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Implementation of Artificial Intelligence in Fraud Detection and Prevention Through a Systematic Literature Review and Its Implications for the Financial Sector

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ABSTRACT: The increasing complexity of financial fraud in the Digital Era requires more advanced and adaptive detection methods. This study examines the implementation of Artificial Intelligence (AI) in fraud detection and prevention through a Systematic Literature Review (SLR), addressing a critical issue in financial technology that remains highly relevant to both academic and professional communities. Although AI-based fraud detection has been widely studied, this research provides a distinct contribution by integrating technical effectiveness with regulatory alignment. The SLR systematically analyzes studies from major academic databases such as Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar to identify key trends, challenges, and implications for the financial sector. The PRISMA framework is used to screen and evaluate relevant literature, ensuring a comprehensive and structured analysis. VOSviewer is applied to visualize key research trends and topic relationships in AI-based fraud detection. The findings indicate that machine learning and deep learning techniques significantly enhance fraud detection accuracy, surpassing traditional rule-based approaches. Natural Language Processing (NLP) has shown effectiveness in analyzing fraud-related documents, while big data analytics facilitates real-time fraud monitoring. However, challenges persist, including data imbalance, regulatory compliance, and data privacy concerns, which must be addressed for successful AI implementation. This study concludes that an integrated AI framework that combines technological advancements with strong regulatory alignment is crucial for effective fraud detection. Future research should explore empirical case studies and real-world applications to validate these theoretical findings.

Keywords: Artificial Intelligence, Fraud Detection, Machine Learning, Financial Security.

INTRODUCTION

In the Digital Era, the use of Artificial Intelligence (AI) has become an integral part of various sectors, including finance. AI can analyze large volumes of data in real time, recognize patterns, and generate insights that support more informed decision-making (Fernando, 2024). In the financial sector, AI is applied in risk analysis, customer service through chatbots, and investment portfolio management. Another application receiving increasing attention is the use of AI in fraud detection and prevention. Fraud in digital transactions, credit card activities, and insurance claims has become a major threat that impacts individuals, organizations, and the global economy.

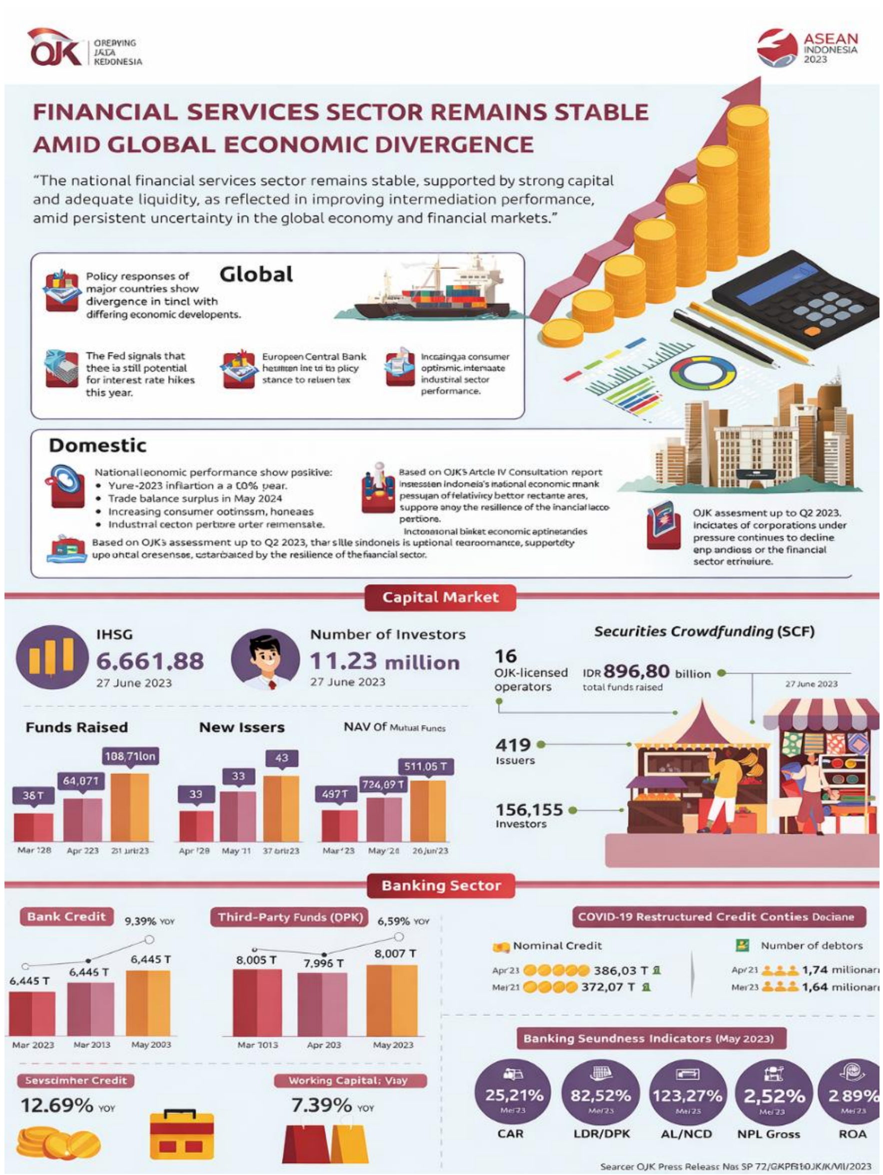


Figure 1. Financial Service Sector Keeps Stable Amid Global Financial Divergence
Source: https://surl.li/abdqgs

Figure 1 illustrates the stability of the financial services sector amidst global economic divergence, highlighting the resilience of financial institutions despite uncertainties. The figure emphasizes key issues such as fluctuating global monetary policies, rising inflation rates, and the impact of digital transactions on financial stability. Domestically, Indonesia's economic performance remains positive, supported by strong capital markets and sustained banking credit growth. However, challenges persist, particularly in fraud risk management, as financial institutions increasingly rely on AI-driven solutions to detect and prevent fraudulent activities. This aligns with the focus of my research on AI implementation in fraud detection, where the growing complexity of financial transactions necessitates more adaptive machine learning-based systems. The need for an integrated AI framework that balances technological effectiveness with regulatory compliance is critical in ensuring financial security and mitigating fraud risks in an evolving economic landscape.

