The Role of Artificial Intelligence in Early Detection of Financial Statement Fraud in Digital Financial Institutions, AI-Fraud Behavior Integration Model

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The Role of Artificial Intelligence in Early Detection of Financial Statement Fraud in Digital Financial Institutions, AI-Fraud Behavior Integration Model

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ABSTRACT

The novelty of this study lies in its qualitative exploration of how Artificial Intelligence is conceptualized, adopted, and integrated into fraud detection systems in digital financial institutions, especially in developing countries. This study also makes Renaldo-Veronica AI-Fraud Behavior Integration Model. This study uses a qualitative exploratory approach, aiming to understand the perceptions, practices, and challenges associated with the use of Artificial Intelligence (AI) for early detection of financial statement fraud in digital financial institutions. The model uncovers how behavioral drivers of fraud (pressure, opportunity, rationalization) intersect with AI adoption drivers (perceived usefulness, ease of use, intention). The Renaldo-Veronica AFBI Model advances fraud theory by integrating psychological and technological constructs in a single analytical framework. Introduces digital rationalization as a modern form of fraud justification, expanding the Fraud Triangle for the AI era. Future research can use quantitative validation of the Renaldo-Veronica AFBI Model using structural equation modeling (SEM) or PLS to test relationships between fraud and AI adoption constructs.

Keywords: Artificial Intelligence; Early Detection; Financial Statement Fraud; Digital Financial Institutions; Renaldo-Veronica AI-Fraud Behavior Integration (AFBI) Model

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INTRODUCTION

The rapid digital transformation of financial institutions has led to an exponential increase in the volume and complexity of financial data. While digitization has improved operational efficiency and customer experience, it has also introduced new vulnerabilities, particularly in the area of financial statement fraud. Traditional audit mechanisms and manual oversight struggle to keep up with the dynamic nature of digital transactions and financial reporting in real-time systems (Dharmawati et al., 2023).

Artificial Intelligence (AI), with its ability to process large data sets, detect patterns, and make predictions, offers a powerful solution to address these challenges. By leveraging machine learning algorithms, natural language processing, and anomaly detection models, AI can support auditors (Suhardjo et al., 2022), regulators, and internal compliance officers in identifying irregularities and potential fraud before they cause significant damage. As digital financial institutions continue to grow in size and influence, there is an urgent need to explore how AI can be effectively used as a tool for early fraud detection (Renaldo et al., 2021).

Financial statement fraud has long been a critical concern in the financial sector, and its complexity has deepened in the era of digital financial institutions. Fraudulent activities such as revenue manipulation, asset misrepresentation, or undisclosed liabilities can severely undermine public trust and result in regulatory sanctions or financial collapse. Conventional detection approaches often rely on retrospective analysis, which may be too late to prevent losses (Faisal et al., 2024).

In the digital era, financial institutions operate with real-time data streams and complex transaction chains that are difficult to monitor manually. Despite the increasing adoption of digital systems, many organizations still lack a robust and proactive fraud detection framework. Meanwhile, AI-based solutions remain underutilized, especially in smaller or emerging digital financial institutions, due to a lack of expertise, resources, or trust in automated systems (Bastomi et al., 2023).

This phenomenon highlights a critical gap in technology implementation and policy: how AI can be operationalized not only as a reactive audit tool (Hadi et al., 2024), but as an intelligent, real-time early warning system in detecting financial statement fraud.

The novelty of this study lies in its qualitative exploration of how Artificial Intelligence is conceptualized, adopted, and integrated into fraud detection systems in digital financial institutions, especially in developing countries. While most existing research focuses on quantitative models or algorithmic performance, this study provides in-depth contextual insights from practitioners, auditors, IT experts, and compliance officers.

Key contributions include: Investigating real-world perceptions and challenges faced in implementing AI for early fraud detection; Mapping the integration process between AI systems and financial reporting frameworks in digital institutions; Identifying best practices and potential risks in using AI to flag suspicious reporting behavior (Putra et al., 2024); Developing a conceptual framework that bridges the capabilities of AI with practical, ethical, and regulatory considerations in the digital financial sector; Renaldo-Veronica AFBI Model.

