STRATEGIES FOR IMPLEMENTING MACHINE LEARNING FRAUD DETECTION IN THE U.S. FINANCIAL INDUSTRY

by

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Abstract

The purpose of the abstract is to provide a concise and accurate synopsis of key elements of your capstone project. Set the abstract as a single block-style paragraph with no initial indent. Address the following topics (400 words maximum). **Research topic summary (1-5 sentences),** a concise summary of your capstone research topic. Explain the rationale for your study and the need for the study the capstone addresses. Indicate your research questions, matching the wording used in your capstone sections. **Research Methodology (1-2 sentences).** Summarize the research methodology used in the study. **Population and sample (1-2 sentences).** Describe the population and sample, including high-level demographic information regarding your participant pool. If secondary data were used, describe the data set. **Data analysis (1-2 sentences)** provides a concise summary of your data analysis. **Findings (1-3 sentences)** Provide a concise summary of your research findings and conclusion(s). Describe the practical implications of your project and the deliverable you created.

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Acknowledgments

This acknowledgments page is optional. The acknowledgments differ from the dedication in that they recognize individuals who have supported your scholarly efforts related to the advanced doctoral manuscript or who have held a role in your academic career as it relates to the research of the advanced doctoral manuscript. This might mean a mentor and committee members, advisor, online or colloquia faculty, and other support people from Capella or other organizations. If you received financial support from fellowships, grants, or other organizational support, note it in this section. The acknowledgments are also appropriate for thanking statisticians, transcriptions, those who have provided permission to use an instrument, and the like.

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SECTION 1. PROJECT DESCRIPTION

Overview of the Project

In an age of technological progress, we're as easy as ever to do financial transactions, and so is the size of financial fraud in the United States. Whether it's ATM fraud, credit card fraud, identity theft schemes, wire transfer fraud, or account takeovers, it's common knowledge that fraud schemes are getting increasingly sophisticated, and financial services institutions are meeting the challenge. In addition, American consumers reported the lowest amount of credit card fraud in the third quarter of 2024, at just about $58 million in dollars (Statista, 2025). The number highlights the imperative need for smarter and more responsive fraud detection systems that can detect and prevent illegal activities in real time.

Current fraud detection methods rely on manual decision making and pre-defined rules, and may not be able to respond to new and developing challenges in fraud posing in the financial services. With the advent of new technologies such as Artificial Intelligence (AI) and machine learning algorithms, there are opportunities to develop more sophisticated and adaptive algorithmic fraud detection strategies. Not all financial institutions (CIO, 2024) are making full use of AI technologies to detect fraud. In fact, in the face of increasingly sophisticated fraud schemes, organizations will need to do more than simply rely on technology and introduce more of a management-driven approach to innovation. Despite the need for better fraud detection, many organisations struggle with technology issues, organizational silos, and management risk and know how gaps that prevent them from implementing better fraud detection. The challenges underline a lack of practice by general managers, who don't have a clear plan on how to integrate AI strategic and operational frameworks within institutions.

A major challenge in the financial industry, including the U.S., in an era of growing digital financial transactions by financial institutions like banks or financial technology (fintech) firms (Brogi & Lagasio, 2024), is fraud. While these payment systems are convenient to use, they don't have enough time to manually intervene against fraud (Vanini et al., 2023). But there is a huge expectation upon institutions to implement an effective fraud detection system that can identify anomalies, trigger an alarm on questionable transactions, and act automatically almost instantly (milliseconds). Business goals aligned with machine learning capacities reduce fraud in financial institutions by a huge margin, according to Abikoye et al (2024). The importance of managerial skills and preparedness in fully achieving the value of machine learning initiatives was highlighted by Bevilacqua et al. (2025). The organizational efforts have an important role to play in the long-term success regarding the activities of fraud detection and limit risk exposure. The machine learning algorithms would be used to detect fraudulent activities at financial institutions in the U.S. Anomaly detection in machine learning would enable financial institutions to implement an effective fraud prevention system, recognizing fraudulent activities (Dama et al., 2024). The underlying issue at hand is the lack of leadership approaches in the context of implementing machine learning in financial institutions for addressing fraud operations (Gupta et al., 2025). The issue here is that many financial institutions have a management that doesn't possess the advanced procedures and operations required to combat financial fraud using advanced technologies such as machine learning (Chenguel, 2020). However, once a technological solution has been identified, the challenge lies in the managerial process for the uptake of the solutions and getting them to become part of the organisational processes and decision-making systems. The project's potential impact is the ability of financial entities to gain recognisable benefits and the creation of a more secure financial system offering consumers protection from fraudulent transactions, through active fraud identification and prevention.

Financial institution managers may have a new piece of knowledge or information resulting from the significance of the proposed project that helps them pinpoint fraud earlier to minimize the financial losses. This adoption of machine learning technology is aided by effective leadership practices, enabling proactive detection of fraud events and reducing them to a minimum (Bevilacqua et al., 2025). So, machine learning can contribute to combating brand new frauds and improving the health of the organisation's finances. For this reason, the problem that will be addressed by the project will be sudden and disappointing deployment and administration of smart fraud detection systems by a business. Focusing on managerial aspects of integrating machine learning technology, the data from this project may provide a way forward for financial institutions interested in updating fraud prevention measures to guarantee long-term security and confidence in the digital world.

Problem Statement and Purpose

The overall business issue is that fraud incidents lead to loss in both profitability and customer satisfaction in the U.S. financial industry (Shi et al., 2023). Traditional fraud detection systems can't detect fraud and affect the organization's performance. The Federal Trade Commission (FTC) reports that Americans lost $90 to $501 million from fraud in the United States in 2025. The increasing losses reveal that fraud is not only a continual problem, but it's also becoming more sophisticated, and it is a threat to consumer trust and organizational stability.

The specific business problem is that some technology managers in the U.S. financial industry do not have the effective resources and technology strategies to implement machine learning-driven fraud protection (Bello & Olufemi, 2024). While financial institutions have access to advanced technologies, a lot of times leadership flaws, failure to receive strategic support, or other reasons make it difficult to implement a fraud detection system, impacting organizational performance (Afjal et al., 2023). Around 2.6 million consumers have reported fraud as a result of misaligned leadership by consumers, saying they needed more leadership in integrating advanced technology (FTC, 2025). The effects of this particular business challenge are multifaceted, leading to increased vulnerability to fraud, loss of customer confidence, and significant financial losses (Lamey et al., 2024). Keeping up with the gap between technology and strategic leadership issues is one of the most important problems in the context of financial industry management.

