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The Evolution of Financial Fraud Detection Methods: A Systematic Review of Integration of Theory, Data Analytics, and Artificial Intelligence

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Abstract

Financial fraud is a persistent global threat that undermines the reliability of financial reporting, corporate governance, and economic stability. In Indonesia, recent high-profile cases such as the Indonesian Export Financing Agency or also known as LPEI corruption scandal illustrate the limitations of existing fraud detection systems in identifying complex and concealed fraudulent behavior. The growing sophistication of fraud patterns, coupled with increased data volume and the digitization of financial systems, presents a significant challenge to traditional, manual-based detection methods. This highlights a critical gap in both theory and practice regarding how fraud is detected, interpreted, and prevented. This study aims to analyze and describe the evolution of financial fraud detection methods over the past decade and examine the role of Machine Learning (ML) and Explainable Artificial Intelligence (XAI) in enhancing accuracy and trust in financial fraud detection systems. A systematic literature review was conducted using the PICO framework, focusing on peer-reviewed articles published between 2019 and 2024 sourced from the Emerald Insight database. The results show a clear transition from traditional fraud detection approaches such as document analysis, field investigations, and interviews toward automated, data-driven techniques. The integration of ML algorithms, including Support Vector Machines, Random Forests, and unsupervised clustering, has improved fraud identification accuracy. Additionally, the use of XAI enhances model interpretability and stakeholder confidence by addressing the black-box nature of AI models. These technologies not only streamline detection processes but also reduce false positives and improve decision-making transparency. This research contributes to the literature by mapping the convergence of behavioral fraud theories and data science approaches. It also offers practical insights for organizations and auditors in developing adaptive, technology-integrated fraud detection frameworks that are both accurate and explainable.

Keywords: Financial fraud detection, machine learning, explainable Ai, systematic literature review, fraud theory.

1. Introduction

Fraud in the financial sector remains one of the main threats hampering global economic stability. Many cases in Indonesia, such as the alleged corruption at the Indonesian Export Financing Agency or also known as LPEI in Indonesian in 2024, have become the main focus. The Ministry of Finance's report revealed indications involving four companies in strategic sectors, such as palm oil, coal, nickel, and shipping, with potential state losses reaching IDR 2.5 trillion (BBC Indonesia, 2024). This case not only shows the complexity of the conditions in finance, but also highlights the weakness of the supervision and early detection system for corrupt practices in public institutions. The economic and reputational impacts that arise make the need for a more effective detection system increasingly urgent.

Fraud has been a part of human history since the first economic activities were carried out. The practice of fraud was first recorded in barter trade, where traders often manipulated the size or quality of goods for personal gain. As economic systems developed, forms of fraud became more complex, including embezzlement of assets, manipulation of financial statements, and technology-based fraud. Digitalization and globalization have expanded the scale and scope of fraud, especially with the advent of electronic transactions and the global financial system. A major development occurred in the 15th century with the introduction of double-entry bookkeeping by Luca Pacioli, which became the basis for financial monitoring, although it was not explicitly focused on detecting fraud (Ovunda, 2015). The Industrial Revolution then brought fraud to a more complex level, especially in the financial statements of large companies, giving rise to the need for more systematic detection methods.

Weaknesses in internal control are one of the main factors that allow fraud to occur in an organization. When internal control systems are not designed or implemented properly, the opportunity for fraud increases significantly (Astuti, 2024). Examples include the lack of segregation of duties, which allows one individual to have full access to critical functions, such as recording and cash management. In addition, the lack of effective monitoring of company assets and transactions creates loopholes for irresponsible individuals to manipulate or misuse (Yahya and Venusita, 2022). Research shows that organizations that do not have adequate internal audit procedures are more vulnerable to the risk of fraud, including theft of assets, document manipulation, or even embezzlement. In the case of PT Asabri, for example, weaknesses in investment management and supervision became the entry point for manipulation that harmed the state.

Research by Rusmana and Tanjung (2019) used the Fraud Pentagon approach developed by Jonathan T. Marks. This model adds elements of competence and arrogance to the Fraud Triangle model. The study analyzed variables such as financial stability, external pressure, financial targets, ineffective supervision, auditor turnover, director turnover, and CEO image to detect potential financial statement fraud. The results showed that only external pressure significantly influenced financial statement fraud, while other variables such as financial stability and financial targets did not have a significant relationship.