This research provides a foundation for future empirical studies and offers guidance for financial institutions, auditors, and policymakers seeking to enhance fraud resilience through advanced technologies.

LITERATURE REVIEW

Financial Statement Fraud in the Digital Age

Financial statement fraud remains one of the most egregious forms of white-collar crime, often involving intentional misstatements or omissions in financial statements to deceive stakeholders (Rezaee, 2005). With the advent of digital financial institutions, the risk landscape has changed significantly. These institutions handle high-frequency transactions and large data sets, creating a complex environment that can obscure fraudulent activity from traditional audit mechanisms (Meidijati & Amin, 2022).

In the digital environment, fraud can be more difficult to detect due to automation, system loopholes, and the lack of real-time human oversight. This has created a growing demand for intelligent and adaptive systems, such as Artificial Intelligence (AI), to assist in proactive fraud detection (Gupta & Mehta, 2021).

The Fraud Triangle Theory: A Behavioral Perspective

The Fraud Triangle Theory, developed by Donald Cressey (1953), provides a behavioral framework for understanding the root causes of fraud. This theory states that fraud occurs when three elements are present (Utami et al., 2019):

- Pressure: Financial or personal pressure that motivates fraudulent behavior.

- Opportunity: Weaknesses in internal controls that allow fraud to be committed.

- Rationalization: Internal justification for unethical actions.

In the context of digital financial institutions, AI directly addresses the "opportunity" element by enhancing oversight and anomaly detection. For example, machine learning models can monitor transactions in real time, flag suspicious entries, and detect patterns that deviate from standard behavior (Boutaba, 2018). AI reduces the opportunity for manipulation by automating the detection process and minimizing reliance on manual audits, which can miss subtle indicators of fraud (Renaldo et al., 2022).

In addition, AI systems can support fraud detection even when the fraud is well-concealed through complex financial instruments or layered transactions, conditions that are common in digital environments.

Technology Acceptance Model (TAM): Adoption of AI Tools

While AI offers significant potential in fraud detection, its effectiveness depends on human acceptance and institutional readiness. The Technology Acceptance Model (TAM) by Davis (1989) is a widely used theory to explain user acceptance of technology. According to TAM, two primary factors influence adoption:

- Perceived Usefulness (PU): The extent to which a person believes a technology will improve their job performance.

- Perceived Ease of Use (PEOU): The extent to which a person believes a technology will be free of effort.

Applying TAM to AI in fraud detection, auditors and financial analysts are more likely to adopt AI tools if they perceive them to be accurate, interpretable, and easy to integrate into existing workflows. However, barriers such as a lack of technical understanding, fear of job displacement, or data privacy concerns can hinder adoption (Żywiołek et al., 2022).

Furthermore, in digital financial institutions, many of which are agile but under-regulated, organizational culture plays a key role. Without proper management support and training, adoption of AI-based fraud detection tools can face resistance, regardless of the sophistication of the tool.

Integrating AI into Fraud Detection: A Dual Theory Perspective

Combining the Fraud Triangle Theory and TAM provides a comprehensive perspective to explore the role of AI in fraud detection. While the Fraud Triangle helps explain why individuals commit fraud and how AI reduces the opportunities to do so, TAM helps explore how organizations and individuals respond to the adoption of AI tools.

This study fills a gap in the literature by qualitatively investigating:

- How AI-based fraud detection tools are perceived and adopted in digital financial institutions.
- How these tools impact fraud risk, specifically the opportunity dimension.
- What organizational, cultural, and technological factors facilitate or hinder the adoption of AI in financial fraud monitoring (Junaedi et al., 2024).

METHODOLOGY

Research Design

This study uses a qualitative exploratory approach, aiming to understand the perceptions, practices, and challenges associated with the use of Artificial Intelligence (AI) for early detection of financial statement fraud in digital financial institutions (Sekaran & Bougie, 2016). Qualitative research is appropriate due to the emerging nature of AI technology, the context of fraudulent behavior, and the complex decision-making process in adopting new technologies (Creswell & Creswell, 2023).

This design allows for the integration of two theoretical frameworks, the Fraud Triangle Theory and the Technology Acceptance Model (TAM), to explore not only fraud mechanisms but also the drivers and barriers to AI adoption.