Alignment with Program

A Doctor of Business Administration (DBA) project on leveraging machine learning technology with strategic leadership in financial institutions is a perfect match because the project is aimed at solving a high-impact business problem, and it is focused on the financial industry. Financial fraud continues to be a major problem in the financial services industry in terms of both expenses and complexity (Hilal et al., 2021). So the project is about the operators and operator failures at the strategic level that prevent the machine learning and therefore cause financial losses, regulatory risk, and/or reputational damage. The Journal highlighted the significance of the role that leadership can play in enhancing financial operations by incorporating machine learning technology. Therefore, this proposed project is a good match for the Doctor of Business Administration (DBA) emphasis in interdisciplinary leadership and strategic management. Exploring the financial manager's capability to make the decisions to implement advanced technology provides valuable insights into improving the operations financially in an organization and reducing the risk of fraud (Dama et al., 2024). The work of the project in the

DBA is based on the problem-solving process, doing research related to the business applications.

Purpose Statement

The proposed generic qualitative inquiry aims to elicit the views of technology managers in the financial industry who have thus far adopted resources and technology strategies to combat machine learning-driven fraud detection and protection in the U.S. financial sector. The proposed project will delve into the concepts of Leadership strategy in the adoption of machine learning technology for fraud detection (Dama et al., 2024). The target population will be financial managers in U.S. financial service institutions in the U.S.

Gap in Practice

The difference is that some U.S. financial industry managers still haven't embraced effective machine learning-driven strategies to minimize fraud detection failures, which leads to continued financial losses and customer dissatisfaction (Chen et al., 2025). According to the statistics from the Federal Bureau of Investigation, BEC attacks increased in 2022 from 17,348 in 2021 to 21,832 attacks, resulting in losses of approximately $2.7 billion (Lalchand et al., 2024). Fraud detection using standard systems is not keeping up with the changing methods of fraudsters and tends to be fraudulent. The practice gap is not an issue associated with the unavailability of fraud detection technologies but due to a lack of a leadership strategic approach to implement the machine learning technology (Hariyani et al., 2024). The disparity means the specific problem that financial institutions face is that of being vulnerable to fraud tactics that cannot be detected by existing systems, leading to monetary loss. The ideal state is when managers of financial institutions are actively leveraging the predictive power of machine learning, real-time identification of fraudulent activities, and high accuracy in detecting and preventing fraud (Pattnaik et al., 2024). The findings from the project may be helpful to practitioners who are looking to narrow the gap and understand that the use of more advanced analytical techniques in the fight against fraud can be useful. Besides, the outcome should be considered as part of a business's general strategic plan.

Theoretical Framework

The work investigates the opinions of U.S. financial technology (FinTech) Managers using resource and technology measures of those who have adopted ML technology (machine learning) in fraud detection and protection. The qualitative research study was practically oriented, where the technology acceptance model (TAM) was originally developed by Davis (1989). The TAM has been adopted as a popular explanatory model of the adoption of emerging technologies. It continues to be highly relevant in the study of strategic, behavioral, and managerial issues in the implementation of machine learning in financial institutions (Davis & Granić, 2024). The theoretical basis offers valuable insights into the intricate decision-making processes leading to effective technology integration in high-stakes financial contexts.

Perceived usefulness at a manager level reflects what managers think the machine learning systems have the potential to achieve in terms of better fraud detection results and adding value to the organisation. The ease of use signifies the degree to which managers believe that the implementation of machine learning systems will not be complex and demanding excessive effort for financial organizations (Joseph & Eaw, 2023). Perceived ease of use may shape managers' attitudes toward ML adoption, especially if others in an organization are reluctant to adopt ML because of their perceived difficulties in implementing it. The sequential technology acceptance model constructs of attitude towards use, intention to use behavior, and actual system use offer a systematic framework to understand how managers form perspectives, develop intention, and finally adopt machine learning technology.

The TAM is one of the most-used models for explaining the adoption of new technologies, especially within an organizational context, in general management literature. According to the TAM, two main factors that affect the acceptance of a technology are its ease of use (EU) and usefulness (U). The TAM is an appropriate model for the project because it allows for an explanation of how financial managers at U.S. financial institutions might or might not implement machine-learning-based fraud-detection systems, especially given the seemingly clear advantages of these technologies.

An important secondary model is the unified theory of acceptance and use of technology (UTAUT), which is an extension of TAM, adding constructs of performance expectancy, effort expectancy, social influence, and facilitating conditions. (Borhani et al., 2021) By adopting this framework, both scholars and practitioners it helps to have a more nuanced perspective of technology adoption in organizations. For the project, the other variables will be used to understand the factors outside of the manager's influence that could affect their decision to implement machine-learning-based fraud-detection systems, including the organizational culture, leadership support, and training.

The focus of the specific problem explored is to understand the managerial perspectives in the context of the technology acceptance model. The research questions are laid out to explore perceived usefulness and ease of use, which shape executives' perceptions of machine learning technology adoption, what drivers would trigger behavioral intentions, and what impediments would exist for implementing the system. The proposed project questions can be directly mapped to the TAM for constructs (perceived usefulness and perceived ease of use), which can be explored while focusing on the decision-making views of managers in the adoption of a technology. The conceptual framework to understand the attitude of financial institutions' managers towards the machine learning technology that is used to detect fraud is one of the conceptual frameworks employed in the current project, which is called the TAM by Fred Davis (Pajany, 2021). The basic constructs of the TAM model directly impact the attitude formation process (Borhani et al., 2021). The strategic approach to the use of technology that the TAM model of perspective towards the new technology directly corresponds to the result of the performance of the organization. Therefore, the framework is quite applicable in forming the thinking on management decision- making, mainly in financial services.

The TAM is based on five constructs; perceived usefulness and perceived ease of use are the two most important constructs to predict the acceptance of technology. Perceived usefulness indicates the user's perception of the system's usefulness for improving job performance. The perceived usefulness is associated with how managers and senior management form thoughts on how increased accuracy in fraud detection, efficiency in operations, and improvement in competitive edge can be achieved. The constructs impact users' attitudes towards the technology, the intention to use the technology, and the actual use of the system. Perceived ease of use shows the financial managers' perceptions of the availability and ease of use of the machine learning system. These constructs have an impact on the attitude towards technology, the attitude towards intent to use technology, and system use of the user of technology.