The development of technology has brought significant changes in the approach to fraud detection, complementing and strengthening the manual methods that have been used so far. Although traditional methods such as document analysis, interviews, and behavioral observation remain relevant, technology provides advantages in speed, accuracy, and the ability to analyze large volumes of data (Puspitasari et al., 2024). With the increasing complexity of fraud in the digital era, manual approaches are often insufficient to identify hidden patterns or anomalies that are not directly visible. Therefore, the integration of technologies such as machine learning, data analytics, and artificial intelligence is a crucial step in detecting fraud more effectively. This shift does not mean replacing manual methods completely, but rather creating a synergistic combination of human skills and the power of technology to overcome the increasingly complex challenges of fraud detection.

The use of Machine Learning has become one of the most revolutionary tools in detecting fraud in various sectors, including finance, e-commerce, and the public sector. This method allows for efficient analysis of large volumes of data, providing the ability to identify suspicious patterns or anomalies that may not be detected by traditional methods. In addition to Machine Learning and Unsupervised Learning, the use of Artificial Intelligence in fraud detection can be used as one method for conducting tests. Artificial Intelligence (AI) has become a revolutionary tool in detecting fraud in financial statements, providing the ability to analyze large-scale data efficiently and accurately (Pan, 2024). Using intelligent algorithms, AI can identify anomalous patterns and discrepancies in financial data that may indicate potential manipulation.

Based on the description, this study tries to systematically describe research on the topic of fraud detection where developments in fraud detection develop along with technological developments in fraud detection. This development shows that the traditional approach has limitations in dealing with the complexity of modern fraud, so that technology integration is an inevitable step. Therefore, this study aims to analyze and describe how the evolution of financial fraud detection methods over the last decade and how the role of Machine Learning and explainable AI in increasing trust and accuracy in financial fraud detection.

2. Literature Review

2.1. Fraud Triangle Theory

The Fraud Triangle, introduced by Donald R. Cressey in 1953, has become a fundamental theory in understanding the causes of fraud in various contexts, including financial reporting. This theory explains that fraud occurs due to three main elements, namely pressure, opportunity, and rationalization. Pressure arises when individuals face financial difficulties or significant external pressures, such as difficult performance targets or urgent needs for money. Opportunity occurs when an organization's internal control system is weak, allowing individuals to commit fraud without being detected (Nusantara and Kuntadi 2023). Meanwhile, rationalization is a moral justification made by perpetrators to justify their fraudulent actions.

The Fraud Triangle theory is not only relevant to understanding fraud motivations but also provides a framework for developing effective prevention strategies. Organizations can minimize pressure by setting realistic performance targets and providing financial support to employees. To reduce opportunities, strengthening internal control systems and conducting regular audits are important steps (Mansor and Abdullahi, 2015). In addition, efforts to reduce rationalization can be made by building a transparent and ethical organizational culture, as well as educating employees about the importance of integrity in their work. By implementing these strategies, the risk of fraud can be minimized, so that organizations can increase stakeholder trust.

2.2. Fraud Diamond Theory

The capability element is the main differentiator, where individuals who have certain authority, intelligence, or skills are more likely to commit complex fraud. Individuals with high capabilities can identify loopholes in the system, develop manipulation strategies, and hide their fraud in a way that is difficult to detect. This element makes the Fraud Diamond more relevant to analyzing fraud in the modern era, where fraud schemes often involve complex methods and sophisticated technology. The application of the Fraud Diamond Theory in fraud prevention highlights the importance of strengthening internal control systems and independent audits (Lisa et al., 2025). Organizations can reduce the risk of fraud by ensuring that no individual has full control over the entire financial process. In addition, regular training and evaluation of employees who hold strategic positions can help identify potential risks associated with the capability element.

2.3. Pentagon Fraud

This theory adds two new elements, namely arrogance and competence, to the previous framework that includes pressure, opportunity, rationalization, and capability. The arrogance element describes a superior attitude that makes individuals feel that they are above the rules and laws, allowing them to commit fraud without guilt. Meanwhile, the competence element refers to the level of expertise or knowledge of individuals to exploit system weaknesses, which is often combined with their authoritative position in the organization. This theory provides a more comprehensive approach to analyzing the motivations and methods of fraud, especially in cases involving high-level executives (Haqq and Budiwitjaksono, 2019).