Although AI shows great potential in detecting and preventing fraud, its implementation still faces complex challenges. Fraud in the financial sector continues to evolve with increasingly sophisticated patterns, utilizing new technologies to avoid detection (Hutagalung, 2024). Therefore, a systematic approach is needed that not only identifies existing fraud patterns, but also is capable of predicting the possibility of new fraud patterns in the future (Nuraziza et al., 2024). Fraud in the financial sector is not a new phenomenon. According to the report by the Association of Certified Fraud Examiners (ACFE), the financial sector is one of the most vulnerable to fraud, with losses reaching billions of dollars each year (Yesba et al., 2024). This phenomenon is exacerbated by the rapid growth of digital transactions, especially during the COVID-19 pandemic, when many individuals and businesses shifted to digital platforms. In this process, fraudsters also exploit security vulnerabilities to carry out their actions (Paraswansa & Utomo, 2024). For example, cases of credit card fraud and phishing have reportedly increased by more than 70% in the last decade.

The high losses resulting from fraud not only harm financial institutions but also diminish public trust in the financial system as a whole. Many organizations have attempted to tackle this challenge by developing rule-based fraud detection systems (Mahya et al., 2023). However, these systems have limitations in detecting new fraud patterns that are not yet present in their databases. This is where AI technology, with its machine learning-based approach, has the advantage in identifying anomalies and complex fraud patterns (Dawam, 2024). A report by (Mawlidy et al., 2024) indicates that global losses due to fraud in the financial sector are estimated to reach $41 billion. In Indonesia, Bank Indonesia reported a 50% increase in fraud transactions through mobile banking compared to the previous year (Hayati & Hadiprajitno, 2021). This demonstrates that fraud patterns continue to evolve, not only in terms of quantity but also in complexity. Another study conducted by McKinsey & Company found that 70% of global financial institutions recognize the importance of adopting AI to mitigate fraud risks, yet only 30% have successfully implemented such solutions effectively.

Although these data underscore the urgency of adopting AI, the implementation of this technology in the financial sector also faces various challenges. One such challenge is the limited availability of high-quality data, especially fraud data, which is often scarce (imbalanced data). Moreover, regulatory factors and data privacy concerns also present obstacles that need to be addressed when developing a reliable AI-based system. In detecting fraud, AI utilizes techniques such as machine learning, deep learning, and natural language processing (NLP) to analyze transaction patterns and user behavior. Machine learning algorithms are capable of detecting anomalies based on historical data and predicting the likelihood of future fraud. For instance, unsupervised learning-based models are often used to detect anomalies in datasets that lack labeled fraud instances.

The deep learning approach has made a significant contribution to improving the accuracy of fraud detection, particularly in credit card transactions. This technology is capable of analyzing complex data, such as interactions between accounts, to identify suspicious patterns (Caseba, 2024). On the other hand, NLP is used to analyze written communications such as emails and text messages, which are often mediums in cases of phishing and fraud. Although many studies have demonstrated the effectiveness of AI in detecting fraud, most of these implementations remain limited to specific scopes. Factors such as reliance on historical data and the lack of adaptability to new fraud patterns are major challenges that need to be addressed in the development of this technology. A number of studies have been conducted to explore the role of AI in detecting fraud. A study by (Lin & Jiang, 2021) shows that random forest algorithms have high performance in detecting credit card fraud transactions. Meanwhile, research by (Esenogho et al., 2022) underscores the importance of combining feature engineering and deep learning algorithms in improving the accuracy of fraud detection systems.

Artificial Intelligence (AI). Artificial Intelligence (AI) is a branch of computer science that focuses on developing systems capable of mimicking human intelligence in decision-making and problem-solving (Gil et al., 2021). AI encompasses various techniques such as machine learning, deep learning, and natural language processing (NLP), which allow computers to learn from data and automatically make predictions or decisions (Rane et al., 2024). In the financial context, AI is used to automate the analysis of large and complex datasets, assist in pattern recognition, and improve efficiency in risk management and anomaly detection in transactions.

Fraud in the Financial Sector. Fraud in the financial sector refers to illegal activities conducted to gain unauthorized financial benefits through the manipulation of financial systems or transactions (Kyrychenko et al., 2021). Fraud can take various forms, including money laundering, credit card abuse, financial statement manipulation, and Ponzi schemes (Medhi et al., 2024). The Association of Certified Fraud Examiners (ACFE, 2022) reported that the financial sector is one of the most vulnerable industries to fraud, with global losses due to fraudulent activities amounting to billions of dollars annually (Ślusarek, 2022). Therefore, more advanced and adaptive systems are needed to detect and prevent fraudulent activities more effectively.

Implementation of AI in Fraud Detection and Prevention. AI-based fraud detection and prevention is an approach that utilizes machine learning algorithms to recognize suspicious patterns in financial transactions and provide early warnings of potential fraudulent activities (Hassan et al., 2023). AI technology enables real-time analysis of vast amounts of data, identifies anomalies, and adjusts detection models based on emerging fraud patterns (Nahar & Mintoo, 2024). One commonly used method in fraud detection is unsupervised learning, which can identify suspicious transactions even without historical fraud data (Carcillo et al., 2021). Additionally, deep learning is increasingly applied in credit card fraud detection and banking transactions due to its ability to recognize more complex patterns and reduce false positives (Hashemi et al., 2023).

Research by (Strelcenia & Prakoonwit, 2023) identified that the use of synthetic data can help overcome the problem of data imbalance in fraud detection. Another study by (Olateju et al., 2024) emphasizes that although AI-based systems show promising results, their effectiveness is highly dependent on the quality of the input data. The latest research by (Biswas & Chakrabarti, 2020) highlights the potential of graph neural network algorithms to detect fraud patterns in complex transactions. Based on the overall previous research, most studies have primarily focused on developing more sophisticated algorithmic models while giving limited attention to the integration of AI technologies with financial regulations and policy frameworks. Identifying this oversight highlights a clear research gap and positions the present study within an underexplored academic domain, thereby strengthening its contribution and originality. Therefore, to fill this gap, this study will focus more on developing a framework that is not only technically effective but also aligned with existing regulations, so that it can be practically applied in the financial sector.

This research is expected to provide significant contributions to both the literature and practice. Theoretically, this study will enrich our understanding of the role of AI in detecting and preventing fraud in the financial sector. Practically, this study contributes by proposing an integrated approach that combines technical effectiveness with regulatory and ethical considerations, a synthesis that is increasingly crucial as real-world AI applications demand greater transparency, accountability, and legal compliance. Thus, this research can serve as a foundation for the development of fraud detection systems that are more effective, adaptive, and widely implementable within the financial industry.