The study examines the relationship between managerial attitudes and perceptions of strategic readiness to adopt machine learning technology and the constructs of TAM and its potential for successful adoption of the technology, and support from organisations. The framework allows for the proposed project to consider the the manager's's perspective. This framework directly contributes to the concept of the project to analyze the perception of managers concerning ML in financial institutions. This means that the fusing of the worlds of finance, technology, and management also represents a theoretical lens and that the DBA-level research that focuses on understanding the processes of technology adoption decision-making could be relevant to consider.

Though the main model that is utilized in the project is the original TAM, the extension of the model provides TAM that considers additional variables like subjective norms and expounds the perceived usefulness via the social influence and cognitive instrumental action, improving the comprehension of organizational technology adoption standpoints (Granić, 2024). In the same way, the unified theory of acceptance and use of technology (UTAUT) combines the constructs, such as performance expectancy, effort expectancy, social influence, and facilitating conditions. The model likely has a wider scope in terms of the range of factors impacting organizational and environmental perspectives on adoption (Zin et al., 2024). While TAM2 and UTAUT will not be used as the main framework, the extended constructs of the models will be used for the development of interview questions and the thematic coding procedures in data analysis.

The significance of the TAM for the study of the slow technology adoption of machine learning in the financial sector is that it is a model that enables the prediction of important factors that influence managers' adoption perspectives and strategic alignment. The project will analyse TAM to identify common reasons for some financial institutions to be more amenable to machine learning-based fraud detection systems when compared to others. The results can be translated into how to implement machine learning in more effective ways in accordance with the management perspectives and organizational contexts.

In other business areas, such as social or information and communications technology

(ICT), TAM and extended constructs have been used to determine technology adoption views on fraud prevention effectiveness. The framework aligns with the proposed project's goal of examining financial managers' views on the value and accessibility of machine learning in fraud prevention and operational efficiency. TAM is highly relevant to the investigation as the model focuses on the user perspective on acceptance, a key factor in the challenges faced by strategic investments in machine learning in financial institutions (Rawindaran et al., 2021). TAM does not address technical implementation models but rather focuses on the cognitive and behavioral parts of perspectives on adoption, in parallel with the managerial focus of the project.

The TAM gives a structure to follow when doing a literature review and is a systematic method of organizing and comparing studies of TAM and the views on technology adoption in financial sectors. Thathsarani and Jianguo (2022) conducted a qualitative study with 487 Small and Medium Enterprises (SMEs) in Sri Lanka, and they found that from SMEs' perspective on digital adoption with the TAM lens, digital adoption is around financial context and significantly impacts the performance of SMEs. The scholars also showed that financial organisations are under regulatory pressure, have a strong drive to move fast toward digital transformation, and their customer security requirements are ever-growing, all of which affect the evaluation of potential technologies to be adopted by managers. However, Masumbuko and Phiri (2024) showed TAM application and called for the adoption of the framework for improving the strategic management, technological capability and user acceptance perspectives.

The project introduces a new perspective of the TAM model, applicable to the fraud detection systems in the financial industry, where the adoption of AI and machine learning is both important and complicated. The project makes a research contribution by providing insights on executive perspectives and readiness for integration of machine learning around a specific context.

The shift from the technology acceptance at the user level to the managerial perspective in the analysis of TAM application will fill the technological capability and adoption of decision-making frameworks. The proposed project aims to provide actionable strategies with regards to effective fraud reduction – via the lifting of managerial perspective to match technology potential. The TAM will be used to develop semi-structured interview questions that would elicit rich, qualitative responses from the financial executives on issues pertaining to the perspectives on Machine learning adoption (Ebot, 2024). Questions will focus on attitudes towards usefulness of machine learning for fraud prevention, expectations of ease/difficulty of integration, and other contextual factors such as regulatory pressures, organizational culture and leadership buy-in that may impact views on integration. Depending on the model used (such as TAM2 or UTAUT), the constructs in this project are based in the original TAM model in order to keep the theory consistent, but should also be considered for addition into the analysis.

In the Data Analysis phase, financial institution managers' data will be coded using qualitative and thematic approaches. Although TAM constructs will be not explicitly specified in coding frameworks, these might be conceptual models from which to better understand emergent themes involving adoption perspectives. The project will analyse the commonalities in management attitudes in the process of the adoption and the strategic integration of machine learning systems for fraud detection (Masumbuko & Phiri, 2024). The TAM in the usage instrument was chosen because it represents technology adoption perspectives as it relates to technology usage within an organizational context, especially in the financial organization where managers make strategic decisions regarding technology. Regulatory oversight, upbeat digital change, and rising customer security requirements are all exerting pressure on financial companies' capacity to evaluate potential for new technology adoption by their managers.

The project data can have a number of contributions to the literature. The data will reflect financial managers' attitudes towards strategies for implementing machine learning in fraud detection and risk management, first. Second, the study will take a look at the organizational factors that influence machine learning adoption perspectives such as risk tolerance, regulatory compliance, technological infrastructure and managerial readiness. Third, the alignment between constructs of TAM and the real-world challenges of implementing machine learning in financial fraud prevention settings will be explored (Gupta et al., 2025). Study data might be utilized to understand better how to promote more effective strategies for the adoption of machine learning by practitioners and policymakers. The project may help to bridge existing theory-practice gaps in financial management, working to better use and choose technology to enhance performance in organizations, with a focus on managerial perspectives of technology adoption.

Project Context

Innovations in payments and financial services have been picking up the ground running in the U.S. financial industry because of this rapid change in financial services transactions and the process of digitalization. As the world moves towards digitization, so too does financial fraud, with increasingly advanced and widespread practices. Today, credit card fraud, wire fraud, the threat of identity theft and account takeover, among other areas of fraud are growing in sophistication and are affecting consumers and institutions alike. But there are some adjustments that should be strategic in the financial field to combat the limitations of fraud detection systems, in particular implementing machine learning for real-time fraud detection that makes an intelligent use of data (Heß & Damásio, 2025). Losses reported by consumers was the basis for the need for the change. However, the amount of money lost by victims of fraud was, at best, $90 million, and, at worst, $501 million, according to the Federal Trade Commission (2025). The financial institutions that have yet to get rid of legacy rules-based systems that lack real-time adaptability continue to be vulnerable. There are technologies to identify fraud patterns extremely well but there's a lack of leadership strategies on how to get the best results from.