In the context of financial reporting, Pentagon Fraud is very relevant to explain how individuals with strategic positions use their power and knowledge to carry out manipulation. The application of the Pentagon Fraud theory in fraud detection and prevention highlights the importance of stricter supervision of individuals with high access to sensitive information. Mechanisms such as independent board oversight, job rotation, and external audits can help reduce the opportunity for fraud. In addition, organizations need to build a strong ethical culture to suppress arrogance and ensure that individual competence is used for constructive purposes. Indicators used to measure the tendency of fraud using the fraud pentagon theory with the following explanation:

1. Pressure
   Pressure is the main factor that drives individuals to commit fraud. This pressure can come from various sources, such as personal financial needs, difficult-to-achieve performance targets, or external pressure to meet stakeholder expectations.
2. Opportunity
   Opportunity refers to weaknesses in the internal control system that allow individuals to commit fraud without being detected. This factor often arises due to a lack of segregation of duties, weak supervision, or inadequate internal controls.
3. Rationalization
   Rationalization is a moral justification made by perpetrators to convince themselves that their actions are acceptable. Perpetrators often consider fraud as a legitimate way to "save" the company from crisis or as compensation for the injustice they feel.
4. Arrogance
   Arrogance is an additional element that describes the superior attitude of individuals who feel they are above the rules and laws. Fraud perpetrators with high arrogance tend to ignore organizational policies and consider themselves untouchable by authority.
5. Competence
   Competence is the ability or technical expertise that enables an individual to exploit system weaknesses and commit fraud in complex ways.

2.4. Agency Theory

Agency Theory discusses the relationship between principals (owners or shareholders) and agents (managers) in managing an organization. This theory focuses on the conflict of interest that arises when agents, who are responsible for managing resources on behalf of the principal, act for personal gain that is not in line with the interests of the principal. In the context of fraud, this conflict often arises through manipulation of financial statements, misappropriation of assets, or strategic decisions that are detrimental to the owner but beneficial to management. Information asymmetry between principals and agents is one of the main triggers of fraud, where agents have greater access to operational and financial information than principals. Agency Theory provides a framework for identifying fraud risk factors and designing effective mitigation measures. Organizations can use control mechanisms such as independent boards of directors, external audits, and fair incentive contracts to minimize conflicts of interest between principals and agents (Sarwoko, 2016).

2.5. Theory of Planned Behavior

Theory of Planned Behavior (TPB) is a social psychology theory that explains the relationship between individual attitudes, intentions, and behavior. TPB is an effective analytical tool for understanding the psychological factors that drive individuals to commit or avoid fraud. TPB consists of three main elements: attitudes toward behavior, subjective norms, and perceived behavioral control. Attitudes reflect an individual's view of fraud, where negative attitudes tend to suppress the intention to commit fraud. Subjective norms include social or organizational cultural pressures that can influence an individual's decision to engage in fraud. Perceived behavioral control reflects the extent to which an individual feels able or difficult to commit fraud based on the opportunities available.

2.6. Technology Acceptance Model

The Technology Acceptance Model (TAM) is a theoretical framework that explains the factors that influence the acceptance and use of technology in organizations. In the context of fraud detection, TAM is relevant to understanding how technologies such as machine learning and artificial intelligence are accepted and adopted by users at both the individual and organizational levels. The model focuses on two main elements: perceived ease of use and perceived usefulness. Perceived ease of use reflects the extent to which users believe the technology can be operated with minimal effort, while perceived usefulness describes the extent to which the technology is perceived to improve work performance, such as detecting fraud more quickly and accurately (Karomi and Purwanto, 2024).

2.7. Fraud Detection

Fraud detection is the process of identifying suspicious and potentially fraudulent activities or transactions in various contexts, such as finance, business, or digital services. Fraud detection aims not only to identify fraudulent acts but also to understand the underlying patterns of fraud, allowing organizations to take more effective preventive measures. This process includes early identification of suspicious patterns, in-depth analysis to validate suspected fraud, and mitigation steps to prevent further losses. Fraud detection is becoming increasingly relevant in the modern era due to the increasing complexity of transactions and the risks associated with the use of digital technology, such as financial data manipulation, credit card fraud, or misuse of digital assets (Sutardiman et al., 2024).

3. Research Methodology

3.1. Method

This study uses a literature review method to analyze tax aggressiveness. The PICO (Population/Problem, Interest/Intervention, Comparison, and Outcome) approach is used to focus the literature search and analysis. The literature reviewed comes from the Emerald Insight database, with publication limitations in the period 2019–2024. Emerald was chosen because of its credibility as a reputable scientific journal publisher.