Research Methodology: A Novel Integrated Framework

The novelty of this methodology lies in the integration of two traditionally separate domains:

- Behavioral Fraud Analysis (Fraud Triangle Theory) and

- Technology Adoption Behavior (TAM).

Integrated Conceptual Framework

Table 1. Integrated Conceptual Framework

Dimension	Source Theory	Focus in This Study
Pressure	Fraud Triangle	External/internal pressures faced by managers to commit fraud
Opportunity	Fraud Triangle	How AI systems reduce opportunities to commit or hide fraud
Rationalization	Fraud Triangle	Justifications for unethical decisions in digital environments
Perceived Usefulness (PU)	TAM	How practitioners view AI as helpful in detecting fraud
Perceived Ease of Use (PEOU)	TAM	How intuitive and implementable AI systems are
Behavioral Intention	TAM	Whether fraud examiners and IT teams intend to adopt AI

This hybrid lens allows the study to simultaneously explore fraud motivators and technology rejection or acceptance in real-world situations.

Data Collection

Method: Semi-structured in-depth interviews. Participants: Internal auditors of digital financial institutions; Compliance officers; IT professionals or AI developers working in fraud detection; Financial managers or CFOs. Sample Size: 12–15 participants, using purposeful sampling and snowballing to identify experts. Location: Interviews conducted via video call, recorded with consent.

Table 2. Sample Questions Mapped to Theory

Question Example	Related Theory
"What internal or external pressures make financial misreporting more likely in digital systems?"	Fraud Triangle - Pressure

Question Example	Related Theory
"How does your institution use AI to monitor and detect suspicious activities?"	Fraud Triangle - Opportunity
"What are your biggest concerns or doubts about AI's reliability in fraud detection?"	TAM - Perceived Usefulness
"How easy or difficult was it to integrate AI into your audit/reporting systems?"	TAM - Perceived Ease of Use

Data Analysis

This study will apply Thematic Analysis (Braun & Clarke, 2006) to identify and interpret patterns in participant responses. Steps: Transcribe interviews verbatim; Conduct open coding to identify emerging themes; Use deductive coding guided by the Fraud Triangle and TAM constructs; Conduct cross-case analysis to compare responses across agencies and roles; Develop a model that illustrates the interaction between fraud motivations and AI adoption behaviors

Validity and Reliability

To enhance trustworthiness, the study will adopt: (1) Triangulation: Cross-check themes from different participant roles (auditor, IT, compliance); (2) Member Check: Share interpretations with participants to obtain feedback. (3) Audit Trail: Document decision-making during analysis. (4) Peer Debriefing: Consult with academic peers to challenge assumptions and interpretations

Ethical Considerations

Informed consent will be obtained from all participants. Identities will be anonymized in transcripts and reports. Research ethics approval will be obtained from relevant institutional review boards

Novelty Methodology

This study contributes methodologically by:

- Creating a dual-theory qualitative framework that combines understanding of fraud behavior with technology adoption behavior
- Introducing the AI-Fraud Readiness Matrix, a qualitative model that maps how an institution's fraud risk profile interacts with their stage of AI adoption
- Enabling contextual diagnosis of gaps, why some institutions fail to prevent fraud despite the availability of AI

RESULT AND DISCUSSION

Result

Fraud Triangle Themes

a. Pressure to Commit Fraud

Participants noted that tight growth targets, investor expectations, and liquidity demands put significant pressure on management, especially in early-stage digital financial institutions. “When monthly performance targets are not met, there is pressure to slightly change the numbers, just to maintain trust with stakeholders.” (P7, Finance Manager). This confirms the “pressure” element of the Fraud Triangle Theory and highlights the need for AI systems to be sensitive to red flags related to rapid changes in revenue or inconsistencies in growth metrics.

b. Opportunities Exploited Through System Gaps

Several participants noted that fraud often occurs in systems that lack strong digital oversight. Manual overrides, access control loopholes, and unmonitored financial APIs are common weak points. “Our legacy systems did not flag high-volume transactions processed outside of business hours. That’s where fraud creeps in.” (P4, Internal Auditor). This supports the “opportunity” element and reinforces AI’s role as a risk mitigation tool. Participants who used AI-based anomaly detection reported a significant reduction in undetected irregularities.

