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

by

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Of the Requirements for the Degree

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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

The digital age has been followed by an age of never-before-seen convenience in financial transactions; however, it has also increased the magnitude of financial fraud in the United States. The financial sector is constantly fighting against increasingly complex kinds of frauds, from credit card scams, identity thefts, wire transfer frauds and account takeovers (Afjal et al., 2023). Further, American consumers filed approximately $58 million worth of credit card fraud in the third quarter of 2024, which was the lowest reported amount for that year (Statista, 2025). The number testifies the imperative need for more intelligent and more responsive fraud detection systems to detect and prevent illegal activities in real-time.

Existing approaches to fraud detection are generally based on human judgment and pre-programmed rules, which may not be able to respond to the new threats of fraud in financial organizations. Emergent technological development, including the use of artificial intelligence (AI) and machine learning algorithms, offer potential for the building algorithmic fraud detection approaches that are more advanced and responsive (Pattnaik et al., 2024). Some financial institutions are not fully leveraging artificial intelligence to combat fraud (CIO, 2024). As fraud schemes become more sophisticated, organizational managers must look beyond technological solutions and adopt a management-oriented approach to innovation (McKinsey & Company, 2022). Despite advancements in technology, organizational resistance, unclear leadership, and poor cross-functional alignment are often the reasons for the underutilization of fraud detection tools. The challenges point to a gap in practice: many general managers do not have a clear roadmap for integrating AI's strategic and operational frameworks within institutions.

The U.S. financial industry, including banks and financial technology (fintech) companies, is highly vulnerable to fraud due to the volume and speed of digital transactions (Brogi and Lagasio, 2024). Real-time payment systems, on the one hand, while being convenient, leave little scope for manual intervention against fraud (Vanini et al., 2023). Institutions are under severe pressure to implement a fraud detection system that works and can detect anomalies, highlight suspicious behavior, and initiate automated responses within milliseconds. Abikoye et al. (2024) reported that strategic alignment between machine learning capabilities and organizational goals is very useful for reducing fraud incidents experienced by financial institutions. Bevilacqua et al. highlight the importance of managerial capability and organizational preparedness in achieving the business value of machine learning initiatives. Organizational efforts are key to the the long-term success of fraud detection initiatives and to minimizing risk exposure.

The project objective is to use machine learning algorithms to detect fraudulent activities in US financial institutions. The anomaly detection capabilities of machine learning will enable managers to use an efficient fraud detection system to identify fraudulent activities (Dama et al., 2024). The root problem identified is the need for leadership strategies to implement machine learning technology to combat fraud in financial institutions (Gupta et al., 2025). The challenge is that management in financial institutions typically lacks the strategic thinking and operational models to use state-of-the-art technologies, such as machine learning, to effectively address financial fraud (Chenguel, 2020). In the case of technologies, the disconnect in practice lies in the managerial capacity to embed solutions into organizational practices and decision-making systems. The project's significance is to provide substantial benefits to financial organizations and make the financial system safer for consumers by actively identifying and preventing fraudulent transactions.

The significance of this project may provide new insights for managers of financial institutions, helping them reduce economic losses by enabling them to detect fraud faster and more accurately. The application of effective leadership strategies will ensure the implementation of machine learning technology, which helps in the reduction of the occurrence of fraud events by being proactive in detecting them (Bevilacqua et al., 2025). Thus, building a culture of innovation with the help of machine learning would help address new fraud threats and ensure the organization's financial stability. Therefore, this project focuses on a business issue in general management: the ineffective deployment and administration of innovative fraud detection systems. Focusing on the managerial aspect incorporating machine learning technology. With data coming from this project, there may be a way forward for financial institutions to update their fraud prevention measures to ensure long-term security and confidence in the digital world.

Problem Statement and Purpose

The general business problem is that fraud incidents reduce profitability and customer satisfaction in the U.S. financial industry. Traditional fraud detection systems are not effective at detecting fraud and can impact organizational performance. According to the Federal Trade Commission (FTC),, the amount of money lost by U.S. consumers due to fraudulent activities was $90 to $501 million (FTC, 2025). The growing losses mean that fraud is not only here to stay but also becoming more complex, presenting a serious and ongoing threat to consumer trust and organisational stability.