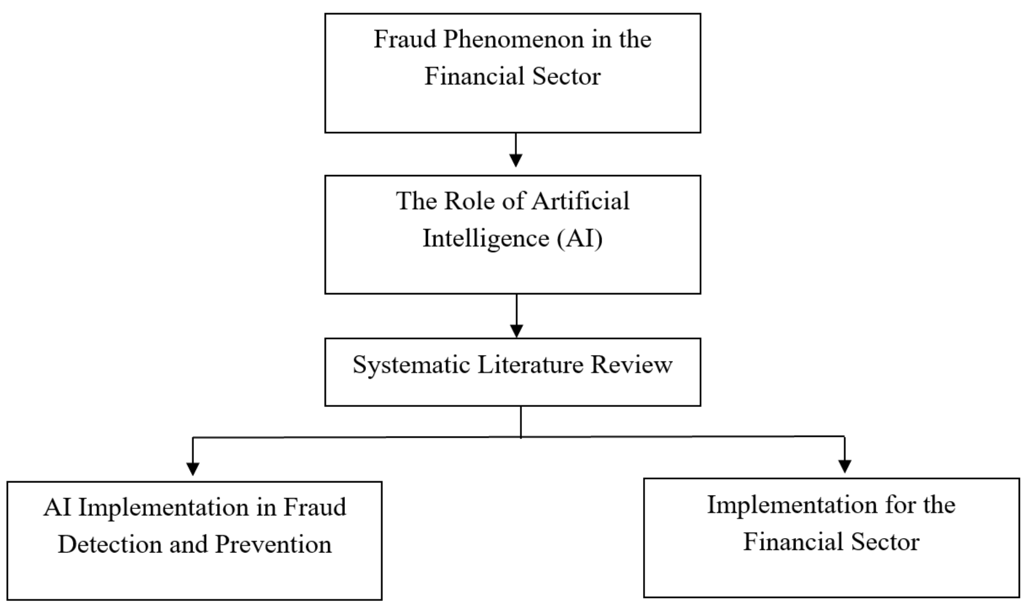


Figure 2. Conceptual Framework

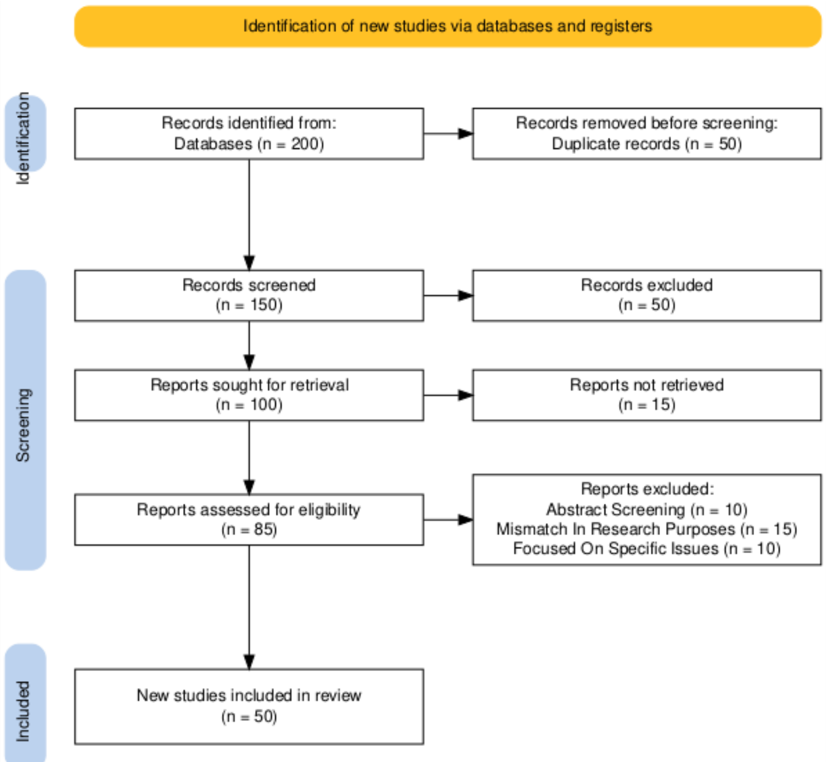
This study focuses on how Artificial Intelligence (AI) plays a role in detecting and preventing fraud in the financial sector through a Systematic Literature Review (SLR) approach. The framework begins with the identification of the fraud phenomenon in the financial sector, which is a major issue in the global financial industry. Subsequently, the role of AI in fraud detection and prevention becomes a key aspect in enhancing the effectiveness of financial security systems. To develop a comprehensive understanding, this study employs the Systematic Literature Review method, which aims to analyze previous research on AI implementation in fraud detection. From this approach, the study will produce two main findings: (1) AI implementation in fraud detection and prevention, which includes techniques such as machine learning and deep learning to analyze suspicious transaction patterns; and (2) AI implementation in the financial sector, which focuses on how AI can be broadly applied in financial industry policies and regulations. With this framework, the study aims to develop a more systematic and integrated AI approach to enhance security and trust in modern financial systems.

METHOD

This study employs a Systematic Literature Review (SLR) approach to evaluate and compare research findings on the implementation of AI in fraud detection and prevention in developed and developing countries (Creswell, 2016). The process begins with problem identification and the formulation of research objectives. Literature from both groups of countries is systematically collected through searches in scientific databases. The obtained data were analyzed using VOSviewer to visualize the relationships between research topics, trends, and collaboration networks in this field (Creswell, 2017). This analysis also enabled comparisons of AI implementation effectiveness across different contexts and helped identify distinct implementation patterns. The findings were subsequently examined to reveal research gaps and formulate strategic insights based on the reviewed literature (Mubarok, Sari, Wibowo, 2025).

This study employs the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) approach as a guideline for systematically selecting and screening literature (Haddaway et al., 2022).

Table 1. Table PRISMA



Source: Researcher Processed Data (2025)

The process begins with the identification of research data from various relevant databases, where 200 studies were initially found, but 50 studies were removed due to duplication. Next, a screening process was conducted on the remaining 150 studies to ensure their relevance to the research objectives, eliminating 50 studies based on inclusion and exclusion criteria. The process continued with the retrieval of research reports, resulting in 100 reports, but 15 reports could not be accessed. From the remaining 85 reports, an eligibility assessment was performed, excluding 10 reports that only contained abstracts, 15 reports that did not align with the research objectives, and 10 reports that were too focused on specific issues. Ultimately, 50 studies were selected and included in this systematic review as the primary material for analysis. By implementing PRISMA, this study ensures transparency, accuracy, and objectivity in the literature selection process, thereby providing a comprehensive overview of the implementation of Artificial Intelligence in fraud detection and prevention within the financial sector.