The essence issue is a lack of managerial and strategic aspects on the side of machine learning solutions. Even the financial institutions' technology pioneers who have access to better technologies with the support of AI are missing the capacity and leadership to integrate the technologies into the organizational mechanisms (Ejiga et al., 2024). A misalignment can cap the potential of machine learning tools and enable fraud incidents to continue to go unaddressed. According to Afjal et al., (2023) those institutions that are just not synchronized with the core business of fraud detection are at a much higher risk of loss of financial business. Not availability of technologies is the reason why the intelligent fraud detection technologies were not used; lack of leadership driven integration strategies is the reason commented Chenguel (2020). The current lack of practice indicates there is a lack of readiness to deal with innovation and consequently a loss of consumers' trust and increased threats to the business.

For the proposed project, one of the key requirements is strategic leadership and organizational preparedness to gain the business value of machine learning projects (Bevilacqua et al., 2025). Dama et al. (2024) proposed that technology managers must have a more-targeted understanding of leadership approaches to be able to integrate the machine learning-based technologies into the fight against fraud. As per McKinsey & Company (2022), many of the financial companies are facing challenges in introducing AI technologies to their businesses, due to the lack of a roadmap or planning by the general managers. While executive support and good cross-functional alignment are a prerequisite for the machine learning's potential to be realised, Pattnaik et al. (2024) have confirmed that machine learning contributes to anomaly detection. The institutions need to be taken through a strategic transformation process, led by a project and to close this implementation gap.

Nature of the Project

The proposed project for AI integration in financial institutions is viable, given the increasing adoption of AI in the finance industry and the availability of existing machine learning models for fraud detection. According to CIO (2024), despite their use of AI tools, financial entities have not been able to fully leverage AI's potential as enterprise-wide strategies have not included AI. Initial system setup based on institutional objectives plays a huge role in fraud reduction by configuring the machine learning system, according to Abikoye et al. (2024). Therefore, the work could inform similar organisations to the technology managers studied in the project about how to change their tendency of failure by gaining insights into their perspectives of how successfully the project implemented the machine learning driven system.

The financial services industry is a high-stakes fraud risk – especially the fintech subsectors following the accelerating growth in number and speed of digital transactions. Where fraud is occurring in real time payments, peer payments and banking via mobile apps, there is little room for any kind of intervention. The automated monitoring of such transactions based on this information with the use of machine learning techniques would be required, due to the speed of transactions that cannot be matched with manual systems, according to Vanini et al. (2023). Statista reported that there had been unmistakably $58 million in credit card frauds in the third quarter of 2024 (2025), highlighting that real-time digital platforms have turned into a popular spot among fraudsters. Modern banks are feeling the pressure from regulators and reputation and so are fintech businesses – to move forward with fraud detection. If strategic machine learning integration is not in place, there may be not only financial losses, there may be an additional loss of customer trust.

The vision of the proposed project is to address the present vulnerabilities, with special emphasis on strategies and technologies for leadership. On this basis, the study explores the project in the context of management and information systems and therefore discusses the effect of perceived usefulness and ease of use in the before-adoption phase of the use of such technologies by the decision makers particularly under the TAM. Davis and Granić (2024) described that TAM remains a valuable lens to look at executive actions in significant high-stakes technology decisions. Financial institutions are now facing new fraud issues as machine learning also poses the challenge technically, then it will need managerial willpower and strategic direction (Hilal et al., 2021). The project will therefore be nestled in the core business issue – increasing the resilience of the organisation by successful fraud mitigation, and leadership of digital innovation.

Scope

The designed project is unclear as it is limited to a narrow focus on exploring strategic leadership practices in the financial industry in the U.S. adopted by technology managers that have implemented machine learning based fraud detection systems. The investigation should be dovetailed with the issue of the lack of strategic direction to effectively implement machine learning technologies, and the rise of financial losses due to fraud. The project is not meant to assess all financial operations where the application of machine learning can be relevant, but rather focuses on the processes of managerial decision making that will affect the integration and effectiveness of machine learning fraud detection tools.

The proposed project is bounded by the qualitative viewpoint from a population or segment: technology managers from financial institutions (financial companies and banks in the United States). The research aims to delve deeper into a well-defined gap, specifically the need to align strategic leadership in order to use machine learning technologies to fight fraud. While as noted by Chenguel (2020), financial organisations have already got the tools, there are also leadership constraints that don't allow these tools to be integrated into its operations. The project vision will focus on understanding the actionable insights to be gained in order to further and support strategic improvements in managerial level machine learning adoption.

Significance of the Project

The potential interest of the project is the ever increasing rate of financial fraud that can be committed at the digital level, as well as inadequacy of human judgment and the lack of proper algorithms for financial fraud detection based on traditional rule-based methods. Traditional fraud methods are rapidly evolving and financial institutions are at increased risk because of the rate and sophistication of the various fraud types, such as digital payment fraud. Traditional methods are no longer adequate to face the frauds in real time, and financial institutions are felt the need to improve their fraud detection processes while maintaining the efficiency of transactions (Heß & Damásio, 2025). Parts of Real-time Payment include minimal time for manual interventions, thus automation is key, otherwise mentioned by Vanini et al. (2023).

The project can potentially be applicable to the real-world requirements of technology managers who do not have a direction on how to leverage ML in creating fraud detection frameworks. Research by Dama et al. (2024) claimed that although machine learning can more precisely identify anomaly and fraud behavior pattern detection, few organizations are effectively implementing this technique due to the lack of strategic leadership. Bevilacqua et al.

(2025) stated that the laying out the foundations of an organization and the capability of its management are crucial factors for obtaining any benefit from machine learning projects. Technology managers and executives will gain insights into how technology leadership models and decision-making processes can impact the effectiveness of implementing machine learning and what leadership models are needed to maximize its benefits.

