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Review Article

Artificial Intelligence in Financial Risk Management: A Systematic Review of Applications, Performance, and Challenges

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Abstract

The financial sector is witnessing a transformative age driven by AI's predictive analytics, automated system monitoring, and intelligent decision-making solutions. AI is reshaping financial risk, providing predictive analytics, automatic system monitoring, and clever decision-making tools. This study is a systematic review which addresses the role of AI solutions in financial risk management, worries and results, and a recap of the previous research that took place between 2014 and 2025. The search was undertaken using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) and included papers found in the three main databases: IEEE Xplore, Scopus and Web of Science. Twenty-three studies met the inclusion criteria and were selected for the second phase of-eligible studies, final synthesis. The areas where machine and deep learning techniques were identified are fraud detection, credit risk prediction, anti-money laundering system, operational risk management, and cyber security and financial risk in supply chain – matching the findings. What was most frequently cited in the literature was a combination of several methods, like random forest, support vector machine and gradient boosting algorithms, to convolutional neural networks, long short-term memory networks, or even a combination of both. AI model-based systems have been shown to outperform traditional statistical/rules-based systems in terms of accuracy (+); anomaly detection and classification (-); etc., as per several studies. Equality and trustworthy AI systems for addressing transparency, fairness, interpretation and regulatory compliance at financial institutions, with a greater focus, were also noted in the review. However, there are still some factors that need to be taken into account: There is limited public data available, computational complexity, data imbalance and potential cyber-security issues, as well as the creation of potential algorithmic bias. Lastly, it's worth mentioning the great opportunities AI offers in financial risk management, while de-emphasizing the importance of just, cyber-resilient and AI framework validated AI governance models in order to establish a common set of standards for sustainability and applicability of AI technology in the dynamic financial landscape.

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1. Introduction

Management of financial risks is given a lot of importance in the present-day financial system to attain financial stability and financial sustainability. The bank, insurance company, investment company, and FinTech are taking many risks; the common ones in the finance industry are credit, market, liquidity, operational, fraud risks and cybersecurity risks [1]. Carefully, in history risk management has been solved using statistical/econometric approaches like ARIMA, Logistic regression, Value-at-Risk (VaR) etc., rule-based approaches. These risks have been handled in the past via a logistic regression, Value at Risk (VaR), econometric methods (ARIMA & (rule-based) systems) [2]. Of those techniques, some are able to work for financial decision making but not with large and complex data sets, as well as non-linear relationships, and market volatility.

With digital banking, electronic transactions, algorithmic trading, blockchain, and decentralized finance, the amount of financial information is growing, and becoming more complex. It has therefore posed stringent demands on the financial institutions regarding intelligent systems featuring analytical, adaptive, learning, anomaly detection and forecasting capabilities in real-time [3]. But, the introduction of Artificial Intelligence (AI) technologies such as machine learning, deep learning, natural language processing and reinforcement learning has brought about a new paradigm in financial risk management. One key advantage of AI over traditional statistical models is that it can process structured as well as unstructured data, identify patterns that are not explicitly captured in the data and continuously refine its predictive capabilities [4, 5]. Random forests, support vector machines, artificial neural networks, gradient boosting models and deep learning architectures are commonly used algorithms [6].

The applications of AI go far beyond those in the realm of financial risks these days. In credit risk management but also in assessment of borrower's creditworthiness, machine learning models have been employed to predict the probability of loan default. AI can be used in fraud prevention and AML solutions to identify anomalies and patterns of behavior, in real-time [7]. AI is also being used more frequently in forecasting market risk, optimizing portfolios, managing operational risk and keeping an eye on cyber risk. Financial decision-making processes can significantly benefit from the superior capability of AI systems in predictive accuracy, scalability, automation and adaptability, which may offer significant advantages over traditional analytical approaches [8].

While the benefits of AI in financial risk management are undeniable, challenging technical, ethical and regulatory issues remain associated with this application. However, many like current AI systems are "black box" ones that are hard to interpret, accountable problems, and can be hard to trust by stakeholders. Other challenges include algorithmic bias, cyber security concerns, protection concerns, lack of information quality and model overfitting. The capability to implement such tools increases further for financial institutions if they have to layer on the complexities and ambiguities caused by using explainable, trustworthy AI, and the regulator will have to master and understand all of these plus offer transparencies to their customers and regulators [9].

There appears to be a rising volume of research and development efforts in the area of AI in finance, however, this collection of work is still diffuse and implicit across different applications of finance and AI. Compared to the broad landscape of financial risk management more broadly, the existing studies tend to focus on a particular topic, e.g., fraud detection or credit scoring, but not a summary of the performance of these systems, the associated governance issues, their problems of explainability, the barriers to implementation and the emerging research opportunities for a more comprehensive understanding [10]. Hence, this systematic review is designed to comprehend the role of Artificial Intelligence (AI) technologies in financial risk management, evidence on the use of the different AI techniques, effectiveness of AI techniques to detect financial risks and challenges observed in AI implementation. It also aims at discussing the AI techniques and financial risks associated with financial risk management, predicting the performance of AI in financial risks, and understanding the challenges in terms of governance to have them adopted in financial risk management and find the future directions of research.

2. Methodology

2.1. Review Design

For this study the systematic review approach was used to gain a better understanding of the application of artificial intelligence (AI) in financial risk management. This review has been carried out keeping in mind the guidelines mentioned in Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020), which specify the guidelines for transparency, rigor and reproducibility. Identification, screening, eligibility and inclusion were done according to the PRISMA approach.

2.2. Information Sources and Search Strategy

A comprehensive literature search was conducted using IEEE Xplore, Scopus, and Web of Science due to their strong coverage of AI, finance, and FinTech research.

The search combined keywords such as "artificial intelligence," "machine learning," "deep learning," "financial risk management," "credit risk," "market risk," "fraud detection," and "anti-money laundering." The search string used was:

("artificial intelligence" OR "machine learning" OR "deep learning") AND ("financial risk management" OR "credit risk" OR "market risk" OR "fraud detection" OR "operational risk")

The review period was extended to 2014–2025 to capture both foundational machine learning applications and recent AI advancements in financial systems. The initial search retrieved 530 records from IEEE Xplore, 1,056 from Scopus, and 724 from Web of Science. After applying filters (year, language, relevance, and document type), about 510 records remained for title and abstract screening.

2.3. Eligibility Criteria

Only those studies that provided an empirical and/or methodological contribution with the method used are accounted for, which include financial risk management studies. The techniques covered a spectrum from machine learning to deep learning, to explainable AI, and to reinforcement learning in all of the following areas: credit risk, fraud detection, market risk, operational risk, cybersecurity and anti-money laundering.