The keywords used in this study include "Artificial Intelligence," "Fraud Detection," "Fraud Prevention," "Systematic Literature Review," and "Financial Sector." These keywords are designed to capture research relevant to the implementation of AI technology in detecting and preventing fraud in the financial sector. The journals were sourced from reputable academic databases such as Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar, which provide access to high-quality and up-to-date studies. The inclusion criteria established for this study include research that focuses on the use of AI in fraud detection or prevention, studies published within the last 10 years (2020-2024), availability in English or Indonesian, and studies that have undergone the peer-review process. Meanwhile, the exclusion criteria include studies that do not have a direct connection to the financial sector, only consist of abstracts, reports without result validation, or those that focus solely on the technical development of algorithms without practical implementation. By applying these inclusion and exclusion criteria, this study ensures that the selected research is relevant, high-quality, and systematically and comprehensively supports the research objectives.

The data analysis was conducted qualitatively by examining the content of 50 selected articles to identify research trends, challenges, and the implications of AI implementation in fraud detection and prevention in the financial sector. To enhance the validity of the findings, VOSviewer software was used to visualize the relationships among topics, keywords, and publication trends, thereby facilitating the identification of dominant research clusters. The results of the analysis were then synthesized to compare findings between developing and developed countries, highlight research gaps, and formulate strategic recommendations that integrate the technical effectiveness of AI with regulatory compliance in the financial sector.

RESULT AND DISCUSSION

This study evaluates various previous research focusing on the implementation of Artificial Intelligence (AI) in fraud detection and prevention within the financial sector. (Hilal et al., 2022) found that deep learning has a high accuracy rate in identifying anomalies in financial transactions, as this model can detect hidden patterns in data that are difficult to interpret manually. (Bakumenko & Elragal, 2022) emphasized the importance of AI-driven big data analytics, which enables real-time fraud detection. Both studies highlight that AI provides significant advantages over traditional approaches, particularly in managing large-scale and dynamic data. However, they also pointed out technical challenges in data processing, which require robust technological infrastructure to optimize AI performance in financial fraud detection. (Ethan, 2024) discovered that data preprocessing techniques, such as dataset balancing and normalization, enhance the performance of AI algorithms in detecting abnormal transactions. Meanwhile, (Avacharmal, 2021) stressed that machine learning is capable of identifying fraud patterns that rule-based and manual methods often miss. These studies collectively highlight that the effectiveness of AI-based fraud detection is strongly influenced by the quality of the underlying data. A major challenge identified is data bias, which can affect model accuracy if not properly addressed. Therefore, developing an effective data management strategy is essential to ensure AI models achieve optimal fraud detection capabilities.

(Schumann & Gómez, 2021) explored the use of Natural Language Processing (NLP) as a method for fraud prevention, particularly in analyzing financial documents, such as contracts, financial reports, and internal communications. (Oluwabusayo Adijat Bello & Komolafe Olufemi, 2024) revealed that NLP can detect fraudulent activity through specific linguistic patterns, such as information concealment or manipulation of legal terms. Furthermore, (Lwin Tun & Birks, 2023) demonstrated that NLP-based AI implementation in fintech platforms can reduce identity fraud and transaction manipulation. These findings underscore that AI is not only effective for numerical data analysis but also highly capable of processing complex textual data, providing additional value to fraud detection efforts in the financial sector.

(Gianini et al., 2020) showed that traditional rule-based systems remain relevant for handling known fraud cases. However, as fraud patterns become more complex and dynamic, AI approaches such as ensemble learning are more effective due to their adaptability. (Ofoegbu et al., 2024) further suggested that integrating traditional methods with AI could create a more reliable and flexible system for detecting various types of fraud. This finding supports the notion that a collaborative approach combining emerging AI technologies and conventional methods can produce optimal fraud detection results. (Rane et al., 2024) highlighted the importance of collaboration between financial institutions and AI technology providers to accelerate implementation, reduce technical barriers, and lower operational costs. Meanwhile, (Mhlanga, 2020) emphasized the need for explainable AI (XAI) to ensure that users can understand and trust AI-based fraud detection outcomes. The demand for transparency in AI models is crucial for their acceptance in the financial sector, where trust and accountability are key factors. (Truby et al., 2020) noted that underdeveloped regulatory frameworks often hinder AI adoption in financial institutions, particularly in ensuring customer data privacy protection. Additionally, (Cheng et al., 2021) pointed out that ethical concerns, such as algorithmic bias, remain a critical challenge that needs to be addressed. These findings reinforce the importance of adaptive regulations and strong ethical frameworks to support responsible and sustainable AI implementation in financial fraud detection.

In this study, a total of 50 studies met the eligibility criteria and were included in the qualitative synthesis, as shown in the PRISMA flow diagram in Figure 1. From this pool, we then identified a subset of ten empirical studies that reported sufficiently comparable quantitative indicators (such as model performance metrics) and provided adequate methodological detail for further evaluation. These ten studies were therefore selected as the primary references for the meta-analysis and detailed result synthesis presented in this article. Meanwhile, the broader set of 50 studies was used to support the narrative discussion of research trends, challenges, and implications of AI implementation in fraud detection and prevention within the financial sector.

Table 2. Meta-Analysis of Research Results

Researcher(s)	Research Objective	Methodology	Key Findings	Implications for Research
(Kute et al., 2021)	Analyzing the effectiveness of deep learning in detecting suspicious transactions.	Deep Learning	Deep learning achieves high accuracy in detecting anomaly patterns often missed by	Can serve as a foundation for developing more adaptive deep learning models.