The project could also have a considerable impact on the experience of customers in the U.S. financial services sector and regulatory compliance. Well, if fraud detection is shoddy, it works against the customers' confidence, stability of the operation, and reputation of the industry. Lamey et al. (2024), underscored that lack of efficacy in fraud prevention policy puts financial institutions at risk of ongoing financial losses and loss of consumer trust. The outcomes of this research will provide benefits for the several stakeholders. Findings from financial technology managers and executives can be leveraged to establish evidence-based strategies and plans for resource allocation that bolster machine learning-based fraud prevention systems. Compliance bodies can gain from wisdom that can aid in the implementation of machine learning in a way that is parallel to compliance standards, enhancing oversight and setting uniform standards across institutions. Overall, customers and investors will benefit from a more secure and trustworthy financial environment, free from fraud.

Beyond practical aspects the study aims to make a contribution to literature as it would fill a gap in understanding the factors affecting the adoption of machine learning for fraud detection in financial setting, including organizational, technological, and leadership factors. Even though previous studies have focused on the technical details of the machine learning algorithms, there are not many studies which show how and why the implementation of machine learning algorithms in actual financial operations is deciding on their success or failure (Lamey et al., 2024). This research will fill the gaps in the literature in relation to technology adoption frameworks focusing on the TAM and how well it can be implemented into practice, especially within the financial fraud prevention sector. The findings and insights can be used in future academic studies and in the best practices of technology-based projects to promote financial integrity.

Historical Background and Current Trends

To appreciate the evolution of fraud detection using machine learning in the U.S. financial sector and the potential impact of strategic leadership for technology integration, it is important to understand the historical context and the prevailing sentiment about tech adoption for fraud detection. However, as the financial sector modernizes and banking moves into the digital realm, there is a need to use more dynamic and data-oriented solutions to combat financial fraud (Hilal et al., 2021). Initially depending on rule-dependent systems and people checking books, monetary establishments slowly started to see the weaknesses of the standard fraud detection processes in opposition to a growing the majority of more superior cyber-crime.

With these advancements, machine learning has proven to be a game-changing technology that can identify fraud quickly with predictive modeling and pattern recognition. However, a key challenge is the strategic deployment of these systems, even with the technology advances that have been made (Ejiga et al., 2024). A recognition of the evolution and trends in the field can help grasp the reasons for the slow adoption of machine learning, despite the mounting financial losses and vulnerability of customers (Heß & Damásio, 2025). The section delves into the timing and trajectory of fraud detection, the advances of machine learning technologies, and the strategic challenges that are now impacting the implementation of these technologies across the financial sector.

The issue that the proposed project will tackle is that despite the capabilities of most machine learning algorithms for fraud detection it is not being effectively implemented in financial institutions. Ever-changing fraud techniques are becoming a major challenge in fraud detection in the U.S. financial services industry as Afjal et al. (2023) outlined. The current fraud detection measures are mostly rule-based detection methods or with human intervention, which are not sufficient for real time-fraud detection in a fast evolving digital economies. The problem statement defines the main issue not as a lack of advanced technology adoption, but rather as financial managers noting that they struggle to adopt machine learning systems because of low leadership, and lack of strategy to adopt those technologies. This is directly related to the concept of TAM that states that usefulness (whether the technology is valuable for fraud detection) and ease of use (how difficult it is perceived to be to adopt the technology) are important factors in the process of adoption. Financial managers might be reluctant to invest in machine learning because they think that it is hard to implement or they don't know how it can help them with their fraud detection.

Historical Background

The history of fraud detection in the U.S. financial industry has been influenced by the evolution of the financial service technologies from the past, the real-time financial services and the sophistication of the fraudulent actions (Hilal et al., 2021). Digital banking has helped improve access to financial services but also led to more sophisticated fraud schemes'shifting from paper-based to digital banking.The switch from paper banking to digital banking has helped facilitate financial access, but has also introduced new, more sophisticated fraud schemes. In the early 2000s, detecting fraud was based on rigid rule-based systems and manual process (West & Bhattacharya, 2016). At the same time, however, it's essential to realize that this type of system wasn't sufficient for long, because, as cybercriminals got better at exploiting customer data and technological loopholes, they soon outpaced the established approach. Since the arrival of real-time payment systems, the amount of time to detect and prevent fraudulent payments has drastically diminished, calling for more sophisticated and automated systems, according to Vanini et al. (2023).

Digital transformation of the financial sector (since 2010) has involved innovation as well as vulnerabilities. Mobile banking, online payments, and peer-to-peer money transfers have transformed how consumers interact with finances, but also provide opportunities for fraudsters to exploit financial systems (Rahman et al., 2024). Not only is there a rise in the amount of fraud, but fraud rings are also getting more sophisticated. According to Statista (2025), credit card fraud costing about $58 million occurred in the third quarter of 2024 alone, highlighting that credit card fraud is increasing despite credit card infrastructure improvements.

In the early 2010's, the idea of using machine learning became a worthwhile option, as researchers and tech companies started to use artificial intelligence to look for patterns and anomalies within large amounts of data. Pattnaik et al. (2024) also reported that the machine learning algorithms are able to process billions of transactions in real-time, promptly recognize suspicious patterns, and minimize the likelihood of undetected fraud. The algorithms continuously learn and update themselves in order to be effective against changing fraud threats as opposed to static rule-based systems (Hilal et al., 2021). Nevertheless, although many machine learning applications are technically ready for use in the Financial Sector (FS), the internal challenges of Financial Institutions have prevented them from using these tools (Heß & Damásio, 2025).

One of the biggest challenges in using machine learning for fraud detection is the absence of strategic direction and organizational support. Afjal et al. (2023) pointed out that while institutions have in place AI and machine learning, the disconnect with business models drastically diminishes the impact of AI. Additionally, literature is replete with findings on a lack of leadership certainty, poor collaboration between different functions and resistance to change, all of which indicate that technology is not the only answer to challenges related to fraud. Bevilacqua et al. (2025) highlighted that managerial preparedness and strategic leadership are key factors in harnessing the full potential of machine learning endeavors. First coined by Davis (1989), the TAM became popular for understanding technology adoption in business situations through its perceived usefulness and perceived ease of use framework.