These studies covered a time span of 2014–2016 and were considered to be scientifically respectable from studies done in this period. Non-empirical studies, such as editorials, books and theses, as well as opinion papers, were excluded.

2.4. Study Selection Process

Articles were initially screened based on the title and abstract and article were screened as full texts based on the PRISMA guideline.

Next, after the screening process, 12 studies from IEEE Xplore, eight from Scopus and three from Web of Science were found to be meeting the inclusion criteria and thus were included in the final review process. This is summarized in a flow diagram according to the PRISMA declaration.

2.5. Data Extraction

A structured form for the data extraction was created to ensure a uniform data collection and include data on publication details, financial risk domain, AI techniques, datasets, validation methods, evaluation metrics, key findings and limitations.

The methodological clarity, transparency of the data sets, rigor of the validation process, and complete reporting were used to evaluate the quality of the studies. More focus was given to studies that had a better designed and reproducible methodology.

2.6. Risk of Bias and Quality Assessment

The almost all of the included studies were computational studies; hence a narrative Quality assessment approach was used. Some things assessed were transparency of datasets, techniques of validation, reproducing, explainability and reporting of performance. In general, methodological quality of studies included was moderate-high. The most used techniques were the cross validation, ensemble learning and comparative benchmarks techniques.

Table 1: Risk of Bias and Quality Assessment of Included Studies

Study	Dataset Transparency	Validation Method	Risk of Bias	Key Limitation
Mashrur et al. [11]	High	Systematic survey synthesis	Low	Limited empirical benchmarking
Bussmann et al. [12]	Moderate	Empirical validation	Low	Limited dataset diversity
Shi et al. (2025)	Moderate	Train-test validation	Moderate	Potential overfitting risk
Lei et al. (2023)	Moderate	Comparative modeling	Moderate	Limited external validation
Addo et al. [13]	High	Comparative testing	Low	Limited explainability
El Hajj & Hammoud (2023)	Moderate	Mixed-methods analysis	Moderate	Limited benchmarking
Pranto et al. [14]	Moderate	Incremental validation	Low	Scalability concerns
Fritz-Morgenthal et al. [15]	High	Framework analysis	Low	Limited empirical testing
Song et al. [16]	Moderate	Ensemble benchmarking	Low	Regional dataset limitation
Mubalaike & Adali [17]	Moderate	Experimental evaluation	Moderate	Limited interpretability
Alarfaj et al. [18]	Moderate	ROC-AUC benchmarking	Moderate	Class imbalance bias
Raghavan & Gayar (2019)	Moderate	Comparative validation	Moderate	Small scope
Zhou et al. [19]	Moderate	Neural network validation	Moderate	Scalability concerns
Hashemi et al. [20]	Moderate	Ensemble validation	Low	Limited deployment testing
Choi & Lee [21]	Moderate	Framework implementation	Moderate	Limited real-world testing
Nabrawi & Alanazi [22]	Moderate	ML comparison	Low	Domain-specific dataset
Chang et al. [23]	High	Explainable ML validation	Low	Early deployment stage
Malik et al. [24]	High	Hybrid benchmarking	Low	Computational complexity
Pamisetty et al. [25]	Moderate	XAI validation	Low	Regulatory gaps
Hassani [26]	High	Fairness analysis	Low	Conceptual focus
Jensen & Iosifidis [27]	Moderate	AML review	Moderate	Limited datasets
Deshpande [28]	Moderate	Framework analysis	Moderate	Limited empirical testing
Khanum et al. [29]	Moderate	Benchmarking	Low	No longitudinal testing

A bias has been found and the following biases exist: dataset limitation, class imbalance for the fraud detections, overfitting, external validation is not adequate. Many of the studies have been conducted with private/specific data sets, thus reducing the likelihood of obtaining the same results. However, despite this, there are some models out there that are gaining traction and becoming more popular, such as ‘explainable AI proficient like SHAP and LIME with deep learning models. There may also be ’publication bias’, in that preferred studies are those that work. Despite the above limitations, the overall quality of overall evidence was moderate to high was determined.

2.7. Data Synthesis

The large variation regarding the AI model (in terms of datasets and metrics used to assess the AI model) made it impossible to conduct a meta-analysis. Thematic synthesis method (narrative) was used. The AI techniques were identified as belonging to three dimensions, which were the financial risk domains, predictive performance, explainability, governance issues and implementation challenges.

3. Results

3.1. Study Selection

The total number of records obtained from the systematic search were 2310, and these were retrieved from IEEE Xplore (530), Scopus (1056) and Web of Science database (724). Titles and abstracts of 510 studies were screened after the limiting of the database according to article publication year, language, document type and document relevance to the topics. The full text eligibility assessment was then conducted to verify the eligibility and exclusion criteria according to the definition of eligibility. Twenty-three studies published from 2014 to 2025, following the screening and methodological assessment, were included in the final ones that were synthesized. Studies selected used the PRISMA 2020 Framework to summarize their methodology as summarized in the Figure 1 [30]:

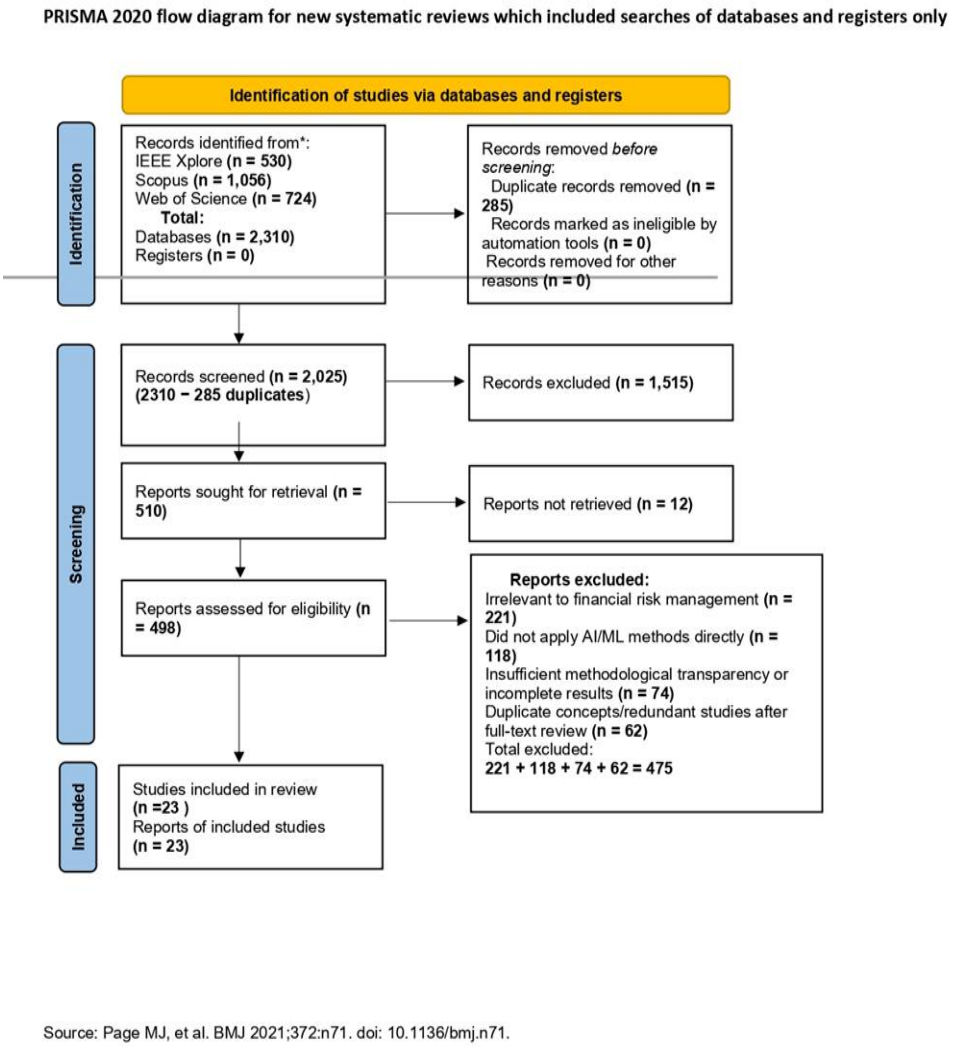

Figure 1: PRISMA 2020 flow diagram illustrating the identification, screening, eligibility assessment, and inclusion of studies in the systematic review.

3.2. Characteristics of Included Studies

The included studies investigated diverse applications of artificial intelligence (AI) in financial risk management, including credit risk prediction, fraud detection, anti-money laundering (AML), cybersecurity risk management, supply chain financial risk, and operational risk analytics. Machine learning approaches such as random forests, support vector machines (SVM), logistic regression, gradient boosting algorithms, ensemble learning, and artificial neural networks were commonly applied. Deep learning architectures, including convolutional neural networks (CNN), long short-term memory (LSTM) networks, restricted Boltzmann machines (RBM), and hybrid AI systems, were increasingly used for predictive analytics and fraud detection tasks.

Several studies emphasized explainable AI (XAI), fairness, governance, and responsible AI implementation within financial institutions. Validation metrics commonly included accuracy, precision, recall, specificity, F1-score, Matthews correlation coefficient (MCC), and area under the receiver operating characteristic curve (ROC-AUC).

Table 2: Characteristics of Included Studies

Study	Financial Risk Domain	AI Technique(s)	Key Findings
Mashrur et al. [11]	General financial risk management	ML/DL survey	Identified major AI trends and research gaps
Bussmann et al. [12]	Credit risk	Explainable ML, Shapley values	Improved transparency in credit scoring
Shi et al. (2025)	Financial risk prediction	CNN, LSTM	Reduced credit, liquidity, and market risks
Lei et al. (2023)	Supply chain financial risk	SVM, CGOA, SMA	Improved financial crisis prediction
Addo et al. [13]	Credit risk	ML and deep learning	Tree-based models more stable than ANN
El Hajj & Hammoud (2023)	Trading and financial operations	AI/ML systems	Highlighted governance and regulatory concerns
Pranto et al. [14]	Fraud detection	Blockchain and ML	Achieved 98.93% fraud detection accuracy
Fritz-Morgenthal et al. [15]	Financial model governance	Explainable and trustworthy AI	Proposed governance framework for AI risk models
Song et al. [16]	Financial statement fraud	Ensemble ML methods	Ensemble models outperformed single classifiers
Mubalaike & Adali [17]	Financial fraud detection	RBM, SAE, EDT	RBM achieved superior fraud detection accuracy
Alarfaj et al. [18]	Credit card fraud	CNN and deep learning	Achieved 99.9% accuracy and 98% ROC-AUC
Raghavan & Gayar (2019)	Fraud detection	KNN, SVM, CNN, DBN	Benchmarked ML and DL fraud models
Zhou et al. [19]	Credit risk management	PSO-BP neural network	Improved predictive efficiency using big data
Hashemi et al. [20]	Banking fraud detection	LightGBM, XGBoost, DL	Improved fraud detection with ensemble learning
Choi & Lee [21]	IoT financial fraud	ML and ANN	Proposed IoT fraud detection framework
Nabrawi & Alanazi [22]	Healthcare insurance fraud	RF, LR, ANN	Random forest achieved best predictive performance
Chang et al. [23]	Creditworthiness prediction	Explainable ML	Improved transparency in supply chain finance
Malik et al. [24]	Credit card fraud	Hybrid ML models	AdaBoost + LGBM achieved best performance
Pamisetty et al. [25]	Credit scoring	XAI, XGBoost, LSTM	Hybrid XAI model improved accuracy and fairness
Hassani [26]	Credit scoring bias	ML fairness analysis	Demonstrated societal bias reinforcement
Jensen & Iosifidis [27]	Anti-money laundering	Statistics and ML	Highlighted AML data and interpretability challenges
Deshpande [28]	Financial cybersecurity risk	AI cybersecurity framework	Improved AI-related threat detection
Khanum et al. [29]	Fraud detection	SVM vs rule-based systems	ML outperformed rule-based fraud systems

3.3. AI Techniques Applied in Financial Risk Management

The studies included found that machine learning is the prevalent approach to AI. Some popular models were performed, such as Random Forest, Support vector machine, Logistic regression, Gradient Boosting algorithm, decision Tree. In addition, ensemble learning models were utilized in many papers as well. Moreover, predictive analytics and fraud detection are also areas of interest applied by deep learning techniques such as CNN, LSTM, RBM and Hybrid Neural Architectures.

Several studies showed superiority of hybrid and ensemble AI compared to individual AI models. Song et al. [16] also found the ensemble classifiers outperformed logistic regression, neural network and the decision tree in financial statement fraud detection; Malik et al. [24] compared seven pairings and found the best fraud detection performance with the hybrid (AdaBoost + LightGBM) algorithm. Oracle's Hybrid CNN-LSTM models also exhibited predictive stability and improved the predictive accuracy of financial risk prediction and financial reporting tasks.