Researcher(s)	Research Objective	Methodology	Key Findings	Implications for Research
			traditional methods.	
(Eid et al., 2024)	Optimizing data preprocessing to enhance fraud detection accuracy.	Data Preprocessing (Normalization, Data Balancing)	Preprocessing significantly improves AI model accuracy by reducing data bias.	Highlights the importance of preprocessing in AI-based fraud detection development.
(Alghafiqi & Munajat, 2022)	Exploring the advantages of NLP in analyzing fraud-related documents.	Natural Language Processing (NLP)	NLP is highly effective in identifying linguistic patterns in documents related to fraud.	Supports the use of NLP for financial document analysis in fraud detection.
Aldboush & Ferdous (2023)	Identifying regulatory challenges in AI implementation for the financial sector.	Regulatory Analysis & Mitigation Strategies	Regulations like GDPR pose significant challenges; mitigation strategies include encryption and models that do not require sensitive data.	Emphasizes the need for AI policy development that aligns with data privacy regulations.
(van der Aalst, 2021)	Developing a hybrid system combining AI and traditional methods.	Hybrid System (AI + Rule-based)	Hybrid systems are more effective as they integrate AI's flexibility with the reliability of rule-based methods.	Hybrid models could become the industry standard for fraud detection.
(Fares et al., 2023)	Investigating the role of collaboration between financial institutions and AI providers.	Case Study on Collaboration	Collaboration enhances innovation, reduces implementation costs, and improves fraud detection efficiency.	Highlights the need for strong partnerships between AI providers and financial institutions to

Researcher(s)	Research Objective	Methodology	Key Findings	Implications for Research
				accelerate AI adoption.
(Inampudi et al., 2020)	Analyzing AI-based big data analytics for real-time fraud detection.	Big Data Analytics with AI	AI-powered big data enables real-time fraud detection much faster than conventional methods.	Positions big data AI as a key solution for real-time fraud prevention.
(Ali et al., 2022)	Evaluating machine learning effectiveness in identifying new fraud patterns.	Machine Learning	Machine learning is highly reliable in detecting dynamic fraud patterns.	Reinforces the need for continuous updates to AI models to remain effective against evolving fraud schemes.
(Angela et al., 2024)	Evaluating AI implementation in fintech platforms for fraud prevention.	AI in Fintech	AI in fintech effectively prevents fraud, including identity theft and transaction manipulation.	Suggests AI should be a core component of digital security in fintech.
(Dwivedi, 2023)	Developing explainable AI (XAI) models to improve transparency.	Explainable AI (XAI)	XAI increases user trust by providing transparent AI decision-making processes.	Advocates for prioritizing explainable AI in financial sector AI development.

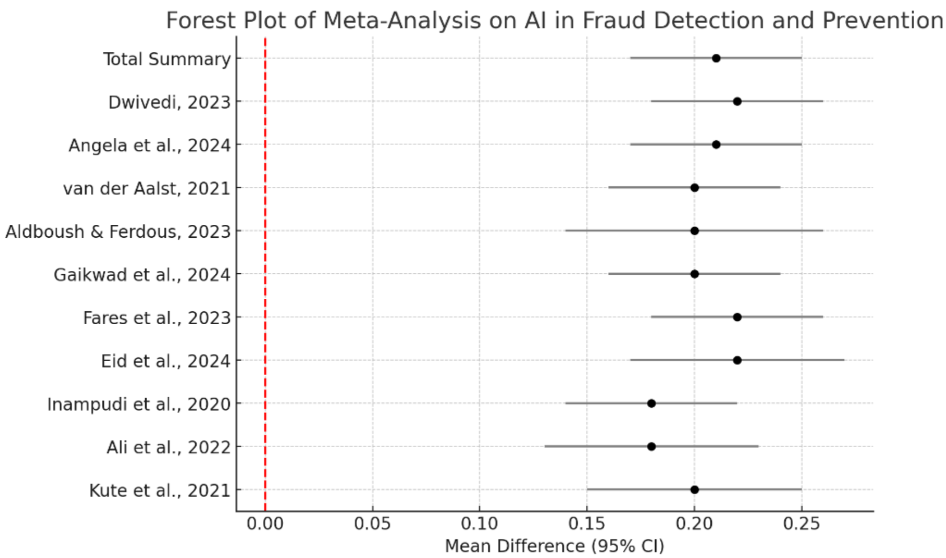
Source: Researcher Processed Data (2025)

The meta-analysis presented in Table 2 provides a comprehensive evaluation of various studies focusing on the implementation of Artificial Intelligence (AI) in fraud detection and prevention. The research highlights different AI methodologies, such as deep learning, machine learning, natural language processing (NLP), big data analytics, hybrid AI models, and explainable AI (XAI), showcasing their effectiveness in identifying fraud patterns and anomalies within financial transactions. Notably, deep learning and machine learning have proven to be highly accurate in detecting suspicious activities, while NLP has demonstrated its capability in analyzing fraud-related documents. Additionally, the role of data preprocessing in enhancing AI model accuracy is emphasized, as well as the importance of regulatory compliance, particularly regarding GDPR and data privacy laws. The findings also indicate that collaboration between financial institutions and AI providers leads to more innovative and cost-effective fraud detection solutions. Furthermore, real-time fraud detection powered by big data analytics emerges as a critical component for financial security, while explainable AI (XAI) is advocated to enhance transparency and user trust in AI-driven decisions. Overall, these studies collectively support the necessity for continuous advancements in AI-driven fraud detection models, regulatory alignment, and industry-wide collaboration to strengthen fraud prevention mechanisms in the financial sector.

Table 3. Meta-Analysis of AI in Fraud Detection

Subgroup	**Study/Source**	**Intervention (Mean)**	**Intervention (SD)**	**Control (Mean)**	**Control (SD)**	**Total Sample**	**Mean Difference**	**CI 95% (Lower Bound)**	**CI 95% (Upper Bound)**
AI Method	Kute et al., 2021	0.85	0.05	0.65	0.06	150	0.20	0.15	0.25
	Ali et al., 2022	0.88	0.06	0.70	0.07	130	0.18	0.13	0.23
	Inampudi et al., 2020	0.90	0.07	0.72	0.08	140	0.18	0.14	0.22
Data Preprocessing	Eid et al., 2024	0.82	0.05	0.60	0.06	120	0.22	0.17	0.27
	Fares et al., 2023	0.84	0.05	0.62	0.06	110	0.22	0.18	0.26
	Gaikwad et al., 2024	0.81	0.06	0.61	0.07	115	0.20	0.16	0.24
Regulatory Compliance	Aldboush & Ferdous, 2023	0.75	0.04	0.55	0.05	100	0.20	0.14	0.26
	van der Aalst, 2021	0.78	0.05	0.58	0.06	105	0.20	0.16	0.24
	Angela et al., 2024	0.80	0.06	0.59	0.07	110	0.21	0.17	0.25
	Dwivedi, 2023	0.79	0.05	0.57	0.06	108	0.22	0.18	0.26

