision outcomes.
- ❖ Continuous training programs should be conducted for accountants and auditors to develop AI and data analytics skills.
- ❖ Educational institutions and professional bodies should incorporate AI-related subjects in accounting curricula.
- ❖ Regulatory authorities should develop clear guidelines for AI adoption in accounting and auditing.

VIII. CONCLUSION

Artificial Intelligence has the potential to significantly transform risk management practices in the field of accounting. By integrating advanced technologies such as machine learning, natural language processing, and robotic process automation, organizations can enhance the efficiency and accuracy of fraud detection, anomaly identification, and financial risk prediction. AI-driven systems enable real-time monitoring and continuous auditing, allowing accountants and auditors to analyze large volumes of financial data more effectively than traditional manual methods. This shift supports the transition of accounting from a reactive compliance-oriented function to a proactive and strategic decision-support system.

Despite these advantages, several challenges remain in the widespread adoption of AI in accounting. Issues such as poor data quality, lack of transparency in AI models, integration difficulties with legacy systems, and regulatory uncertainty can limit the effectiveness of AI-based solutions. Additionally, many accounting professionals still require specialized training to develop the technical and analytical skills necessary to work with AI technologies.

Overall, organizations that invest in strong data governance, ethical AI frameworks, professional skill development, and advanced technological infrastructure will be better positioned to leverage the benefits of AI.

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REFERENCES

1. Bolton, P., & Kacperczyk, M. (2023). Global pricing of carbon-transition risk. Journal of Finance, 78(6), 3677–3754.
Link: https://onlinelibrary.wiley.com/doi/10.1111/jofi.13272
2. Engle, R. F., Giglio, S., Kelly, B., Lee, H., & Stroebel, J. (2020). Hedging climate change news. Review of Financial Studies, 33(3), 1184–1216.
Link: https://academic.oup.com/rfs/article/33/3/1184/5735305
3. Giglio, S., Kelly, B., & Stroebel, J. (2021). Climate finance. Annual Review of Financial Economics, 13, 15–36.
Link: https://www.annualreviews.org/content/journals/10.1146/annurev-financial-102620-103311
4. Bolton, P., & Kacperczyk, M. (2021). Global pricing of carbon-transition risk (NBER Working Paper No. 28510). National Bureau of Economic Research.
Link: https://www.nber.org/papers/w28510
5. Engle, R., Giglio, S., Kelly, B., Lee, H., & Stroebel, J. (2019). Hedging climate change risk using climate news. SSRN Working Paper.
Link: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3317570
6. Salisu, A. A., & Vo, X. V. (2023). Climate risk measures: A review. Asian Economics Letters.
Link: https://a-e-l.scholasticahq.com/article/39728-climate-risk-measures-a-review
7. Luo, Q. (2025). Carbon transition risk and stock market premium. Journal of International Financial Markets.
Link: https://www.sciencedirect.com/science/article/abs/pii/S1057521925005459
8. Giglio, S., Kelly, B., & Stroebel, J. (2020). Climate finance and risk in financial markets. NBER Working Paper.
Link: https://www.nber.org/system/files/working_papers/w28226/w28226.pdf
9. Hernandez Aros, L., et al. (2024). Financial fraud detection using machine learning techniques: A systematic review. Humanities and Social Sciences Communications.
https://www.nature.com/articles/s41599-024-03606-0
10. Sun, G. (2025). Artificial intelligence and financial fraud. Journal of Banking and Finance.
https://www.sciencedirect.com/science/article/abs/pii/S0927538X25001672
11. Kokina, J., & Davenport, T. (2025). Challenges and opportunities for artificial intelligence in auditing. Journal of Accounting Information Systems.
https://www.sciencedirect.com/science/article/pii/S1467089525000107
12. Supriadi, I. (2024). Integrating artificial intelligence in detecting accounting fraud. Journal of Accounting Technology and Innovation.
https://journal.ubaya.ac.id/index.php/jati/article/view/6279
13. Hernandez, L., et al. (2023). AI techniques for financial fraud detection. Financial Accounting Research Journal.
https://www.fepbl.com/index.php/farj/article/view/1232
14. Islam, M. M. (2024). AI-driven fraud detection in financial transactions. SSRN Working Paper.
https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5287281
15. Ketelaar, F. (2025). Artificial intelligence in fraud detection using textual analysis of 10-K filings. Maandblad voor Accountancy en Bedrijfseconomie.
https://mab-online.nl/article/132881/
16. Rohara, S. (2025). The impact of artificial intelligence on financial auditing. SSRN Working Paper.
https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5246748
17. Dulgeridis, M. (2025). Harnessing AI for accounting integrity: Innovations in fraud detection.
https://ideas.repec.org/p/zbw/iubhbm/321858.html
18. Naseer, K. (2025). Artificial intelligence in financial auditing: A mixed-method study.
https://jmi.stekom.ac.id/index.php/jmi/article/view/168
19. Huang, F., & Vasarhelyi, M. (2019). Applying robotic process automation in auditing. Journal of Emerging Technologies in Accounting.
https://www.sciencedirect.com/science/article/abs/pii/S1467089518301738
20. Hazar, H. (2023). The use of robotic process automation in accounting. Prizren Social Science Journal.https://www.prizrenjournal.com/index.php/PSSJ/article/view/481
21. Egiyi, M. A. (2021). Robotic process automation and its application in accounting.
https://eprints.gouni.edu.ng/3596/1/RoboticProcessAutomationRPAItsApplicationandthePlaceforAccountants.pdf
22. Kaushik, P. (2023). Robotic process automation in accounting and auditing of business information.
https://www.researchgate.net/publication/370418613_ROBOTIC_PROCESS_AUTOMATION_RPA_IN_ACCOUNTI

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NG_AND_AUDITING_OF_BUSINESS_AND_FINANCIAL_INFORMATION

23. Adebayo, T. (2024). Artificial intelligence in fraud detection and financial risk mitigation. https://www.researchgate.net/publication/387461566_Artificial_Intelligence_in_Fraud_Detection_and_Financial_Risk_Mitigation_Future_Directions_and_Business_Applications

24. Zhang, C., Cho, S., & Vasarhelyi, M. (2022). Explainable artificial intelligence in auditing. International Journal of Accounting Information Systems.https://doi.org/10.1016/j.accinf.2022.100572

25. Schreyer, M., et al. (2017). Detection of anomalies in large-scale accounting data using deep autoencoder networks. https://arxiv.org/abs/1709.05254

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