The number of research around explainable approaches to AI that would bring more transparency and interpretability are on the rise. Bussmann et al. [12] envisioned the interpretation of credit score's decision through Shapley's approach and Pamisetty et al [25] proposed the application of Shapley values and LIME in credit risk prediction systems to foster fairness and trust in digital banking systems. The role of trustworthy and auditable AI systems in financial institutions and regulatory compliance was another key theme emphasized by

Fritz-Morgenthal [15].

3.4. Financial Risk Domains Addressed

The set of studies included involved the most studies on financial risk analysis with respect to fraud detection. The following research projects were conducted with the application of machine learning and deep learning for fields of Credit Card Fraud, Healthcare Insurance Fraud, Financial Statement Fraud and Transaction Anomaly Detection. There is increased interest in using AI-driven fraud prevention systems that can be online and keep track of transactions at all hours of the day.

Many large areas of research were tied to the area of credit risk management. Few studies were reviewed in the areas of loan default prediction, explainable credit scoring, AIs and creditworthiness of borrowers. The use of methods that increase the interpretability, fairness, and acceptance of AI-driven credit and risk decisions for people and entities continued to increase.

Others financial risk domains were anti-money laundering, financial risk systems via IoT and supply chain financial risk. Jensen and Iosifidis [27] called attention to the increasing integration of machine learning in anti-money laundering processes, especially in applications related to detecting suspicious activity and risks associated with the clients. Deshpande [28] further introduced the new cyber threats that will arise with the advent of an AI-powered financial system and went through the process financial institutions can use AI to combat and identify threats.

3.5. Predictive Performance of AI Models

Most studies showed an AI financial risk management system had high predictive power. The machine learning and deep learning models yielded superior results compared to the conventional models based on statistics and rules in terms of fraud detection, credit scoring and financial risk prediction. Some of the common evaluation methods were: the accuracy, precision, recall, specificity, F1-score, MCC and ROC-AUC.

The use of deep learning models benefited the fraud detection applications. Alarfaj et al. [18] employed deep learning architectures to achieve achieving 99.9% accuracy and 98% ROC-AUC in fraud detection for credit card payments. Mubalaike et al. [17] evaluated the model of the restricted Boltzmann machine to detect fraud with an 81.53% accuracy rate, which is higher than that of other machine learning models.

On all comparisons, the AI based models performed better than traditional models. Song et al. [16] reported that financial fraud assessment can be better done using ensemble machine learning strategies as compared to logistic regression and decision tree models. Khanum et al. [29] reported that the machine learning system outperformed the rule-based system, the overall accuracy was 95% with F1 Score of 90%.

Explainable AI models also showed high performance in their predictive capabilities with improved transparency. Using this hybrid LSTM-XGBoost model, with addition of SHAP and LIME techniques, Pamisetty et al. [25] demonstrated improvement in prediction accuracy with 94.1% accuracy and interpretability of the algorithm. The outcomes suggest that there might exist an optimal system of financial risk management which can preserve the predictive performance and at the same time be explainable.

3.6. Explainability, Governance, and Ethical Concerns

Explainability, fairness, accountability and responsible governance of AI was one recurring question that was raised in the research. While there was consensus that further research is required, the studies raised a number of significant issues concerning black-box AI systems, such as overall user trust and the complexity of regulation for financial institutions. Explainability was especially crucial in sector applications like credit scoring, loan approval, fraud investigations, and making monetary decisions.

Bussmann et al. [12], Fritz-Morgenthal et al. [15], Chang et al. [23], and Pamisetty et al. [25] all stressed the importance of creating models that are both interpretable and can keep its prediction accuracy without compromising on transparency. The research papers stressed the importance of explainable Artificial Intelligence systems to ensure financial governance and the regulation of financial decisions.

There were opportunities related to the ethical aspects of algorithmic bias and discrimination as well. Views on the social implications of training machine learning systems have also been independently illustrated by Hassani [26] that inequalities in credit assessment can be reproduced and perpetuated in machine learning systems if trained with a socially-biased set of data. These results highlight the significance of fairness-aware AI models and fairness mitigation techniques in financial institutions. A few studies also emphasized the importance of AI governance, regulatory compliance, privacy protection and auditing practices to encourage responsible and responsible use of AI in the financial sector.

3.7. Operational and Implementation Challenges

While the studies mentioned in the reportage showed positive outcomes from the implementation of financial risk management systems using AI, there were still some indications in those studies and analyses that there are potential challenges to adoption of a large-scale financial risk management system using AI. The most commonly mentioned complications were data imbalance, data quality issues, privacy issues, cyber threats and high computational expense and inaccessibility of publicly available financial data.

Most of the studies of fraud detection assume data is highly imbalanced a small percentage of the data are fraudulent while a large percentage of the data are monetary transactions from a relatively large sample of transactions. Various techniques are also used to increase the power of prediction such as balancing methods like SMOTE, Bayesian optimization and ensemble learning, if the data is an imbalanced one.

Other issues which also came up while implementing were establishing privacy and communicating between organizations. Instead, they came up with the multi-party machine learning solution, on the blockchain, that offers some improvement in fraud detection and better privacy safeguard of transactions, said Pranto et al. [14] However, one big hurdle in AML research is that there aren't any public AML data sets that are available, Jensen and Iosifidis said [27].

Similar issues such as explainability of more complex AIs and scale are forcefully confronting financial institutions its primary function of just an institution in general. The studies all highlighted several other sustainability-related aspects that resonated with a heightened interest and relevance for the successful roll-out of AI predictive performance, governance, transparency and fairness.

4. Discussion

In order to explore how AI can potentially be used in financial risk management, the literature of the twenty-three studies was extracted by scouring the publications for the past decade and a half (2014-2025). The outcomes reveal that AI technologies are currently becoming a major force to transform the financial risk management sector by providing more precise prediction analysis, smart monitoring solutions, automated decision-making and improved methods for detection of anomalies. However, in the few papers studied indicated in this review, it can be seen that machine learning and deep learning remains the most promising evolution to detect fraud, predict credit risk, set anti-money laundering (AML) system, perform operation risk analysis and cyber security threat detection system [11, 13, 18]. Explainable [12], trustworthy and governance-oriented financial institutions (FI) AI systems are also highlighted as part of the review.

Not surprisingly, there was a long list of new machine learning (and deep learning) based applications for financial risk management that were discussed. Most studies used the methods of Artificial neural networks (ANNs) [31] or Ensemble learning methods including Random Forest, Support vector machine (SVM) algorithm or Gradient boosting machine (GBM) algorithm [16, 20]. Moreover, it is one of many drawbacks of the purely statistic and rule-based approach to financial domain (like large amounts of data, high dimension and heterogeneity). But in the financial risk management industry, also heavily data-driven, a PM system can do a better job (as in the above example) at potentially spotting the non-linear relationship and hidden behavioral patterns of financial risk than traditional system, as described by [11].