The particular business problem, however, is the lack of adequate resources and technology strategies among technology managers in the US financial industry to enable the implementation of machine-learning-driven fraud protection (Bello and Olufemi, 2024). Despite the availability of advanced technologies, poor leadership and a lack of strategic support have been the leading factors in the failed implementation of fraud detection systems, which negatively affect organizational performance (Afjal et al., 2023). Leadership gaps in integrating complex technologies have been a major problem, with approximately 2.6 million consumers reporting fraud due to misaligned strategies (FTC, 2025). This particular business problem leads to several negative consequences, including prolonged exposure to fraudulent activity, loss of customer confidence, and significant financial losses (Lamey et al., 2024). A consistent relationship between technological capabilities and strategic leadership is a key issue in the broader context of financial industry management.

Alignment with Program

The project on leveraging machine learning technology through strategic leadership in financial institutions is a great fit for a Doctor of Business Administration (DBA), as it aims to solve an impactful business problem in the finance industry. Financial fraud is one of the costliest and most sophisticated problems in the banking and financial services industry (Hilal et al., 2021). Thus, the project intends to examine failures in strategic management as a contributor to the unsuccessful adoption of machine learning,, resulting in financial losses, regulatory risks, and reputational damage. The issue highlighted the importance of how leadership can assist in improving financial operations by integrating machine learning technology (Pattnaik et al., 2024). Thus, the project is a very good match for the Doctor of Business Administration (DBA) emphasis on interdisciplinary leadership and strategic management. Exploring the financial manager’s ability to decide whether to implement advanced technology provides crucial insights into how to improve an organization's financial operations and reduce the risk of fraud (Dama et al., 2024). The project under the DBA focuses on solving complex problems in the business world through applied research.

Purpose Statement

The goal of this generic qualitative inquiry is to understand the perspectives of technology managers in the US financial industry who have implemented resource and technology strategies to support machine-learning-based fraud detection and protection. The project will discuss leadership strategies for adopting machine learning for fraud detection (Dama et al., 2024). The target population will include financial managers in the United States who work at institutions that serve the banking and financial services industry.

Gap in Practice

The difference in practice is that some managers in the U.S. financial industry have not adopted effective machine learning-based fraud detection, resulting in ongoing financial losses and customer dissatisfaction (Chen et al., 2025) as the statistics of the Federal Bureau of Investigation shows that the number of cases of business email fraud in 2022 increased up to 21,832 cases that resulted in losses of $2.7 billion (Lalchand et al., 2024). Not using standard systems to detect fraud, which is not keeping up with the evolving ways fraudsters operate and tends to lead to fraudulent activity. The reason for the practice gap is not the unavailability of fraud detection technologies but the lack of a strategic leadership approach to implement machine learning technologies (Hariyani et al., 2024). The gap is manifested as a particular issue: financial institutions are subjected to complex financial fraud schemes that remain undetected by existing systems, resulting in monetary losses. An ideal state is one in which the managers of financial institutions actively use the predictive power of machine learning systems to detect and prevent fraud in real time with high precision (Pattnaik et al., 2024). Project findings can help practitioners interested in closing the gap by highlighting the potential value of adopting more sophisticated analytical methods to prevent fraud. In addition, results must be taken in the context of a firm's overall strategic plan.

Theoretical Framework

The research focuses on views from the US financial sector technology managers who have adopted machine learning (machine learning) based fraud detection and protection systems by the application of resources and technology measures. The qualitative research study was practical based on the technology acceptance model (TAM) that was first developed Davis (1989). The TAM has gained wide popularity to explain the adoption of emerging technologies. The framework remains a powerful tool in the research on the strategic, behavioral, and managerial aspects of machine learning adoption in financial institutions (Davis & Granić, 2024). The theoretical foundation provides critical understandings of the complex decision making processes that contribute to the successful integration of technology in high stakes financial environments.