The changes in fraud detection strategies have also been influenced by cultural and social factors. The unprecedented rise in the consumers' dependence on digital financial services, especially with the onset of the Covid-19 pandemic, has established a new sense of normalcy which focuses on financial security. The economic fallout from and caused by the pandemic has also spurred thieves to maliciously increase phishing, ID theft, and synthetic frauds. According to McKinsey & Company (2022), more than three-quarters of financial executives attributed the significance of investing in more advanced fraud detection technologies, yet they did not have a clear plan for strategic investments. The CIO (2024) stated that several banks had even tried out AI capabilities, but not more than 30% could operationalise because of organisational differences.

Clearly, the nature of fraud and the means available to defend against fraud has changed throughout history and with technology. There is a gap in terms of where we can deploy and use technology, which is the major issue. Chenguel (2020) and Hariyani et al. (2024) agreed that there is a need for leadership to adapt to facilitate innovation and create structures to integrate machine learning into their everyday tasks. The financial and reputational consequences of delivering ineffective fraud detection creates an emphasis on the importance of the change. If that's a high-risk economy in the digital age, strategic leadership and organizational alignment are not only a means to innovation but are mandatory to safeguard institutional integrity (Rahman et al., 2024). The topic is one that has evolved over the last 20 years to show that advanced fraud detection is not about tools it is about transformation, with a strategic vision, collaboration and operational excellence, which must be undertaken at the hands of our leaders.

Current Trends

The trend shadowing financial fraud detection in the U.S. financial industry, for instance, shows that there is increased interest in the use of AI for financial fraud detection due to the complexity of emerging financial fraud schemes (Bello & Olufemi, 2024). Financial institutions have fast-tracked their digital transformation initiatives since 2020, generating potential opportunities as well as challenges for finances institutions to manage fraud risk. As more consumers have made the shift toward real-time payments, mobile banking and contactless banking, this has increased the possibility of fraud, and advanced fraud detection is needed to reduce this risk. The developments highlight the limitations of traditional fraud detection methods and reinforce the demand for more time-sensitive and proactive solutions.

In recent years, machine learning has become a pivotal tool in the fight against fraud, but research and experience indicate that while there is a lot to be excited about, it is important to proceed with care. Pattnaik et al. (2024) highlight the technical edge that anomaly detection models have over rule based systems as it can detect anomalies in real time. That shows the definite technical capability of machine learning, but there is more than that when Afjal et al. (2023) prove that not all the financial organisations have been able to operationalise these tools;

in fact, less than half of the financial organisations did. They found that there is a lack of enactment that is there is a disconnect between the technological capacity and organizing alignment. There appears to be tension between stressing the correctness of the models on the one hand and boundaries to integration on the other, including lack of leadership and lack of inter-departmental coordination.

This is reinforced by the consulting companies and also by studies on governance. In this respect, McKinsey & Company (2022) states the imperative need for machine learning to be regarded as a strategic enterprise priority and not just a technical upgrade. Mudawar et al., (2018) and Ahmed et al., (2024); Bevilacqua et al., (2025) also mention that governance and managerial capability are determining factors- that incidents of fraud taking place in businesses with strong governance frameworks were reduced as much as 30% in the businesses. One importance factor raised by McKinsey is the "Executive Vision" and another one by Bevilacqua et al. is the "Organizational Readiness" at the managerial and operational level. This indicates a shift in "fraud prevention" from merely moving it to the data science space to a leadership and culture shift.

COVID-19 has been a stress test of old fraud detection methods which revealed weaknesses in the legacy methods. Zhu et al. (2021) observed the growing opportunities for fraud due to the adoption of digital transactions, and Hariyani et al. (2024) noted the effective approaches of new fraud methods like synthetic identity fraud. In fact, Odufisan et al. (2025) reported that these pressures had engendered a fast-paced adoption of machine learning by most financial institutions. The pre-pandemic to post-pandemic disparity between what could be and what is, is represented here by being underutilized (Afjal et al., 2023) and then suddenly needing to fill that gap. This transition also points to a growing trend—fraud detection is no longer a reactive process, but a proactive one, and machine learning is an important strategic component of it to manage the continual changing of fraud fingerprints.

These are just a few thought leaders in the artificial intelligence and finance sectors, including the financial industry regulatory authority (FINRA) and the federal reserve, who have been calling for tighter adherence and enforcement to intelligent fraud detection systems. As financial fraud evolves with increasingly advanced fraud tactics, regulatory agencies are increasingly finding themselves supporting integration of machine learning solutions to improve risk management, as highlighted by Dama et al. (2024). As a result, CIOs and compliance professionals have started looking for options that allow the deployment of technology to better fit the larger risk governance approach.

While we can't discuss machine learning adoption for fraud detection without some outside and inside looking at the technology, there has been a trajectory for the journey of machine learning adoption since 2020. Important literature reveals that among the major factors to consider for a successful implementation are: Cross-functional collaboration, Org. culture, Strategic leadership. Overall, the prevailing trend underscores the critical importance of identifying the potential of machine learning and effective leadership to harness this potential. These banks can benefit from better fraud detection, reduced losses, and improved consumer confidence in an evolving digital financial landscape when they embrace a holistic solution