The best accuracy of financial forecasts and fraud detection was achieved by the usage of Deep Learning methods. The financial forecasting and fraud detection were most accurate with Deep Learning method. However, for the credit card fraud detection, Alarfaj et al. [18] presented extremely high results for fraud detection: 99.9% and 98% that corresponds to deep learning architectures, respectively, in terms of accuracy and ROC-AUC. Similarly, Compagnino 2025 claimed that the models learned through the use of these rounded machines are the most effective way of recognizing fraud transactions compared to the number of other machine learning techniques used to recognize fraud transactions [32]. Other's hybrid/ensemble learning architectures might also prove to be good predictors. Malik et al. [24] demonstrated that the accuracy of the fraud detection problem by separately using AdaBoost and LightGBM classifiers is less than that of the ensemble model of AdaBoost + LightGBM; while Song et al. [16] showed that the ensemble classifiers were superior to the logistic regression and decision tree methods in reducing error rates. Overall, the results indicate that the combination of AI technologies could have positive effects, such as better predictability and resilience within complex financial risk scenarios.

Among all financial risk areas in the relevant literature which were studied most, were the areas of 'fraud detection' and 'credit risk assessment'. This enhanced digitization of financial networks and systems, mobile banking, e-commerce services and online payment systems has made financial crimes and online crime that utilizes the internet and information technology much more prevalent. Consequently, financial institutions have started to use the real-time fraud detection systems that leverage AI capabilities, particularly predictive monitoring and anomaly detection [14, 21] as real-time solutions. It's evident that the results of each of the different models, and the effectiveness of their deviation from the traditional rule-based methods, were ones that definitely gave more capability and capacity in identifying frauds with the introduction of AI. The same result came through in each of the comparisons the AI systems identified fraud effectively and the rule-based ones didn't. In this regard, machine learning techniques shown by Khanum et al. [29] proved to be really helpful when predicting what is to come and yielded excellent results in comparison with rule-based approaches that kick off the preceding move toward AI-based financial safety frameworks.

Credit risk management was the second major industry sector that was discussed in the studies that included the adoption of AI. Application of explainable machine learning techniques for improving borrower risk classification [12, 33], credit scoring transparency and loan default prediction. Once again, with all AI products, explainability is again the focus and has potential concerns around trust, regulatory and fairness in financial decision-making processes. Focusing on the transparency of models, the authors of the aforementioned studies proclaimed that in the digital banking domain, along with helping users to understand the models' transparency, using explainability tools, such as SHAP and LIME, also helps improve the model's predictiveness [34]. The results provide support for the argument that explainability is not in contrast with optimizing performance - either of these characteristics may well coexist in the AI system, designed in a responsible way.

The standout feature in this review is how one becomes increasingly aware and how one gains greater understanding of governance issues, matters of fairness, transparency and ethical issues and how these relate to the context of AI within the financial services space. Several research studies have examined the issue of concerns on the use of black-box AI models, including grappling with uncertainty issues around accountability, regulatory and legal issues, and issues pertaining to biased use of financial decision making [15, 26]. In the world of applications where transparency and audito have a high value, like in credit risk assessment, fraud prevention or loan applications, there was a growing speculation that EXPLAINABLE AI frameworks could be a game-changer [35]. Furthermore, Hassani [26] presented how ML systems derived from socially biased data sets might lead to additional inequalities with respect to genders and ethnicities in lending. Examining the results, it became clear that ensuring the proper and equitable financial practices in financial systems and the formulation of appropriate policies become extremely critical and that there is a need for a strategy that would lead to the reduction of financial biases [36].

In addition, the review highlighted several challenges in operating and implementation that the use of AI tools poses in financial institutions. Data imbalance and poor data quality, high computational complexity, cyber security, privacy considerations and lack of publicly available datasets came to the fore as some commonly found issues [27, 28]. If detection systems ever had to deal with many fraudulent transactions among a large number of non-fraudulent transactions, they would always be a problem, especially when the percentage of unbalanced transactions is high. A few articles that have concerned themselves with the balancing of techniques, ensemble learning approach [20], the Bayesian optimization approach, hyperparameter tuning [22].

Another important concern was around privacy preservation and inter-organizational co-operation was another key concern. In the context of financial transactions and fraud detection, Pranto et al [14] presented a convenient machine learning (ML) framework based on a blockchain system to safeguard privacy and reduce fraud. Unlike, insufficient public anti-money laundering (AML) information was found as a major challenge in the roll-out of AI-based AML systems, as per Jensen and Iosifidis [27]. The analysis reveals that the preparedness of

data management, secure collaboration data environment and opportunities for benchmarking still have room for improvement for future financial risk management systems supported by AI.

The resilience of the environment to disruption while in operation is another prominent security consideration of increasing significance when it comes to an AI-driven financial system is emerging. However, additional space with a raised concern stage on financial scenario AI-powered is functioning opposition. Deshpande [28] points out the advantages and challenges of implementing AI in the financial sector. However, with AI technologies come new cybersecurity risks, such as the potential for exploiting the financial infrastructures automated, algorithmic manipulation and adversarial attacks and boosts, fraud analytics and predictive monitoring, too. In the financial sector, therefore, implementing sustainable AI requires comprehensive cybersecurity systems, governance strategies, regular audits, and the validation of the models.

Amongst the significant Takeaways from this review is the trail of interdependence and mutual dependency emerging in the field of financial risk management systems between AI, blockchain, IoT and big data analytics. To boost the predictive capabilities and the working efficiency several researchers suggested collaborative learning frameworks with blockchain technology and monitoring systems with the help of IoT devices [14, 19]. The changes will most likely result in a wider, mechanized and information-driven financial risk management systems of the future. However, along this comes a variety of new challenges on accountability, compatibility, visibility and scalability. Based on the key findings of this review, a theoretical frame of the financial risk management framework using Artificial Intelligence is introduced as shown in Figure 2 to elaborate the link between the three financial risk areas, three governance domains, and four operational challenges as well as the operational outcomes.