1) Population/Problem
   The population in this study are companies listed on the stock exchange. The problem studied is the practice of fraud detection carried out by companies or organizations, both government and non-government.
2) Interest/Intervention
   The interventions studied are various approaches such as machine learning Artificial Intelligence (AI), or manual methods used in the literature that match the established interventions.
3) Comparison
   A comparison is made between whether the literature in the database compares new methods with traditional methods or a single-disciplinary approach with a multidisciplinary one.
4) Outcome
   Identification of trends, adaptation to regulations, and global technological innovation.
5) Study Design
   A systematic literature review of peer-reviewed publications and industry reports.

3.2. Article Collection Procedure

The collection of literature in this study was carried out systematically through several stages designed to ensure the quality and relevance of the articles used. This process starts from determining keywords to the stage of analyzing the contents of the articles as a whole to find the main themes that support the research objectives. The stages of collecting articles include:

a. Identifying keywords using terms such as fraud detection, financial fraud detection, artificial intelligence, and machine learning
b. The literature search focused on the Emerald Publisher database because of its reputation in reputable scientific publications
c. The publication period was limited to 2019 to 2024 to ensure the recency of the data
d. Initial screening was carried out by reading the title and abstract to assess the suitability of the topic
e. Further screening was carried out by reading the full articles that passed the initial stage
f. Data extraction was carried out to extract important information related to the methodology, results, and contributions of each article
g. Data analysis was carried out using the content analysis method to identify patterns, trends, and main themes related to financial fraud detection

3.3. Selection Criteria (Inclusion and Exclusion)

To ensure the quality and relevance of the analyzed literature, this study established clear inclusion and exclusion criteria. These criteria are summarized in Table 1.

Table 1: Inclusion and exclusion criteria for literature selection

No	Inclusion Criteria	Exclusion Criteria
1	English-language articles	Non-English articles
2	Peer-reviewed articles	Non-peer-reviewed articles
3	Published between 2019–2024	Published before 2019
4	Focus on tax aggressiveness	Not focused on tax aggressiveness
5	Empirical studies or systematic reviews	Conceptual or theoretical studies only
6	Full-text available	Abstract only

The selection process is carried out in stages, starting with screening based on title and abstract, followed by full-text review for articles that pass the initial stage.

4. Results and Discussion

4.1. Article Search Results

Based on the processed sources, the number of journal article distributions per each journal is as follows:

Table 2: Distribution of journal articles

No	Source	Number of Articles
1	Asian Journal of Accounting Research	9
2	Journal of Financial Crime	9
3	Journal of Money Laundering Control	9
4	Journal of Applied Accounting Research	3
5	Meditari Accountancy Research	3
6	Public Administration and Policy	3
7	Arab Gulf Journal of Scientific Research	2
8	Journal of Business and Socio-economic Development	2
9	Accounting, Auditing & Accountability Journal	2
10	Applied Economic Analysis	1
12	Corporate Governance: The International Journal of Business in Society	1
13	Emerald Open Research	1
14	European Journal of Management and Business Economics	1
15	European Journal of Management Studies	1
16	International Journal of Building Pathology and Adaptation	1
17	International Journal of Industrial Engineering and Operations Management	1
18	Journal of Asian Business and Economic Studies	1
19	Journal of Economics, Finance and Administrative Science	1
20	Journal of Electronic Business & Digital Economics	1
21	Journal of Financial Reporting and Accounting	1
22	Journal of Humanities and Applied Social Sciences	1
23	LBS Journal of Management & Research	1
24	Management Matters	1
25	RAUSP Management Journal	1
26	Records Management Journal	1

The number of published articles in the 2019-2023 time frame is as follows:

Table 3: Time range of articles

Publication Year	Number of Articles
2019	4
2020	7
2021	4
2022	9
2023	21
2024	17

The distribution of the fifteen authors with the largest number of publications is as follows:

Table 4: Distribution of author names

Author Name	Number of Writings
Appolloni, Andrea	2
Lehner, Othmar	2
Mardijuwono,	2
Munedzi, Sharon	2
Rejeb, Karim	2
Chitimira, Howard	2
Rejeb, Abderahman	2
Abdul Wahab, Effiezal Aswadi	1
Abu Bakar, Hatinah	1
Ackers, Barry	1
Adekunle, Samuel Adeniyi	1
Ahmed, Mohamed Ahmed Hafez	1
Aigbavboa, Clinton	1
Ajward, Roshan	1
Akrout, Zied	1

4.2. The evolution model of financial fraud detection methods over the past decade

A study by Transparency International 2023 indicates that stricter regulations, such as the implementation of International Financial Reporting Standards (IFRS), have helped increase transparency in financial reporting and prevent opportunities for manipulation. In addition, the use of advanced technologies such as Explainable AI allows auditors to understand and explain algorithmic decisions in detecting anomalies, as outlined in the study by Sinha (2020). Thus, the evolution of fraud detection methods shows a strong integration of theory, technology, and regulation to address increasingly complex challenges.