At manager level, perceived usefulness is what managers think the machine learning systems might possibly do to enhance the outcome of fraud detection and provide strategic organizational value. Perceived ease of use refers to the extent to which managers perceive that implementation of the machine learning system will be without unduly difficult or complicated for financial organizations (Joseph & Eaw, 2023). High perceived ease of use plays a role in the management of the attitude of managers towards the adoption of machine learning technology, particularly among decision-makers who may be placed to the position against the acceptance of technologies due to perceived complications in the implementation of the technology. The sequential technology acceptance model constructs, attitude towards use, intention to use behavior and actual system use, provides a systematic framework to understand how managers form their perspectives, adoption intentions and eventually implement machine learning technology.

In the whole of general management literature, the TAM is one of the most popular frameworks to understand the adoption of new technologies, especially in an organizational setting. TAM assumes that acceptance of a technology is primarily influenced by the ease of use and usefulness of the technology (Pajany, 2021). In the context of the project, TAM is an appropriate framework, as it can help to explain why financial managers at financial institutions in the US may or may not adopt fraud detection systems based on machine learning despite the apparent benefits of these technologies.

A very relevant secondary framework is the unified theory of acceptance and use of technology (UTAUT), which is a variation on TAM where constructs like performance expectancy, effort expectancy, social influence and facilitating conditions are included (Borhani et al., 2021). The framework that is both for scholars and practitioners makes it possible to have a nuanced understanding of the influences that impact technology adoption within organizations. In the context of the project, the addition of the additional variables will help to explain the external factors such as organisational culture, leadership support, and training which can influence a manager's decision to integrate machine learning-based fraud detection systems.

The particular problem considered under exploration is focused to know the managerial perspectives in the framework of the technology acceptance model. The research questions are designed to examine the relationship between the perceived usefulness and perceived ease of use of machine learning technology in adoption perspectives of executives, the factors that will influence the behavioral intention and what are the barriers to the actual implementation of the system. The TAM is directly aligned to the project questions by providing constructs (perceived usefulness and perceived ease of use) which can be used to explore the decision-making views of the managers towards the adoption of technology. In the current project, the TAM by Fred Davis is among the conceptual frameworks that is utilized in comprehending how the financial institution managers attitude towards a machine learning technology utilized to detect fraud is shaped and formed (Pajany, 2021). The attitude formation process is directly influenced by the basic TAM constructs (Borhani et al., 2021). The strategic thinking perspective of TAM is directly related to the results of the performance of the organization on the adoption of technology. Therefore, the framework is quite applicable to shaping thinking on management decision-making, particularly in financial services.

The TAM is based on five underlying constructs and the perceived usefulness and perceived ease of use are the keys of determining the acceptance of technology. Perceived usefulness measures people's beliefs about how a system will increase the performance of their jobs. Perceived usefulness is associated with the manner that managers and senior management come up with ideas about enhanced accuracy of fraud detection, efficiency of operations and enhancement of competitive advantage (Ayodeji, 2024). The constructs have an impact on the attitude of the users towards the technology, the intention to use the technology and the actual usage of the system. Perceived ease of use reveals the point of view of the financial managers about the openness and the ease of the implementation of the machine learning system. The constructs affect, the attitude of the user of technology, intent to use technology and finally use of the system.

With the use of TAM, the study analyzes the connection between the views of managers concerning strategic preparedness, the possibility of successful implementation of strategies, and support by organizations with the TAM constructs in situations of adoption of machine learning technology. The framework makes it easy to achieve the project objective of exploring the managerial perspectives. The framework is directly maintaining the idea of the project which aims to explore the views of the managers about the implementation of machine learning in financial institutions. The TAM is a corresponding theoretical lens of fusing the worlds of finance, technology and management, which implies that the framework is also relevant to consider in the DBA-level research that deals with understanding the processes of technology adoption decision-making.

Though the main model which is utilized in the project is the original TAM, extension of the model provides TAM that considers other variables like the 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). Similarly, the unified theory of acceptance and use of technology (UTAUT) is an amalgamation of constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions. Presumably,, the model extends to a broader range of influences on organizational and environmental factors that underlie perspectives on adoption (Zin et al., 2024). Although TAM2 and UTAUT will not be used as primary frameworks, the extended constructs from these models will inform the development of interview questions and thematic coding procedures during data analysis.