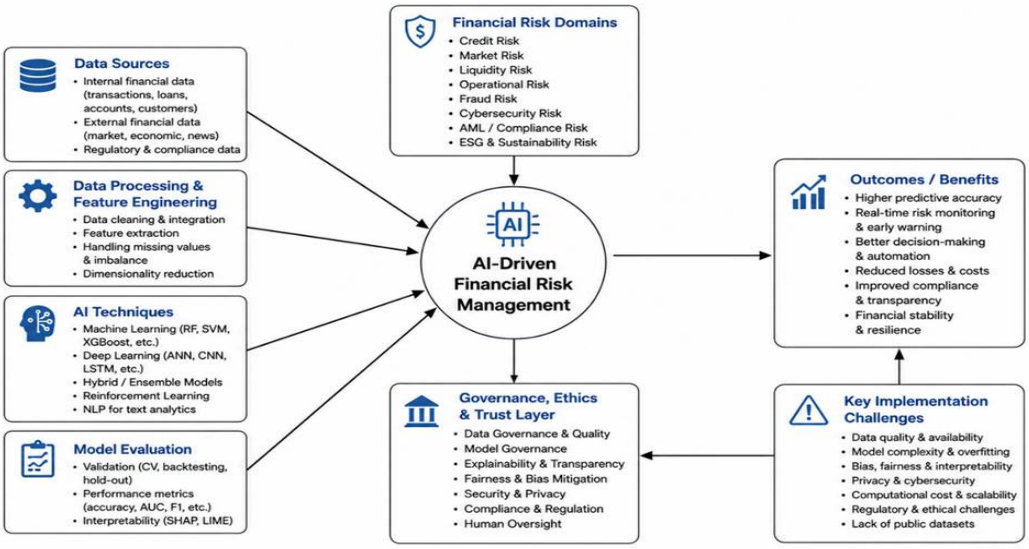

Figure 2: Conceptual Framework of AI-Driven Financial Risk Management

Conceptual framework illustrating the interaction between artificial intelligence techniques, financial risk domains, governance mechanisms, implementation challenges, and operational outcomes within AI-driven financial risk management systems.

Although the results were encouraging, there are still some areas of research needs that are observed. First, there remains a limited amount of work on the operational risk and liquidity risk of financial institutions compared to a limited amount of work on system finance risk and decentralized financial finance for financial institutions. First, there are few studies on operational risk, liquidity risk, system finance risk, and decentralized financial finance, compared with much work on fraud detection and credit risk prediction. Secondly, even though there is a lot of discussion on the existence of explainable AI frameworks, few people are able to put in place fairness-aware and explainable AI systems in practice in the real-world of the regulatory context. Third, several studies mainly aimed at assessment of predictive performance metrics discussed, yet not adequately indicated ethical, legal, or social impacts of implementing AI. Finally, the statistical normalization of data, as well as the benchmarking systems, still represent a difficulty in the aim of promoting further reproducibility and comparison of studies.

Returning to the bottom line, it is evident that AI is significant for financial risk management, bringing a multitude of benefits to the table, including enhanced predictive analysis, and the ability to monitor financial risks intelligently and automatically making better business decisions. However, the sustainability and responsible use of AI in financial services are yet to be proven due to the many key questions regarding explainability, fairness, cybersecurity, governance and operational resilience of financial services [37]. There is, therefore, a need for further research on how to create more explainable and trustworthy AI systems; fair machine learning models; more secure collaborative infrastructure; regular tools for the validation of systems; and governance ways of bridging disciplines to support responsible integration of AI into emerging financial ecologies.

The knowledge gained from this review is applicable to the financial institutions, financial regulators and financial policy makers. AI systems can not only boost financial organizations' fraud detection and risk monitoring capabilities but also serve in the process of credit scoring and enhance probity. AI solutions can also assist financial firms in fraud prevention and automated risk surveillance, boost credit worthiness and enhance probity. However, investments should be directed to the creation of explainable AI frameworks, cybersecurity infrastructure, transparent governance systems, and systems compliance with regulations to achieve successful implementation. Policymakers and regulators need to also create adaptive governance systems that will ensure there is a balance between innovation and accountability, fairness and stability.

5. Conclusion

The aim of this systematic review was to analyze 23 articles from the last ten years (between 2014 and 2025) covering the growing impact of Artificial Intelligence (AI) in Financial Risk Management. The outcomes of the study reveal the impact of AI technologies, particularly machine learning and deep learning methods, on financial risk management, with improved predictive analytics, fraud detection, credit risk assessment, operational surveillance, AML processes, and threat detection in the context of cyber risks. All of the studies reviewed showed higher predictive accuracy, anomaly detection and risk classification performance of AI-based models, compared to many traditional statistical and rule-based models.

The review also found that hybrid or ensemble AI architectures can deliver a better predictive strength than standalone AI algos, especially in the domains of fraud detections and credit risk predictions. Additionally, techniques such as Explainable AI (XAI), like SHAP and LIME, have become increasingly relevant to improve the interpretability and transparency of AI models and earn the trust of stakeholders in financial systems. With these regulatory and ethical concerns arising, there has been growing emphasis on explainable AI and trustworthy AI.

A major challenge is the lack of accurate, real-time data and reliable information sources for the financial risk system to analyze. Another challenge is the absence of accurate up-to-date data and reliable information sources for the financial risk system to analyze. There remain challenges in terms of data imbalance, access to high-quality financial data, cybersecurity risks, privacy aspects, computational complexity and algorithmic bias that restrict the scale and reliability of the use of smart contracts. It also says that transparency and governance issues could be acute if AI is used in black-box models, particularly in critical areas such as credit scoring, preventing fraud and lending approvals.

The findings conclude that AI is revolutionizing the way financial risk management is done today and is allowing greater levels of intelligent automation, predictive analysis, and adaptive decision-making in all aspects of financial risk management. However, allow for explainable, fair, secure and governance-led AI frameworks to materialize for sustainable and ethical integration of AI into financial institutions. These should therefore be priorities for future research, leading to the use of Trustworthy AI Systems, Fairness-Aware Machine Learning Models, Standardized Benchmarking Frameworks, Privacy-Preserving Collaborative Infrastructures and Interdisciplinary Governance Strategies to move towards the responsible integration of AI into financial systems.

6. Limitations of the Review

Though this broad, systematic review paints a picture of the innovation of AI in financial risk management, a few cautions are warranted in regard to this review. Initially, IEEE Xplore, Scopus and Web of Science databases were used to search for indexes. Additionally, studies have not been published may not have been included in the studies listed in other databases or sources. Secondly, publications were taken only in English language which could have led to a language bias and inclusion of missing non-English literature.

Third, there was a huge amount of variation in studies included in this study in relation to datasets, type of AI technology, validation approach, financial risk domains, and assessment tools. Therefore, it was not feasible to attempt to quantify the results directly across the different trials and this therefore limited the use of a formal meta-analysis. On the other hand, a narrative thematic synthesis method was used in reviewing the data. Furthermore, some of the studies in the project included were those for which the data were not publicly available, and thus may have limited the validity and repeatability of the studies included.