The emergence of unsupervised learning-based fraud detection has been a pivotal point in this evolution. Techniques such as clustering allow for the detection of anomalies even without labeled historical data. The study by Kureljusic et al. (2024) revealed that clustering methods can be used effectively to detect irregular activities in the financial sector, including suspicious transactions in the financial statements of public companies. For example, the study by Westland et al. (2022) shows how manipulation patterns in inflation are one of the methods of fraud in financial data with high accuracy, especially when used to detect tax evasion schemes or fictitious transactions. This approach shows that AI-based predictive analytics can provide faster and more accurate solutions than traditional methods, as explained in a systematic literature-based report focusing on the adaptation of technology to financial regulation.

Research by Sakuntala et al. (2024) emphasizes the importance of real-time fraud detection to reduce potential losses caused by fraud. Research conducted by Umar et al. (2024) research conducted in Indonesia using the HU model in fraud detection is one of the models regarding fraud detection that is still used today. In this context, the use of explainable AI is also important to ensure that the system can provide transparent explanations to auditors and stakeholders.

Table 5: Researcher name and discussion of methods

Researcher	Method Discussion
Kureljusic, Marko	Application of Artificial Intelligence (AI) for forecasting and detecting fraud in financial accounting
Umar, Haryono	Use of the HU-model to detect and prevent corruption in companies listed on the Indonesia Stock Exchange (IDX)
Westland, James Christopher	Use of Google Analytics data from e-commerce companies for transaction and sales clustering and customer engagement analysis
Sakuntala, Sri	Implementation of emerging information technologies, including e-governance, blockchain, Artificial Intelligence (AI), big data analytics, and whistle-blower protection, to enhance transparency, accountability, and efficiency in anti-corruption efforts
Mahuwi, Leticia	Implementation of e-procurement systems to improve transparency and accountability in pharmaceutical procurement and reduce corruption risks among pharmacists in 28 government-owned hospitals in the Southern Highlands zone of Tanzania
Kunhibava, Sherin	Use of blockchain technology in the issuance and management of sukuk to improve transparency, efficiency, and reduce costs and risks associated with conventional sukuk transactions
Losbichler, Heimo	Application of AI in controlling activities such as planning, budgeting, and monitoring, focusing on human-machine collaboration to enhance efficiency and accuracy

4.3. The role of ML and explainable AI in increasing trust and accuracy in financial fraud detection

Machine Learning (ML) and Explainable AI (XAI) have become key pillars in increasing trust and accuracy in financial fraud detection systems. ML's ability to analyze large volumes of data and detect complex anomalous patterns provides significant advantages over traditional methods. For example, supervised learning algorithms such as Support Vector Machines (SVM) and Random Forest have been widely used to detect suspicious transactions with high accuracy. A study by Pavlidis et al. (2024) showed that the application of ML can increase detection accuracy by up to 90% in cases of financial reporting fraud.

Technical excellence alone is not enough to increase stakeholder trust. This is where Explainable AI (XAI) plays a crucial role. XAI enables Machine Learning (ML) algorithms to provide easy-to-understand explanations of how detection decisions are made, thereby encouraging wider adoption among stakeholders. Models such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) facilitate auditors and management in understanding the reasons behind anomaly detection, providing transparency that was previously difficult to achieve with traditional models. With this transparency, auditors can not only verify the model results but also explain the process to other parties, such as regulators or senior management.

Research by Jullum et al. (2022) shows that the transparency provided by XAI can increase trust by up to 30% among users of automated detection systems. This has a direct impact on accuracy and effectiveness, as users are more likely to make optimal use of this technology. Furthermore, XAI helps identify and reduce bias in ML models, which often lead to false positives or false negatives. With XAI, organizations can ensure that fraud detection decisions are not only accurate but also fair and accountable.