c. Digital Rationalization and Justification

Participants expressed concern that some employees rationalize unethical behavior by claiming that “everyone adjusts the books a little bit” or that “the algorithm will fix it.” “In fintech, there’s a belief that automation fixes everything. That mindset can lead people to justify bad behavior, assuming the system will catch it or fix it." (P11, Compliance Officer). This extends the "rationalization" aspect of the Fraud Triangle to the digital context, where the technology itself becomes a morally flawed crutch.

TAM Theme: Perceptions of AI Tools

a. Perceived Usefulness (PU)

A majority of respondents agreed that AI improves their ability to detect fraud patterns that humans can't see, such as cross-period anomalies or duplicate transactions. "Our AI flags groups of transactions that appear normal individually but are suspicious in context. That's something a human auditor can easily miss." (P2, AI Engineer). AI is seen as very useful, especially for early detection. However, some caution is needed about false positives and over-reliance without expert oversight.

b. Perceived Ease of Use (PEOU)

Ease of use varies. While the front-end dashboard is appreciated, back-end configuration and model customization are seen as barriers, especially by smaller institutions without strong IT teams. "We have to hire consultants just to interpret the AI output. It's great, but it's not plug-and-play." (P13, Risk Officer). This finding suggests that technical complexity can undermine usability, affecting adoption even when usability is high.

c. Behavioral Intention to Adopt AI

Adoption intention is strong when management demonstrates commitment to innovation. Resistance primarily comes from traditional financial officers or auditors who are skeptical of automation. "Some senior staff still trust spreadsheets more than systems. However, younger teams are pushing for more AI integration." (P9, Compliance Supervisor). This reflects the generational and cultural gap in AI adoption readiness.

Cross-Theoretical Insights

The integration of the Fraud Triangle and TAM frameworks yields several key insights.

Table 3. Cross-Theoretical Insights

Insight	Explanation
AI Reduces Opportunity but Doesn't Remove Rationalization	AI effectively blocks some fraud routes but cannot change ethical mindsets.
High Perceived Usefulness Drives Adoption Despite Complexity	Institutions continue adopting AI even with moderate ease-of-use issues, as long as perceived benefits are high.
AI Implementation Alone Is Not Sufficient	Without strong internal ethics and training, AI becomes underutilized or misinterpreted.

Discussion

The findings suggest that AI has significant potential to reduce fraud risk, particularly by minimizing opportunities. However, ethical pressures and rationalizations are deeply cultural and cannot be eliminated through technology alone.

A dual-theory approach (Fraud Triangle + TAM) provides a holistic view:

- The Fraud Triangle explains why fraud occurs.

- TAM explains how and when organizations are likely to adopt prevention technologies.

Most importantly, the study reveals that AI must be embedded in a broader culture of accountability (Renaldo, 2024), transparency, and continuing education to be effective. Barriers to adoption, such as skills gaps and fear of system complexity, can be addressed through targeted capacity building and co-development with end users.

Novelty Discussion

This study presents several theoretical, methodological, and practical novelties that contribute meaningfully to the literature on fraud detection, technology adoption (Sudarno, Priyono, et al., 2022), and digital financial governance.

Theoretical Novelty: Dual-Theory Integration (Fraud Triangle + TAM)

Most existing studies on financial fraud rely solely on either:

- Behavioral theories like the Fraud Triangle to explain fraud motivation, or

- Technology adoption theories like TAM to assess willingness to use new tools.

This study breaks new ground by integrating both theories simultaneously, creating a unified lens to understand:

- Why fraud occurs (Fraud Triangle: pressure, opportunity, rationalization), and
- How and when AI is adopted to prevent it (TAM: perceived usefulness, ease of use, behavioral intention).

Novel Contribution

This is one of the first studies to synthesize fraud motivation with technology adoption behavior in the context of AI-based financial fraud detection in digital financial institutions.