Last but not least, the field of artificial intelligence and finance is continually changing, so new methodologies, governance structures and regulations can be developed after the end of this review. Thus, the result should be considered in the context of the existing status of research in financial risk management enabled by AI from 2014 to 2025.

7. Future Research Directions

The findings shed light on the field and provided some direction for future research in this domain – AI for financial risk management. The first is that there is increasing demand for AI systems that violate these principles of transparency, equity and accountability to also be explainable, sound and compliant to these principles. The first one is the demand of consumers for an explainable, trustworthy AI systems based on and grounded in principles of transparency, equity and accountability, coupled with prediction. However, these recent developments bring explainable AI techniques such as SHAP and LIME to the table, but the challenge of operationalizing transparent AI solutions remains, especially in the context of financial institutions' efforts to create a more meaningful impact in the real world with AI. Future research directions that are subject of this study desire are interpretable machine learning models and algorithms that are aware of the fairness of credit scoring, fraud detection and lending models.

Secondly, more research is needed regarding the generalization of privacy-preserving collaborative approaches like federated learning, blockchain machine learning and secure multi-party computation (SMPC). The technologies offer improvements in inter-shareholder collaboration and business critical financial data security with regulation compliance. The scarcity of public, synthetic financial datasets, created for fraud detection and anti-money laundering (AML) studies, and others, can be solved with the use of synthetic data generation system.

Thirdly, the emphasis should be placed on fields of financial risk which are not yet sufficiently well researched, including liquidity risk, system risk and financial stability, decentralized finance (DeFi) (DeFi is the second field of financial risk identified), financial crimes using cryptocurrencies (CBDC banter) and financial risks related to the greenhouse effect and global climate change (cold pocket risk). In the current literature, the area's most prominently discussed for fraud detection and credit risk prediction, but others fields that could become more promising for in-depth investigations.

Other topics for research which are new and urgent to discuss include: Adversarial attacks, algorithm manipulation, and automated cyber threats are some potential risks in the financial infrastructure that may arise with the advent of AI. As AI continues to advance, robust cybersecurity frameworks and ongoing AI auditing tools should be explored to ensure perpetuation of financial institutions' security.

As a conclusion, setting industry friendly benchmarking frameworks, underpinning of the methodology of validation should be clear and transparent and understanding of the governance principles regarding the use of AI in financial services should be understood all over the world are the next steps to follow. Enhanced collaboration between the research community, regulators and policymakers, as well as financial institutions, will play a critical role in supporting the successful and responsible, ethical and sustainable use of AI in new and evolving

financial systems.

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Disclaimer (Artificial Intelligence): The author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.), and text-to-image generators have been used during writing or editing of manuscripts.

References

[1] B. Chen, X. Yang, and Z. Ma. Fintech and Financial Risks of Systemically Important Commercial Banks in China: An Inverted U-Shaped Relationship. *Sustainability*, 14(10), 2022. URL https://doi.org/10.3390/su14105912.

[2] A. H. Rabbani, I. Arshad, D. S. Jamal, M. Ali, and D. O. Ali. Financial Risk Forecasting Using AI: Hybrid Econometric–Machine Learning Approaches. *The Critical Review of Social Sciences Studies*, 3(4):795–809, 2025. URL https://doi.org/10.59075/smv2vj25.

[3] Y. Chen, C. Zhao, Y. Xu, C. Nie, and Y. Zhang. Deep Learning in Financial Fraud Detection: Innovations, Challenges, and Applications. *Data Science and Management*, 2025. URL https://doi.org/10.1016/j.dsm.2025.08.002.

[4] A. B. O. Enabulele, D. A. Ojo, J. O. Egwatu, and G. A. Thomas. AI-Augmented Agility: A Comprehensive Review of Generative AI Applications in Agile Project Management. *Journal of Global Economics, Management and Business Research*, 17(3):349–360, 2025. URL https://doi.org/10.56557/jgembr/2025/v17i39877.

[5] K. Tian, Z. Zhu, J. Mbachu, A. Ghanbaripour, and M. Moorhead. Artificial intelligence in risk management within the realm of construction projects: A bibliometric analysis and systematic literature review. *Journal of Innovation Knowledge*, 10(3):100711, 2025. URL https://doi.org/10.1016/j.jik.2025.100711.

[6] I. H. Sarker. Machine Learning: Algorithms, Real-World Applications and Research Directions. *Sn Computer Science*, 2(3):160, 2021. URL https://doi.org/10.1007/s42979-021-00592-x.

[7] Z. Wang. Artificial Intelligence and Machine Learning in Credit Risk Assessment: Enhancing Accuracy and Ensuring Fairness. *Open Journal of Social Sciences*, 12(11):19–34, 2024. URL https://doi.org/10.4236/jss.2024.1211002.

[8] A. M. Elhady and S. Shohieb. AI-driven sustainable finance: Computational tools, ESG metrics, and global implementation. *Future Business Journal*, 11(1):209, 2025. URL https://doi.org/10.1186/s43093-025-00610-x.

[9] A. Skouloudis and A. Venkatraman. Scratching the Surface of Responsible AI in Financial Services: A Qualitative Study on Non-Technical Challenges and the Role of Corporate Digital Responsibility. *AI*, 6(8), 2025. URL https://doi.org/10.3390/ai6080169.

[10] K. Abbas, F. D. Santis, and V. Kolbjørnsrud. Artificial intelligence in accounting: A comparative analysis of adoption in accounting and non-accounting firms. *Journal of Accounting and Public Policy*, 57:107433, 2026. URL https://doi.org/10.1016/j.jaccpubpol.2026.107433.

[11] A. Mashrur, W. Luo, N. A. Zaidi, and A. Robles-Kelly. Machine Learning for Financial Risk Management: A Survey. *IEEE Access*, 8: 203203–203223, 2020. URL https://doi.org/10.1109/ACCESS.2020.3036322.

[12] N. Bussmann, P. Giudici, D. Marinelli, and J. Papenbrock. Explainable Machine Learning in Credit Risk Management. *Computational Economics*, 57(1):203–216, 2021. URL https://doi.org/10.1007/s10614-020-10042-0.

[13] P. M. Addo, D. Guegan, and B. Hassani. Credit Risk Analysis Using Machine and Deep Learning Models. *Risks*, 6(2), 2018. URL https://doi.org/10.3390/risks6020038.

[14] T. H. Pranto, K. T. A. M. Hasib, T. Rahman, A. B. Haque, A. K. M. N. Islam, and R. M. Rahman. *Blockchain and Machine Learning for Fraud Detection: A Privacy-Preserving and Adaptive Incentive Based Approach*. arXiv. Org, 2022. URL https://doi.org/10.1109/ACCESS.2022.3198956.