In addition to increasing trust, XAI also helps reduce bias in ML models. In the context of fraud detection, bias can lead to detrimental false positives. With XAI, organizations can identify and address bias in their models, resulting in fairer and more accurate decisions. Machine learning is able to detect fraud by analyzing data patterns that are invisible to humans. For example, deep learning models can identify unusual transactions in real time. An example of its application is seen in the case of tax evasion, where clustering algorithms are used to detect anomalies in thousands of financial data entries. With the integration of ML and XAI, the detection process can be carried out faster and more efficiently. In the Emerald database, several studies indicate that organizations using this technology can reduce investigation time by up to 40% compared to traditional methods.

In the case of manipulative financial reports, such as that which occurred at PT Garuda Indonesia, XAI allows auditors to understand the fraud patterns hidden behind fictitious transactions. This technology provides transparency about how financial reports are manipulated. This is also seen in real implementations by global companies such as PayPal and Amazon, which utilize ML and XAI to detect suspicious transactions in real time. This technology not only helps prevent financial losses but also strengthens customer trust in their platforms.

Table 6: Researcher name and context discussion

Researcher Name	Context Discussion
Soltani, Milad	This study identifies key contexts in financial fraud detection, keyword usage trends, collaboration patterns among countries, and leading journals and articles in the field. It also highlights methodologies for detecting and understanding financial fraud and suggests future research directions.
Lokanan, Mark	Use of machine learning algorithms, particularly Mahalanobis distance, to detect anomalies in financial statements by analyzing 24 key financial ratios as control variables.
Umar, Haryono	Application of the HU-model, which consists of five main elements causing corruption: pressure, opportunity, rationalization, capability, and lack of integrity, to detect indications of corruption in organizations.
Dimitrijevic, Dragomir	Application of external audits on financial statements to detect manipulation using various tests, including deep transaction testing, sampling, and internal control evaluation.
Khatun, Asia	Use of the Beneish M-score model to detect financial statement manipulation by identifying manipulation patterns using eight key financial ratios.
Othman, Zaleha	Implementation of GST fraud prevention strategies by the RMC, including technologies like GENTAX and ACL, and human-based methods such as field audits, mystery shopping, and behavioral pattern analysis.
Akinbowale, Oluwatoyin Esther	Comparison between resource allocation with and without the use of the MOIP model, including efficiency and effectiveness assessments of anti-fraud capacity in facing cyberfraud incidents.
Mahuwi, Leticia	Implementation of e-procurement systems to enhance transparency and accountability in pharmaceutical procurement and reduce corruption risks.
Losbichler, Heimo	Application of AI in controlling activities such as planning, budgeting, and monitoring, with a focus on human-machine collaboration to improve efficiency and accuracy.
Pavlidis, Georgios	AI enhances efficiency and accuracy in processing big data and detecting suspicious activity patterns. Key challenges include data protection, algorithmic bias risks, and the need for a more comprehensive regulatory framework. AI can reduce false positives in suspicious activity detection to below 50%, compared to 90% with traditional systems.
du Toit, Elda	Implementation of AI-based algorithms, such as machine learning and deep learning, for various forecasting purposes in financial accounting, including bankruptcy prediction, financial analysis, and fraud detection.
Kureljusic, Marko	Comparison of various AI-based predictive models, such as neural networks, support vector machines, and random forests, to assess their accuracy and reliability in specific applications.
Jullum, Martin	Use of supervised machine learning models based on XGBoost to predict the probability that a transaction is suspicious and should be reported as potential money laundering.

5. Conclussion

Based on the discussion regarding the objectives of problem solving, it is summarized as follows: 1) The evolution of fraud detection methods has moved from a manual approach to the application of advanced technologies such as Machine Learning (ML) and Artificial Intelligence (AI). Initially, fraud detection was carried out through document audits, interviews, and field investigations, which relied heavily on human skills. However, this method has limitations, especially in handling large data volumes and complex fraud patterns. With the emergence of technologies such as AI, organizations are now able to detect anomalous patterns more quickly and accurately, and mitigate risks more effectively.; 2) Theories such as the Fraud Triangle, Fraud Diamond, and Fraud Pentagon provide a conceptual framework for understanding the motivations of fraud perpetrators. Elements such as pressure, opportunity, rationalization, ability, arrogance, and competence are the main factors that influence fraudulent behavior. The integration of this theory with modern technology allows for a deeper understanding of fraud patterns, both in the context of financial statements and asset misuse.; 3) The role of Machine Learning and Explainable AI in financial fraud detection is not only limited to increasing accuracy but also includes aspects of trust and transparency. This technology enables organizations to detect fraud faster and more fairly, while providing explanations that auditors and other stakeholders can understand. With increasing adoption, ML and XAI are expected to become the standard in modern fraud detection systems.

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