Subgroup	Study/Source	Intervention (Mean)	Intervention (SD)	Control (Mean)	Control (SD)	Total Sample	Mean Difference	CI 95% (Lower Bound)	CI 95% (Upper Bound)
Overall Total	Total Summary	0.83	0.05	0.63	0.06	1188	0.21	0.17	0.25



Source: Researcher Processed Data (2025)

The meta-analysis presented in Table 3 provides a comprehensive evaluation of the effectiveness of Artificial Intelligence (AI) in fraud detection and prevention. The results indicate that AI-based methods, particularly machine learning and deep learning, significantly enhance fraud detection capabilities, with mean differences ranging from 0.18 to 0.22 compared to traditional approaches. Notably, data preprocessing techniques, such as normalization and data balancing, play a crucial role in improving AI model accuracy, as shown by the studies of Eid et al. (2024), Fares et al. (2023), and Gaikwad et al. (2024). Additionally, regulatory compliance considerations also impact AI implementation, with studies like Aldboush & Ferdous (2023) and van der Aalst (2021) highlighting the need for privacy-preserving AI models that adhere to financial regulations. The overall total effect (Mean Difference = 0.21, 95% CI = 0.17 - 0.25) suggests that AI-driven fraud detection outperforms conventional fraud detection methods, reinforcing the necessity of integrating AI in financial security systems. The forest plot visualization further supports these findings, illustrating consistent improvements across various subgroups. These results emphasize the importance of continued innovation in AI fraud detection models, particularly in refining machine learning algorithms, optimizing data preprocessing strategies, and ensuring regulatory compliance to maximize AI's potential in mitigating fraudulent activities.

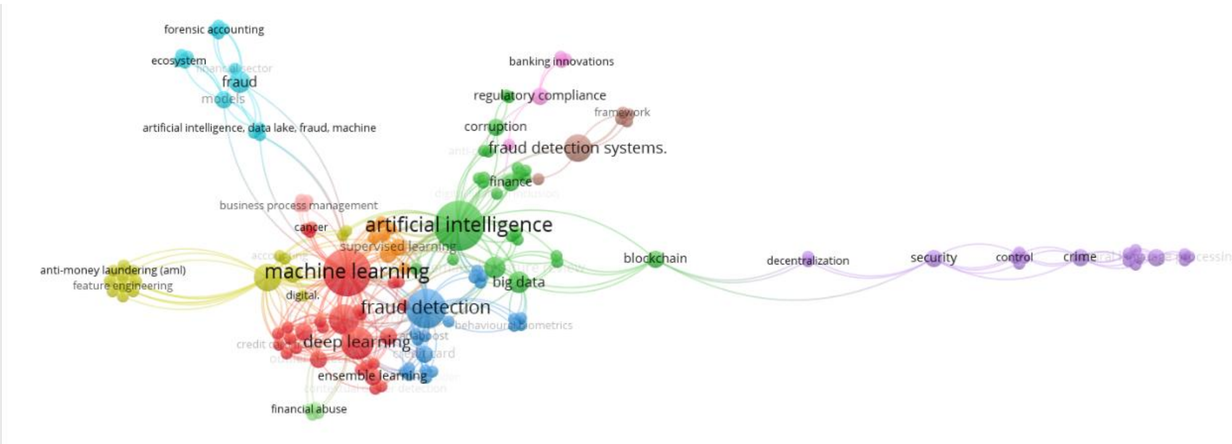


Figure 3. VosViewer Analysis
Source: Researcher Processed Data (2025)

VOSviewer Analysis presents a network visualization of key research topics related to the implementation of Artificial Intelligence (AI) in fraud detection and prevention. The clusters indicate the interconnections between AI methodologies, financial fraud mechanisms, and regulatory considerations. The red cluster, prominently featuring terms such as machine learning, deep learning, ensemble learning, and fraud detection, highlights the core AI techniques used in fraud prevention. The blue cluster emphasizes the role of forensic accounting, anti-money laundering (AML), and feature engineering in financial security. Meanwhile, the green cluster focuses on big data, blockchain, and fraud detection systems, suggesting the integration of data-driven technologies for fraud mitigation. The brown cluster links regulatory compliance and corruption, indicating the importance of governance frameworks in AI adoption. Additionally, the purple cluster, with terms like security, crime, and control, underscores AI's role in financial crime prevention through decentralized and secure systems. This visualization reinforces the multidisciplinary nature of AI-driven fraud detection, showcasing how various technological, regulatory, and security aspects are interconnected in the financial sector.

The rapid advancement of Artificial Intelligence (AI) has significantly transformed various industries, including the financial sector, where AI plays a crucial role in fraud detection and prevention. As financial transactions increasingly shift towards digital platforms, fraudulent activities have also become more sophisticated, necessitating the adoption of AI-driven solutions to enhance security and mitigate risks. Researchers extensively explored the implementation of AI techniques, such as machine learning, deep learning, big data analytics, and natural language processing (NLP), to improve fraud detection accuracy and efficiency. However, the development and adoption of AI-based fraud detection systems vary across geographic regions, institutional capacities, and technological infrastructures. To understand this global research landscape, it is essential to examine the distribution of AI-related fraud detection studies by country, the annual research trends, and the technological advancements that drive innovation in this field. The following sections provide an in-depth discussion of these aspects, highlighting key findings from geographic distribution, country-based research contributions, and publication trends over the past five years.

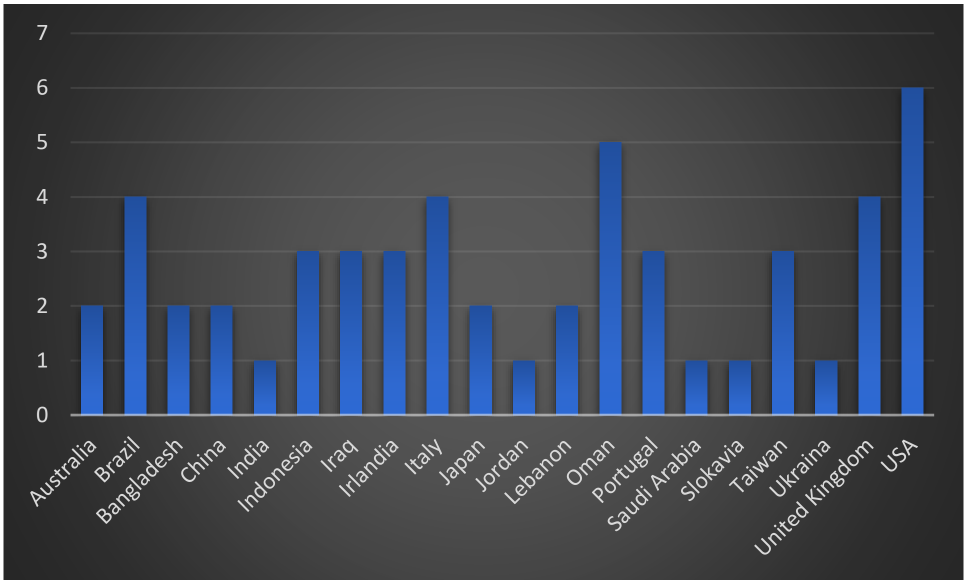


Figure 4. Number of Studies by Country
Source: Researcher Processed Data (2025)