Methodological Novelty: Contextual AI-Fraud Readiness Model

A key output of the research is the formulation of an AI-Fraud Readiness Matrix, which maps institutions based on:

- Their fraud risk profile (e.g., exposure to opportunity, pressure)
- Their AI adoption stage (resistance, exploration, partial integration, full integration)

This model enables:

- Tailored fraud prevention strategies,
- Identification of mismatch cases (e.g., high fraud exposure but low AI use),
- Cross-institutional benchmarking.

Novel Tool: A qualitative diagnostic matrix that can be used by regulators, consultants, and institutions to evaluate organizational readiness for AI-based fraud prevention.

Empirical Novelty: Real-World Perspectives in a Digital Finance Setting

While AI applications in traditional banks have been studied in quantitative models, there is limited qualitative exploration of how AI is perceived, used, or resisted in digitally native financial institutions such as:

- Peer-to-peer lending platforms
- Digital payment startups
- Online financing aggregators

This study captures the lived experiences of auditors, AI engineers, risk officers, and compliance professionals in these settings, revealing:

- Real-world constraints (e.g., API loopholes, false positives, culture gaps)
- Human-AI collaboration issues
- Ethical blind spots in digital-first organizations

Contextual Novelty: One of the first qualitative studies exploring AI fraud detection within emerging digital financial institutions in developing economies, including Southeast Asia.

Conceptual Novelty: Digital Rationalization as a New Form of Justification

A unique finding from this research is the emergence of "digital rationalization", a behavioral justification where fraud is minimized or overlooked because of overconfidence in AI systems.

Example mindset: “If something’s wrong, the system will catch it anyway, so a little adjustment isn’t harmful.”

This adds a modern layer to Cressey’s “rationalization”, tailored for the age of automation and algorithmic oversight.

Behavioral Novelty: Introduction of “digital rationalization” as an AI-era fraud justification mechanism, expanding classical fraud theory.

Summary of Novelty

Table 4. Novelty Summary

Dimension	Novel Contribution
Theoretical	Integration of Fraud Triangle and TAM into one conceptual model
Methodological	Creation of a qualitative AI-Fraud Readiness Matrix
Empirical	First-hand insights from AI practitioners in digital financial firms
Conceptual	Identification of “digital rationalization” as a new fraud mindset
Practical	Strategic recommendations for bridging ethics, policy, and AI

Renaldo-Veronica AI-Fraud Behavior Integration Model (Renaldo-Veronica AFBI Model)

The Renaldo-Veronica AFBI Model is a conceptual framework that combines fraud behavior theory (Fraud Triangle) with technology adoption theory (Technology Acceptance Model – TAM) to explain how digital financial institutions perceive, adopt, and leverage Artificial Intelligence (AI) for early fraud detection. The model emphasizes the interaction between fraud motivation factors (pressure, opportunity, rationalization) and technology acceptance factors (perceived usefulness, perceived ease of use, and behavioral intention) to assess the risk environment (Sudarno, Renaldo, et al., 2022) and adoption behavior in the digital financial ecosystem (Suhardjo et al., 2023).

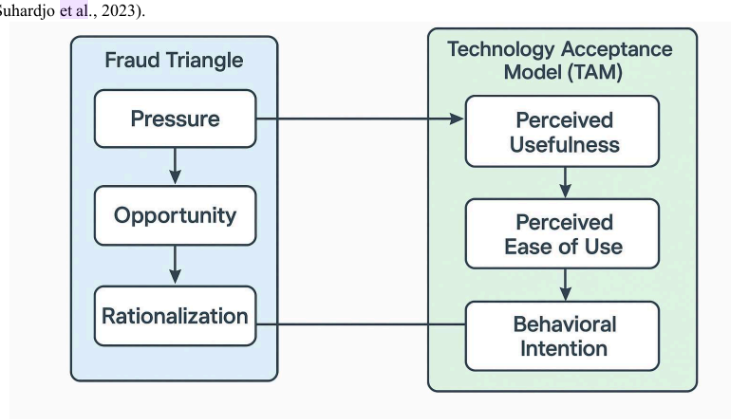

Figure 1. Renaldo-Veronica AI-Fraud Behavior Integration Model (RV-AFBI Model)