[15] S. Fritz-Morgenthal, B. Hein, and J. Papenbrock. Financial Risk Management and Explainable, Trustworthy, Responsible AI. *Frontiers in Artificial Intelligence*, 5, 2022. URL https://doi.org/10.3389/frai.2022.779799.

[16] X.-P. Song, Z.-H. Hu, J.-G. Du, and Z.-H. Sheng. Application of Machine Learning Methods to Risk Assessment of Financial Statement Fraud: Evidence from China. 2014. URL https://doi.org/10.1002/for.2294.

[17] A. M. Mubalaike and E. Adali. Deep Learning Approach for Intelligent Financial Fraud Detection System. In *2018 3rd International Conference on Computer Science and Engineering (UBMK)*, pages 598–603, 2018. URL https://doi.org/10.1109/UBMK.2018.8566574.

[18] F. K. Alarfaj, I. Malik, H. U. Khan, N. Almusallam, M. Ramzan, and M. Ahmed. Credit Card Fraud Detection Using State-of-the-Art Machine Learning and Deep Learning Algorithms. *IEEE Access*, 10:39700–39715, 2022. URL https://doi.org/10.1109/ACCESS.2022.3166891.

[19] H. Zhou, G. Sun, S. Fu, J. Liu, X. Zhou, and J. Zhou. A Big Data Mining Approach of PSO-Based BP Neural Network for Financial Risk Management With IoT. *IEEE Access*, 7:154035–154043, 2019. URL https://doi.org/10.1109/ACCESS.2019.2948949.

[20] S. K. Hashemi, S. L. Mirtaheri, and S. Greco. Fraud Detection in Banking Data by Machine Learning Techniques. *IEEE Access*, 11: 3034–3043, 2023. URL https://doi.org/10.1109/ACCESS.2022.3232287.

[21] D. Choi and K. Lee. An Artificial Intelligence Approach to Financial Fraud Detection under IoT Environment: A Survey and Implementation. *Security and Communication Networks*, 2018(1):5483472, 2018. URL https://doi.org/10.1155/2018/5483472.

[22] E. Nabrawi and A. Alanazi. Fraud Detection in Healthcare Insurance Claims Using Machine Learning. *Risks*, 11(9), 2023. URL https://doi.org/10.3390/risks11090160.

[23] V. Chang, Q. A. Xu, S. H. Akinloye, V. Benson, and K. Hall. Prediction of bank credit worthiness through credit risk analysis: An explainable machine learning study. *Annals of Operations Research*, 354(1):247–271, 2025.

[24] E. F. Malik, K. W. Khaw, B. Belaton, W. P. Wong, and X. Chew. Credit Card Fraud Detection Using a New Hybrid Machine Learning Architecture. *Mathematics*, 10(9), 2022. URL https://doi.org/10.3390/math10091480.

[25] A. Pamisetty, S. Paleti, B. Adusupalli, J. Singireddy, R. Inala, and K. C. Nagabhyru. Explainable AI Systems for Credit Scoring and Loan Risk Assessment in Digital Banking Platforms. In *2025 IEEE 13th International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS)*, pages 1478–1483, 2025. URL https://doi.org/10.1109/IDAACS68557.2025.11322144.

[26] B. K. Hassani. Societal bias reinforcement through machine learning: A credit scoring perspective. *AI and Ethics*, 1(3):239–247, 2021. URL https://doi.org/10.1007/s43681-020-00026-z.

[27] R. Jensen and A. Iosifidis. Fighting Money Laundering with Statistics and Machine Learning. 2023. URL https://doi.org/10.48550/arXiv.2201.04207.

[28] A. Deshpande. Cybersecurity in Financial Services: Addressing AI-Related Threats and Vulnerabilities. *2024 International Conference on Knowledge Engineering and Communication Systems (ICKECS)*, 1:1–6, 2024. URL https://doi.org/10.1109/ICKECS61492.2024.10616498.

[29] A. K. Khanum, C. S, B. Singh, and C. Gomathi. Fraud Detection in Financial Transactions: A Machine Learning Approach vs. Rule-Based Systems. In *2024 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE)*, pages 1–5, 2024. URL https://doi.org/10.1109/IITCEE59897.2024.10467759.

[30] M. J. Page, J. E. McKenzie, P. M. Bossuyt, I. Boutron, T. C. Hoffmann, C. D. Mulrow, L. Shamseer, J. M. Tetzlaff, E. A. Akl, S. E. Brennan, R. Chou, J. Glanville, J. M. Grimshaw, A. Hróbjartsson, M. M. Lalu, T. Li, E. W. Loder, E. Mayo-Wilson, S. McDonald, others, and D. Moher. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, 372:n71, 2021. URL https://doi.org/10.1136/bmj.n71.

[31] G. R. Yang and X.-J. Wang. Artificial Neural Networks for Neuroscientists: A Primer. *Neuron*, 107(6):1048–1070, 2020. URL https://doi.org/10.1016/j.neuron.2020.09.005.

[32] A. A. Compagnino, Y. Maruccia, S. Cavuoti, G. Riccio, A. Tutone, R. Crupi, and A. Pagliaro. An Introduction to Machine Learning Methods for Fraud Detection. *Applied Sciences*, 15(21), 2025. URL https://doi.org/10.3390/app152111787.

[33] K. Goyal, M. Garg, and S. Malik. Adoption of artificial intelligence-based credit risk assessment and fraud detection in the banking services: A hybrid approach (SEM-ANN). *Future Business Journal*, 11(1):44, 2025. URL https://doi.org/10.1186/s43093-025-00464-3.

[34] Shreya and H. Pathak. Explainable Artificial Intelligence Credit Risk Assessment using Machine Learning. 2025. URL https://doi.org/10.48550/arXiv.2506.19383.

[35] K. Toudas, K. I. Roumeliotis, D. K. Nasiopoulos, and G. Georgakopoulos. An Explainable AI Multi-Agent Recommender System for Financial Document Access Control. *Information Systems Frontiers*, 2026. URL https://doi.org/10.1007/s10796-026-10742-2.

[36] I. Aldasoro, L. Gambacorta, A. Korinek, V. Shreeti, and M. Stein. Intelligent financial system: How AI is transforming finance. *Journal of Financial Stability*, 81:101472, 2025. URL https://doi.org/10.1016/j.jfs.2025.101472.

[37] N. A. G. Gamarra. Explainable AI for Financial Risk Mitigation: Governance, Compliance, and Customer Protection in the U. S. Economy. *International Journal of Emerging Research in Engineering and Technology*, 7(1):314–321, 2026. URL https://doi.org/10.63282/3050-922X.IJERET-V7I1P138.