The reason that TAM is relevant in the slow machine learning technology adoption in financial institutions is that the model is able to predict key factors influencing managerial adoption perspectives and strategic alignment. Through investigating TAM elements, the project can see why some financial institutions have more favorable views about machine learning based fraud detection systems than others (Masumbuko & Phiri, 2024). The results can be directly applied to give more effective implementation strategies for machine learning based on managerial views and organisational contexts.

Within the sphere of financial services, TAM and extended constructs have been used to measure technology adoption perspectives for the effectiveness of fraud prevention. The framework is in line with the objective of the project, which is to examine the views of financial managers about the value and accessibility of machine learning in fraud prevention and operational efficiency. TAM is especially suitable for the investigation because the framework stresses the viewpoints of user acceptance, which is a critical factor in understanding the challenges of adoption of strategic machine learning initiatives in financial institutions (Rawindaran et al., 2021). Unlike technical implementation models, TAM addresses the cognitive and behavioural aspects of adoption, aligning with the project's managerial focus.

The TAM builds up a structural foundation of the literature review that provides a systematic method to organize and evaluate the research work concerning views of technology adoption in financial sectors. Thathsarani and Jianguo (2022) applied TAM theory in a qualitative study involving 487 people working in Small and Medium Enterprises (SMEs) in Sri Lanka. They found out that the digital adoption views in financial connection based on the TAM theory have a strong impact on the performances of SMEs. The scholars went further to demonstrate that financial organizations are subjected to high regulatory pressure, aggressive digital change, and growing customer security expectations, and that the latter have an effect on the way in which managers evaluate the potential of emerging technology adoption. Masumbuko and Phiri (2024) demonstrated the application of TAM and recommended the use of the framework for improving strategic management technology capability and user acceptance perspectives.

By applying TAM in fraud detection systems in financial industries, the project expands the applicability of the model into high-risk and high-compliance industries where the adoption of perspectives of AI and machine learning is both critical and complex. The work is a contribution to the literature as it serves to provide context specific information on executive perceptions and machine learning integration readiness.

Expanding TAM application from the user-level of technology acceptance to strategic managerial analysis of the technology acceptance framework to bridge the gaps between technological capability and adoption of technology decision-making frameworks. The project will provide operational strategies for fraud reduction by promoting a better matching of managerial views and the potential of technologies. The TAM will guide in the formulation of semi-structured interview questions to gather rich and qualitative responses from the financial executives on their opinions on machine learning adoption (Ebot, 2024). Questions will have probe the attitude towards the usefulness of machine learning for fraud detection, integration complexity/simplicity beliefs, and other contextual factors, such as regulatory pressure, organizational culture, leadership support for adopting the machine learning perspective etc. While there may be insights to be gained from models such as TAM2 or UTAUT to improve the analysis, the project maintains theoretical consistency by building on the original TAM framework.

During data analysis, the results obtained from financial institution manager interview will be coded using the qualitative thematic approaches. At the same time, TAM constructs will not lead to the construction of initial coding frameworks, but will be used as conceptual models for understanding emergent themes for the adoption perspectives. The project will explore recurrent features of managerial views in the use and strategic integration of machine learning systems for fraud detection (Masumbuko and Phiri, 2024). The TAM was selected because of its relevance to the opinion of technology adoption in an organizational stakeholder, particularly financial organization managers who make strategic technology decisions. Financial organizations face a set of stringent regulations, aggressive digital transformation, and increasing customer security requirements that affect how managers evaluate the potential for emerging technology adoption.

Project data may contribute to the literature in several ways. First, the data will record the views of financial managers on strategies for adopting machine learning for fraud detection and risk management. Second, the study will examine how organizational factors shape perspectives on the adoption of machine learning, including risk tolerance, regulatory compliance, technological infrastructure, and managerial readiness. Third, the project will study the correspondence between TAM constructs and real-world machine learning challenges in the context of financial fraud prevention (Gupta et al., 2025). Study data may provide lessons for how to better use machine learning as practitioners/policymakers. By investigating the intersections of technology acceptance and strategic management perspectives, the project may help close the theory-practice gap in financial management and inform improved organizational performance through more effective technology integration based on managerial adoption.