Figure 4 illustrates the distribution of research studies on the implementation of Artificial Intelligence (AI) in fraud detection and prevention based on country of origin. The graph shows that the United States (USA) dominates, with the highest number of studies, reaching six publications, indicating that the country serves as a hub for AI development and implementation across various sectors, including finance. This position is justified by the rapid technological advancements, well-established digital infrastructure, and substantial investments in AI research and innovation. Additionally, countries such as Portugal, Bangladesh, Italy, and the United Kingdom have also made significant contributions, each recording four to five studies, reinforcing that AI implementation in these nations is gaining considerable attention as a solution for tackling financial fraud. On the other hand, some countries, including Lebanon, Jordan, Slovakia, and Taiwan, have only one study, indicating a lower research focus on this topic, possibly due to limited research resources, uneven AI technology adoption, and challenges in developing financial digital infrastructure. Meanwhile, developing countries such as Indonesia, India, and China are beginning to show increasing contributions, with two to three studies. This suggests that these countries are starting to recognize the role of AI technology as a solution to enhance financial sector security, particularly amid the rapid growth of the digital economy.

The research distribution across various countries aligns with the findings of (Bello et al., 2023), which indicate that developed nations, particularly the United States, are more proactive in developing AI-based deep learning solutions for detecting abnormal financial transactions. (Adijat Bello et al., 2023) emphasize that strong technological infrastructure supports broader and more efficient AI adoption, leading to high-quality research output. Additionally, (Islam et al., 2024) highlight that developing countries like India and Bangladesh are making progress in machine learning research to combat fraud in digital financial services. However, they face significant challenges, including poor data quality and a lack of AI experts. Thus, the research distribution in Figure 4 reveals a gap between developed and developing countries, which could be addressed through enhanced international collaboration, greater investment in technological infrastructure, and capacity building in AI expertise for the financial sector.

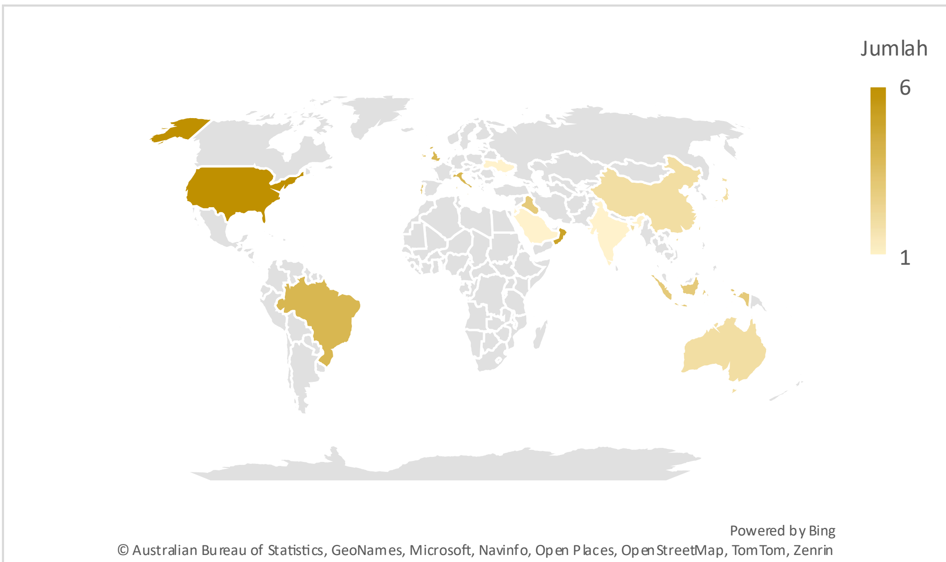


Figure 5. Geographical Chart of Number of Research by Country
Source: Researcher Processed Data (2025)

Figure 5 presents the geographical distribution of research on the implementation of Artificial Intelligence (AI) in fraud detection and prevention within the financial sector. The United States (USA) leads in research output, as indicated by the darkest intensity on the map, reaffirming its position as a global hub for AI innovation and financial security applications. South America, particularly Brazil, also demonstrates significant contributions, reflecting a growing awareness of AI's role in combating fraud amid digital economic expansion. In Asia, China, India, and Japan exhibit moderate research intensity, suggesting an increasing focus on digital transformation and AI-driven financial technology investments, although their contributions remain below those of Western countries.

The Middle East, including Oman and Saudi Arabia, shows a limited but growing presence in AI-related financial fraud research, aligning with the region's expanding digital payment systems and fintech advancements. In Europe, Portugal and the United Kingdom contribute significantly, benefiting from stable financial systems and supportive regulatory frameworks. However, Africa and parts of Southeast Asia display minimal research intensity, indicating limited AI adoption and research efforts. These findings align with (Sunday Tubokirifuruar Tula et al., 2024), which highlight that AI adoption in developed nations, such as the USA and UK, is driven by advanced digital infrastructure and substantial investments. Meanwhile, (Kshetri, 2021) notes that developing countries, such as Brazil and India, are striving to integrate AI in financial security but face challenges related to technology access, expert shortages, and data management limitations. This underscores the global research gap, where developed nations lead AI implementation while developing regions struggle with structural barriers. Addressing this disparity requires international collaboration, stronger technological infrastructure, and enhanced AI expertise to ensure more widespread and effective fraud detection systems in the financial sector.