Table 5. Domain, Cinstruct, and Expalantion of RV-AFBI Model

Domain	Constructs	Description
Fraud Triangle (Behavioral Risk)	Pressure	Internal or external financial pressures that may motivate fraud
	Opportunity	Systemic gaps or weaknesses AI aims to reduce
	Rationalization	Justifications for unethical behavior, including digital rationalization
TAM (Technology Adoption)	Perceived Usefulness	Whether users believe AI improves fraud detection
	Perceived Ease of Use	User-friendliness of AI systems in real-time environments
	Behavioral Intention	The willingness of institutions and staff to adopt AI tools

Model Interaction Logic

AI adoption reduces “opportunity” and can counter “rationalization,” but does not eliminate “pressure.” Conversely, if AI is perceived as complex or useless, behavioral intentions to adopt are weakened, increasing an institution’s exposure to fraud risk.

The Renaldo-Veronica AFBI Model offers a 360° lens, examining:

- Why fraud occurs,

- Whether AI can prevent it, and

- Whether institutions are ready to adopt it.

Theoretical Contributions / Novelties

The Renaldo-Veronica AFBI Model is novel in three ways:

- Theory Fusion: Combines two distinct theories (Fraud Triangle + TAM) into a unified interdisciplinary model.
- Behavioral-Technology Integration: Provides a dual diagnosis, assessing fraud risk profiles and AI adoption readiness.
- The Digital Rationalization Concept: Introduces a new behavioral construct where overreliance on AI drives ethical complacency.

CONCLUSION

Conclusion

This study introduces the Renaldo-Veronica AI-Fraud Behavior Integration (AFBI) Model, a novel framework that combines the Fraud Triangle Theory and the Technology Acceptance Model (TAM) to understand how digital financial institutions adopt Artificial Intelligence (AI) to prevent financial statement fraud. The model uncovers how behavioral drivers of fraud (pressure, opportunity, rationalization) intersect with AI adoption drivers (perceived usefulness, ease of use, intention).

The study also reveals the emergence of a new behavioral construct, digital rationalization, where excessive trust in AI tools weakens ethical vigilance. Qualitative data from practitioners validate that AI is both a preventive mechanism and a potential ethical blind spot when poorly understood or misused.

Implications

Theoretical Implications. The Renaldo-Veronica AFBI Model advances fraud theory by integrating psychological and technological constructs in a single analytical framework. Introduces digital rationalization as a modern form of fraud justification, expanding the Fraud Triangle for the AI era. Practical Implications. Enables regulators, auditors, and fintech leaders to diagnose both fraud exposure and AI adoption maturity. Serves as a decision-making tool for targeted fraud prevention strategies in digital-native financial institutions. Policy Implications. Suggests the need for AI governance protocols in financial reporting and internal audit systems. Highlights the urgency to embed AI literacy and ethical training into compliance programs.

Limitations

The study relies on a qualitative methodology, which may limit generalizability to all financial institutions or regions. The sample size and context (emerging digital finance in Southeast Asia) may not fully reflect broader global dynamics. The analysis does not include quantitative validation of the Renaldo-Veronica AFBI model metrics (e.g., scoring of fraud risk vs. TAM variables).

Recommendations

For Practitioners: Regularly update AI models to match evolving fraud tactics. Combine AI tools with human judgment and ethics training to prevent overreliance on automation. For Institutions: Conduct AI-Fraud Readiness Assessments using the AFBI framework. Encourage interdisciplinary collaboration between compliance officers and AI engineers. For Policymakers: Develop national guidelines for AI use in financial fraud monitoring. Promote sandbox environments for digital finance institutions to test and co-develop fraud detection technologies.

Future Research Directions

Future research can use quantitative validation of the Renaldo-Veronica AFBI Model using structural equation modeling (SEM) or PLS to test relationships between fraud and AI adoption constructs. Expansion to other high-risk sectors like crypto exchanges, insurance tech, or government e-procurement systems. Investigate the ethical implications of AI-based fraud detection, particularly regarding fairness, bias, and algorithmic transparency. Explore cross-cultural differences in how digital rationalization manifests in AI-dominant vs. human-dominant compliance cultures.

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