Project Context

The financial industry in the U.S. is undergoing a fast-paced digital transformation, where innovation in banking, payments, and financial services has made financial transactions faster than ever. As the convenience of the digital world becomes more widespread, the complexity and frequency of financial fraud continue to increase. Incidents such as credit card scams, wire fraud, identity theft, and account takeovers have become more sophisticated and are affecting both consumers and institutions equally. The financial sector requires strategic adjustments to overcome limitations in fraud detection systems, particularly by integrating machine learning to enable real-time, data-driven fraud detection (Heß and Damasio, 2025). The need for the change is grounded in the increasing losses that consumers report. According to the Federal Trade Commission (2025), there was a range of $90 million to $501 million in financial losses due to fraud, indicating a systemic failure in traditional fraud-detection models. Financial institutions that still use static systems, based to some extent on rules and without the adaptability of real-time systems, remain at significant risk. Technology is available to detect fraud patterns with a high degree of accuracy, but a chasm in leadership strategy prevents its best use.

The main problem stems from managerial and strategic failures in applying machine learning solutions. Many financial technology leaders have access to advanced artificial intelligence-driven technologies but lack the necessary frameworks and leadership capacity to effectively integrate them into organizational processes (Ejiga et al., 2024). The misalignment limits the capabilities of machine learning tools, making it possible for fraud incidents to go unaddressed. According to Afjal et al. (2023), institutions that did not align fraud detection technologies with their core business goals had a much higher exposure to financial risk. Chenguel (2020) highlighted that it is not because technology is unavailable; rather, the a lack of leadership-driven integration strategies means that intelligent fraud detection mechanisms are not in place. The current disparity in practice indicates a lack of preparedness in how innovation is handled, which, in turn, has created more operational vulnerabilities and diminished consumer confidence.

One of the needs for the proposed project is the criticality of strategic leadership and organisational preparedness in achieving the business value of machine learning initiatives (Bevilacqua et al., 2025). Dama et al. (2024), says technology managers need to have a greater insight on leadership strategy to integrate machine learning technologies for fraud detection successfully. McKinsey & Company (2022) revealed that the general managers in the financial organizations often do not have a roadmap to incorporate the AI technologies in their business model, which results in inefficiency & unused tools. Pattnaik et al. (2024) confirmed the improvements achieved by using machine learning in anomaly detection. Still, they mentioned that the use of ML has a limited potential in terms of a lack of cross-functional alignment and executive support. A leadership-led project that will help guide institutions through strategic transformation and close the implementation gap.

Nature of the Project

The project's feasibility is based on the growing use of artificial intelligence in the financial industry and the availability of well-developed machine learning models for fraud detection. CIO (2024) found that despite a lot of financial organizations who have issued an AI tool, most of them have not realized the full potential of AI due to poor integration into enterprise strategy. Abikoye et al. (2024) emphasized that aligning machine learning systems with institutional goals is critical to reducing fraud. Therefore, by analyzing the opinions of technology managers who have successfully adapted machine-learning-driven systems in the workplace, the project could offer useful insights to support strategic change in similar organizations.

The financial industry, and especially the banking and fintech subsectors, has become a hotbed of fraud risk due to the volume and speed of digital transactions. Real-time payment systems, peer-to-peer transfers, and mobile banking applications do not give much room for human intervention in fraudulent activity. Vanini et al. (2023) explained that manual systems cannot compete with the speed of transactions, increasing the need for automated machine-learning-based monitoring tools. Statista (2025) reported $58 million in credit card fraud in Q3 of 2024, highlighting how real-time digital platforms have become the primary targets of fraudsters. Fintech companies and banks are under regulatory and reputational pressure to enhance fraud detection practices. Without strategic integration of machine learning, institutions risk not only losing money but also losing customer trust in the long run.