Synthesis of the Scholarly Literature

Synthesis of the Practitioner Literature

Alignment of the Project With the Literature and Discipline

SECTION 2. PROCESS

Project Questions

Project Design/Method

Stakeholders, Participants, and Target Audience

Role of the Researcher

Project Study Protocol

Sample

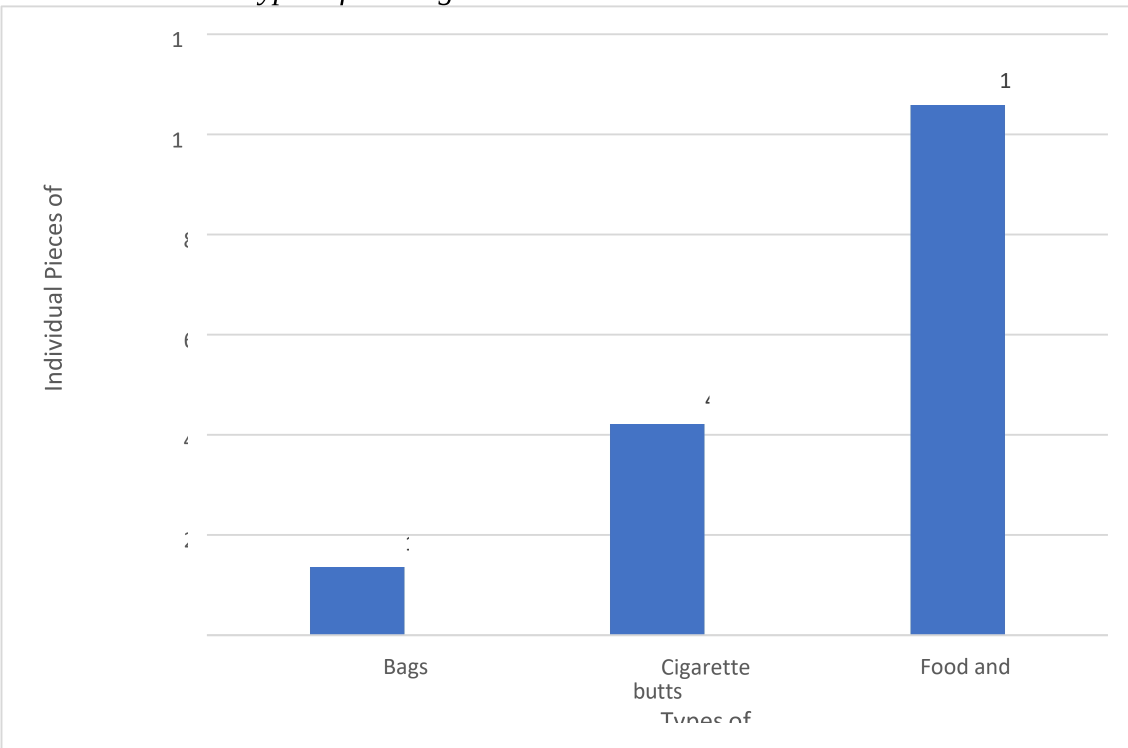
Data Collection

Ethical Considerations

Data Analysis

Figure 1

Types of Garbage



SECTION 3. FINDINGS AND APPLICATION

Relevant Outcomes and Findings

Application and Benefits

Implications

Recommendations for Policy

Recommendations for Practic

Recommendations for Future Work

Conclusion

References

Abikoye, N. B. E., Akinwunmi, N. T., Adelaja, N. A. O., Chidozie, S., & Ogunsuji, M. (2024). Real-time financial monitoring systems: Enhancing risk management through continuous oversight. *GSC Advanced Research and Reviews*, *20*(1), 465-476. https://doi.org/10.30574/gscarr.2024.20.1.0287

Afjal, M., Salamzadeh, A., & Dana, L. P. (2023). Financial fraud and credit risk: Illicit practices and their impact on banking stability. *Journal of Risk and Financial Management*, *16*(9), 386. https://doi.org/10.3390/jrfm16090386

Ahmed, F., Hussain, A., Khan, S. N., Malik, A. H., Asim, M., & Ahmad, S. (2024). digital risk and financial inclusion: Balance between auxiliary innovation and protecting digital banking customers. *Risks*, *12*(8), 133–133. https://doi.org/10.3390/risks12080133

Ayodeji, I. (2024). *Forensic accounting and fraud prevention and detection in the Nigerian banking industry*. https://www.proquest.com/openview/aca05307a360975338fe59b6a3b0c74b/1?cbl=18750&diss=y&pq-origsite=gscholar

Bello, A., & Olufemi, K. (2024). Artificial intelligence in fraud prevention: Exploring techniques, applications, challenges, and opportunities. *Computer Science & IT Research Journal*, *5*(6), 1505–1520. https://doi.org/10.51594/csitrj.v5i6.1252

Bevilacqua, S., Masárová, J., Perotti, F. A., & Ferraris, A. (2025). Enhancing top managers' leadership with artificial intelligence: Insights from a systematic literature review. *Review of Managerial Science*. 1-37. https://doi.org/10.1007/s11846-025-00836-7

Borhani, S. A., Babajani, J., Vanani, I., Anaqiz, S., & Jamaliyanpour, M. (2021). Adopting blockchain technology to improve financial reporting by using the technology acceptance

(TAM). *International Journal of Finance & Managerial Accounting*, *6*(22), 155-171.http://www.ijfma.ir/article_17481.html

Brogi, M., & Lagasio, V. (2024). New but naughty. The evolution of misconduct in FinTech. *International Review of Financial Analysis, 95*, e103489. https://doi.org/10.1016/j.irfa.2024.103489

Bueno, L. A., Sigahi, T. F. A. C., Rampasso, I. S., & Anholon, R. (2024). Impacts of digitization on operational efficiency in the banking sector: Thematic analysis and research agenda proposal. *International Journal of Information Management Data Insights*, *4*(1), e100230. https://doi.org/10.1016/j.jjimei.2024.100230

Chenguel, M. (2020). Financial fraud and managers' causes and effects. *Corporate Social Responsibility*. https://doi.org/10.5772/intechopen.93494

CIO. (2024). *Banks and lenders are still falling short of fully capitalizing on the AI revolution*. Cio.com. https://www.cio.com/article/3513901/banks-and-lenders-are-still-falling-short-of-fully-capitalizing-on-the-ai-revolution.html

Dama, K., Pavan, K., Hrithik, K., & Vyshnavi, R. (2024). Fraud detection in financial transactions. *ResearchGate.com*. https://doi.org/10.13140/RG.2.2.33977.99685

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319-340. https://www.jstor.org/stable/249008

Davis, F. D., & Granić, A. (2024). The technology acceptance model. https://link.springer.com/book/10.1007/978-3-030-45274-2

Ebot, A. (2024). *Technology acceptance model for adopting cybersecurity technology in small and medium business/enterprise: A generic qualitative study*.

https://www.proquest.com/openview/821ddca62bfb9689de0e377a43f7dfba/1?cbl=18750&diss=y&pq-origsite=gscholar

Ejiga, H., Oladapo, N., Okeke, D., & Akinoso, E. (2024). Theoretical frameworks supporting IT and business strategy alignment for sustained competitive advantage. *International Journal of Management & Entrepreneurship Research*, *6*(4), 1273–1287. http://dx.doi.org/10.51594/ijmer.v6i4.1058