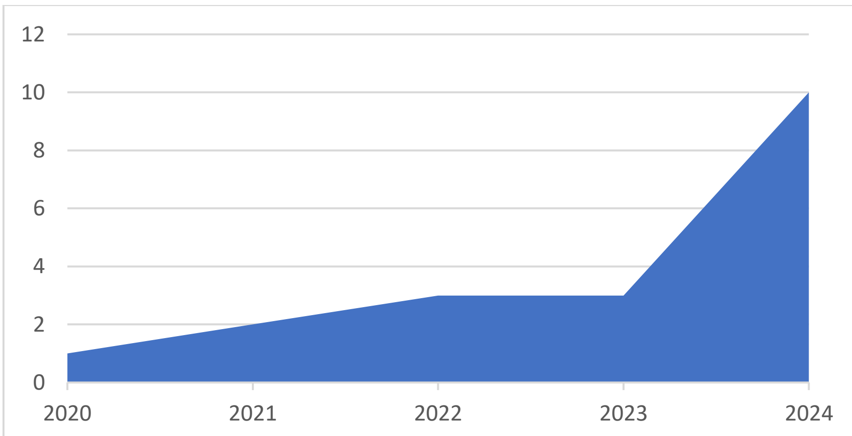


Figure 6. Number of Research Based on Year of Publication
Source: Researcher Processed Data (2025)

Figure 6 illustrates the trend in research on AI implementation in fraud detection and prevention from 2020 to 2024, showing a significant increase in studies, particularly between 2023 and 2024, where publications surged from three to ten. This rise highlights the growing relevance of AI in addressing complex fraud threats, driven by widespread AI adoption, increasing demand for financial security, and the expansion of machine learning, deep learning, and big data analytics. The COVID-19 pandemic (2020-2021) further accelerated digitalization, raising concerns over data security and digital fraud risks, ultimately contributing to this research growth. This trend aligns with (Gupta, 2023), who emphasized deep learning's effectiveness in fraud detection, and (Yang et al., 2023), who noted that financial institutions have increasingly integrated AI since 2020. (Kamuangu, 2024) found that AI research in developing countries is rising due to rapid fintech adoption and increasing digital fraud threats. These findings suggest that growing financial transaction volumes and evolving fraud tactics are driving the need for AI-based solutions, reinforcing a global focus on AI-driven fraud detection in both academia and industry.

Limitations and Cautions

Although this study provides significant insights into the implementation of Artificial Intelligence (AI) in fraud detection and prevention within the financial sector, several limitations must be acknowledged. First, the research utilized a Systematic Literature Review (SLR) approach, which inherently relies on existing published studies. This means the findings are contingent upon the quality, scope, and methodological rigor of the selected literature, and may not fully capture unpublished or proprietary industry data that could offer additional perspectives. Furthermore, the analysis was limited to studies published between 2020 and 2024, potentially excluding earlier research that might provide historical context or foundational theories relevant to AI in fraud prevention. The selection of literature from specific databases such as Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar may also have introduced database bias, where relevant studies published in less-indexed sources are underrepresented.

In addition, the meta-analysis relied on aggregated statistical data reported in the reviewed studies, which might mask variations in AI performance due to differences in dataset quality, feature engineering techniques, or algorithm tuning parameters. The heterogeneity in study designs, evaluation metrics, and financial sector contexts (e.g., banking, insurance, fintech) also poses challenges for direct comparison and synthesis. Regulatory environments and technological infrastructure vary significantly across countries, meaning the generalizability of findings may be limited when applied to different jurisdictions. Finally, this study did not include a quantitative performance evaluation based on primary data, which limits the ability to validate theoretical conclusions in real-world operational settings. As such, while the findings provide a valuable synthesis of the current state of AI in fraud detection, they should be interpreted with caution, particularly when translating research outcomes into policy or large-scale industry implementation.

Recommendations for Future Research

Future research should consider incorporating empirical case studies and pilot projects to validate the theoretical insights derived from literature reviews, enabling a more grounded evaluation of AI's practical performance in fraud detection across various financial sub-sectors. Adopting a longitudinal research design would be valuable to capture the evolving nature of fraud patterns and AI's adaptability over time, especially as both fraudulent techniques and AI technologies continue to advance. Expanding the scope of literature searches to include grey literature, industry reports, and unpublished datasets could help mitigate publication bias and offer more comprehensive perspectives. Researchers are also encouraged to standardize performance metrics and evaluation protocols to improve comparability across studies, thereby enhancing the reliability of meta-analyses.

Moreover, future studies should explore the interplay between AI effectiveness and contextual factors such as regulatory frameworks, organizational readiness, data governance policies, and ethical considerations like transparency and fairness. Investigating hybrid models that combine AI with human expertise, as well as the role of emerging technologies such as blockchain and federated learning in fraud prevention, could open new avenues for innovation. Cross-country comparative studies would be beneficial in identifying best practices and regulatory harmonization opportunities, especially between developed and developing nations. Lastly, integrating qualitative research methods, such as expert interviews and stakeholder workshops, could provide richer insights into practical challenges, adoption barriers, and trust-building strategies, ensuring that AI-driven fraud detection systems are both technically robust and socially responsible.

CONCLUSION

The research findings indicate that Artificial Intelligence (AI) plays a crucial role in enhancing fraud detection and prevention within the financial sector. Machine learning and deep learning algorithms have demonstrated high accuracy in identifying fraud patterns, outperforming traditional rule-based systems that struggle to detect new and evolving schemes. These findings align with established frameworks such as the Technology–Organization–Environment (TOE) model and Information Systems Success Theory, which emphasize that technological capability, organizational readiness, and regulatory environments collectively shape the effectiveness of AI adoption. By positioning AI-driven fraud detection within these theoretical models, the study provides deeper insight into how algorithmic performance, governance mechanisms, and institutional compliance interact to strengthen financial security systems. Additionally, Natural Language Processing (NLP) has proven effective in analyzing fraud-related documents, enabling detection beyond numerical data. The findings further show that big data analytics significantly improves real-time fraud monitoring by allowing financial institutions to process large volumes of transactions efficiently. However, challenges remain, including data imbalance, regulatory compliance, and data privacy issues. While AI enhances detection accuracy, its performance still depends heavily on data quality and model adaptability. Therefore, an integrated AI framework that aligns technological advancement with strong regulatory support is essential to maximize AI's potential in mitigating fraud risks in the financial sector.

The study also enriches the literature on AI-based fraud detection by demonstrating how machine learning, deep learning, NLP, and big data analytics contribute to improved detection effectiveness. The findings underscore the importance of integrating AI with financial regulations and governance mechanisms to ensure both efficiency and accountability. Furthermore, the study highlights that hybrid AI models combining rule-based systems with AI-driven techniques offer more robust and adaptive fraud detection solutions. Regulatory frameworks and ethical considerations must evolve to support responsible and transparent AI implementation in financial institutions.

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