The proposed project aims to address existing vulnerabilities through a focused analysis of leadership strategies and technology use. By situating the project in the context of management and information systems, particularly through the TAM, the study examines perceived usefulness and ease of use in the adoption of the technology among decision-makers. Davis and Granić (2024) emphasized that TAM is a useful construct on how executives behave in relation to high-stakes technology decisions. As financial institutions grapple with the challenge of finding a way to fight the rising threats of fraud, the adoption of machine learning will not be based on the technical feasibility of implementation but on managerial willpower and strategic alignment (Hilal et al., 2021). The project, therefore, makes sense as it is related to the core business challenge of strengthening the resilience of the organization through effective fraud mitigation strategies and leadership-driven digital innovation.

Scope

The scope of the project is very limited to investigate the strategic leadership practices of technology managers of the US financial industry who have implemented machine learning-based fraud detection systems. The investigation comes in line with the problem of increasing financial losses due to fraud and the lack of strategic leadership needed to implement the machine learning technologies successfully. The project does not attempt to evaluate all of the aspects of the applications of machine learning in the field of financial operations. Still, it is focused on the managerial decision-making processes to integrate and effectively use machine learning fraud detection tools.

The project is limited by the qualitative views of a particular population which is technology managers of financial institutions, including banks and fintech operating within the United States. The research fills a well-defined gap in practice which is the misalignment of strategic leadership in the implementation of machine learning technologies to fight fraud. As highlighted by Chenguel (2020), many financial organizations in the business have the tools to integrate advanced fraud detection systems; however, many times, the constraints at the leadership level prevent their successful integration into the business operations. The scope of the project is limited to finding actionable insights in order to aid in strategic improvements in machine learning adoption at the managerial level.

Significance of the Project

The importance of the project is the growing risk of digital financial fraud and the lack of sufficient digital financial fraud detection systems based on human judgment or outdated rule-based algorithms. Financial institutions are exposed to a number of unprecedented risks with the pace and complexity of fraud schemes in the modern world, or more specifically, digital payment infrastructures. Traditional methods have become ineffective against contemporary fraud tactics in real time and institutions are under pressure to make fraud detection more accurate without compromising transaction efficiency (Heß & Damaiso, 2025). Vanini et al. (2023) said that it offers little time for manual intervention, therefore automation becomes one of the most important requirements for real-time payments.

The project addresses a practical need in the community of technology managers who lack strategic guidance in implementing machine learning-based fraud detection frameworks. Dama et al. (2024) stated that machine learning has the potential to identify patterns of anomaly and fraudulent behavior more accurately than traditional systems do. Still, a lack of strategic leadership is hindering its implementation. Bevilacqua et al. (2025) emphasised the importance of organisational preparedness and managerial capability as key to extracting value from machine learning initiatives. Technology managers and executives will benefit from insights into how leadership models and decision-making processes affect the adoption and effectiveness of machine learning.

The project is also significant for improving customer experience and regulatory compliance in the US financial industry. Poor fraud detection is a direct route to a loss of customer trust, operational stability, and the sector's reputation. Lamey et al. (2024) noted that lack of fraud protection puts institutions at the risk of experiencing long-term financial risks and erasing consumer confidence. The findings of this study will benefit several stakeholders. The results can help financial technology managers and executives create evidence-based strategies and models for investing resources to enhance systems for machine learning-based fraud prevention. Regulatory agencies could benefit from taking a look at some of the insights that can match the implementation of machine learning with compliance requirements to better oversee and standardise across institutions. Customers and investors will ultimately benefit from improved fraud security measures that promote transparency and trust in financial transactions.

Besides its practical implications, the study will also contribute to the literature by bridging a gap in the literature on the interrelationships among organizational, technological, and leadership factors and machine learning adoption for fraud detection in financial settings. While previous studies have focused on the technical aspects of machine learning algorithms, there have been few studies on the managerial strategies and implementation challenges that determine their success in financial operations (Lamey et al., 2024). By applying effective managerial practices and resolving implementation barriers, this research will contribute to the existing knowledge on technology adoption frameworks, particularly the TAM, in the context of financial fraud prevention. Insights can be used to inform future academic research and best practices for technology-based initiatives aimed at financial integrity.