Federal Trade Commission. (2025). *New FTC data show a big jump in reported losses to fraud to $12.5 billion in 2024*. Ftc.gov. https://www.ftc.gov/news-events/news/press-releases/2025/03/new-ftc-data-show-big-jump-reported-losses-fraud-125-billion-2024

Feingold, S., & Wood, J. (2024, April 10). *"Pig-butchering" scams on the rise as technology amplifies financial fraud, INTERPOL warns*. Weforum.org. https://www.weforum.org/stories/2024/04/interpol-financial-fraud-scams-cybercrime/

Granić, A. (2024). User acceptance of interactive technologies. *Foundations and Fundamentals in Human-Computer Interaction*, 356-389. https://doi.org/10.1201/9781003495109-12

Gupta, R. K., Hassan, A., Majhi, S. K., Parveen, N., Zamani, A. T., Anitha, R., Ojha, B., Singh, A. K., & Muduli, D. (2025). Enhanced framework for credit card fraud detection using robust feature selection and a stacking ensemble model approach. *Results in Engineering*, *26*, e105084. https://doi.org/10.1016/j.rineng.2025.105084

Hariyani, D., Hariyani, P., Mishra, S., & Sharma, M. K. (2024). Causes of organizational failure: A literature review. *Social Sciences & Humanities Open*, *10*, e101153. https://doi.org/10.1016/j.ssaho.2024.101153

Heß, V. L., & Damásio, B. (2025). Machine learning in banking risk management: Mapping a decade of evolution. *International Journal of Information Management Data Insights*, *5*(1), e100324. https://doi.org/10.1016/j.jjimei.2025.100324

Hilal, W., Gadsden, S. A., & Yawney, J. (2021). A review of anomaly detection techniques and applications in financial fraud. *Expert Systems with Applications*, *193*(1), e116429. https://www.sciencedirect.com/science/article/pii/S0957417421017164

Joseph, P. S., & Eaw, H. C. (2023). Still technology acceptance model Reborn with exostructure as a service model. *International Journal of Business Information Systems*, *44*(3), 404-421. https://doi.org/10.1504/ijbis.2023.134949

Lamey, Y. M., Tawfik, O. I., Durrah, O., & Elmaasrawy, H. E. (2024). Fintech adoption and banks' non-financial performance: Do circular economy practices matter? *Journal of Risk and Financial Management*, *17*(8), 319. https://doi.org/10.3390/jrfm17080319

Masumbuko, C., & Phiri, J. (2024). Technology adoption as a factor for financial performance in the banking sector using UTAUT model. *African Journal of Commercial Studies*, *4*(2), 121-130. https://doi.org/10.59413/ajocs/v4.i2.5

McKinsey & Company. (2022). *Four key capabilities to strengthen a fraud management system | McKinsey*. Mckinsey.com. https://www.mckinsey.com/capabilities/risk-and-resilience/our-insights/four-key-capabilities-to-strengthen-a-fraud-management-system

Odufisan, O. I., Abhulimen, O. V., & Ogunti, E. Olarenwaju. (2025). Harnessing artificial intelligence and machine learning for fraud detection and prevention in Nigeria. *Journal of Economic Criminology*, *7*(2), e100127. https://doi.org/10.1016/j.jeconc.2025.100127

Pajany, P. (2021). *Ai transformative influence: Extending the tram to management student's AI's machine learning adoption - ProQuest*. Proquest.com. https://search.proquest.com/openview/317b9e11c91c8b592822e9cb42b758ba/1?pq-origsite=gscholar&cbl=18750&diss=y

Pattnaik, D., Ray, S., & Raman, R. (2024). Applications of artificial intelligence and machine learning in the financial services industry: A bibliometric review. *Heliyon*, *10*(1), e23492. https://www.sciencedirect.com/science/article/pii/S2405844023107006

Rahman, M., Kaium, A., & Hossain, U. (2024). Examining the dynamics of mobile banking app. Adoption during the COVID-19 pandemic: A digital shift in the crisis. *Digital Business*, *12*(2), e100088. https://doi.org/10.1016/j.digbus.2024.100088

Ramos, S., Lopez, J. A. P., Abreu, R., & Nunes, S. (2024). Impact of fraud in Europe: Causes and effects. *Heliyon*, *10*(22), 8-12 https://doi.org/10.1016/j.heliyon.2024.e40049

Rawindaran, N., Jayal, A., & Prakash, E. (2021). Machine learning cybersecurity adoption in small and medium enterprises in developed countries. *Computers*, *10*(11), 150. https://doi.org/10.3390/computers10110150

Statista. (2025). *Value of fraud loss in the U.S. by payment method 2021*. Statista.com. https://www.statista.com/statistics/958997/fraud-loss-usa-by-payment-method/

Thathsarani, U. S., & Jianguo, W. (2022). Do digital finance and the technology acceptance model strengthen financial inclusion and SME performance? *Information*, *13*(8), 390. https://doi.org/10.3390/info13080390

Vanini, P., Rossi, S., Zvizdic, E., & Domenig, T. (2023). Online payment fraud: From anomaly detection to risk management. *Financial Innovation*, *9*(1). 66. https://doi.org/10.1186/s40854-023-00470-w

Wang, B., Luo, J., Zhang, X., & Gao, L. (2025). Does digital transformation affect corporate fraud? *Finance Research Letters*, *80*(3), e107418. https://doi.org/10.1016/j.frl.2025.107418

West, J., & Bhattacharya, M. (2016). Intelligent financial fraud detection: A comprehensive review. *Computers & Security*, *57*(3), 47–66. https://doi.org/10.1016/j.cose.2015.09.005

Zhu, X., Ao, X., Qin, Z., Chang, Y., Liu, Y., He, Q., & Li, J. (2021). Intelligent financial fraud detection practices in post-pandemic era: A survey. *The Innovation*, *2*(4), 100176. https://doi.org/10.1016/j.xinn.2021.100176

Zin, R., Mokhtar, N., Irfan, A., Ani, C., Husairi, A., Nasrun, M., & Nawi, M. (2024). Unraveling the dynamics of user acceptance on the internet of things: A systematic literature review on the theories and elements of acceptance and adoption. *Journal of Electrical Systems*, *20*(4), 2217-2227. https://pdfs.semanticscholar.org/b422/8ae2ee05db93a186f3ca6f2976741c032fec.pdf

APPENDIX A. TITLE OF APPENDIX A

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