Historical Background and Current Trends

Understanding the historical background and current trends as they relate to machine learning adoption for fraud detection in the U.S. financial industry is key in putting the current challenges in perspective to expose the practical importance of strategic leadership in the technological integration process. Financial fraud has grown more complex as digital banking has been developed and there is a need for more responsive and data-driven solutions (Hilal et al., 2021). Initially relying on rule-based systems and the supervision of humans, financial institutions came to realize the shortcomings of traditional methods of fraud detection as the cybercriminals evolved more sophisticated techniques.

Machine learning has become a life-changing tool that detects fraud in real-time by predictive modelling and pattern recognition. Despite technological advances, there is an acute lack of key deployment strategies for systems (Ejiga et al., 2024). Looking at the trajectory of history and recent development in the field gives a sense of how leadership shortcomings and poor practices within organizations remain an obstacle to the implementation of machine learning, despite the growing financial loss and vulnerability of customers (Heß & Damásio, 2025). The section covers the evolution of fraud detection and development of machine learning technologies, strategic challenges that are currently affecting the implementation effort across the financial sector.

The problem addressed in this project is the ineffective adoption of machine learning for fraud detection in financial institutions, despite its proven capabilities. According to Afjal et al. (2023), fraud detection in the USA's financial sector is increasingly challenging due to evolving fraud techniques. Current fraud detection systems, which tend to employ rules-based algorithms and operate under human supervision, cannot meet the needs of real-time fraud detection in a rapidly digitalising economy. The problem statement states that the major challenge is not the availability of advanced technology, but rather the lack of financial managers implementing machine learning-based systems due to misalignment of leadership and lack of a proper strategy for integrating technology. This directly connects to the TAM, suggesting that adoption is influenced by perceived usefulness (whether the technology is perceived as valuable for fraud detection) and ease of use (how difficult it is to implement). Financial managers may be hesitant to adopt machine learning if they believe that it is difficult to integrate or are not aware of how machine learning can help them add value to their fraud detection processes.

Historical Background

The history of fraud detection in the US financial industry can be explained in terms of development in digital technology, introduction of real-time financial services, and sophistication of fraudulent activities (Hilal et al., 2021). The shift from the paper-based transaction method to digital banking increased financial accessibility, but it also brought new and complex fraud schemes. At the dawn of the 2000s, the majority of fraud detection was static, rule-based, and manual (West & Bhattacharya, 2016). However, such systems soon proved inadequate as cybercriminals began exploiting loopholes in the technology and customer data with increasing precision. According to Vanini et al. (2023), the introduction of real-time payment systems has drastically reduced the time available for the detection and prevention of fraudulent transactions and therefore requires more advanced and automated solutions.

The digital transformation of the financial sector, especially after 2010, brought innovation, among other things, but also vulnerability. The use of mobile banking, online payments, and peer-to-peer transfers revolutionised the experiences of consumers while at the same time opening a door for fraudsters to exploit the financial systems (Rahman et al., 2024). The source of the growing economic menace is not only the number of frauds but also the complexity of the tactics used by malicious players. Statista (2025) reported an estimated $58 million in credit card fraud in the third quarter of 2024 alone, indicating that fraudulent activity has become more prominent despite improvements in digital infrastructure.

Machine learning emerged as a potential solution in the early 2010s, when researchers and technology companies began applying artificial intelligence to detect patterns and anomalies in large volumes of data. Pattnaik et al. (2024) stressed that Machine learning algorithms can be used to process billions of transactions in real time, detect suspicious behavior, and reduce the rate of undetected fraud. The algorithms can learn and evolve constantly, unlike static rule-based systems, making them more applicable to dynamic fraud threats (Hilal et al., 2021). However, despite the technological maturity of machine learning applications, financial institutions have not been able to machine learning the tools due to internal organizational challenges (Heß & Damaiso, 2025).

The absence of strategic leadership and organisational alignment still remains a major challenge in effective implementation of machine learning-based fraud detection systems. Afjal et al. (2023) said that although many institutions do have experience in AI and machine learning the implementation of it in business models makes them less effective. Leadership uncertainty, lack of good cross-functional collaboration and resistance to change are common themes throughout the literature and imply that technology isn't a magic bullet that can combat fraud-related problems. Bevilacqua et al. (2025) highlighted the importance of managerial readiness and strategic leadership in driving values of machine learning initiatives to the maximum. The TAM, first proposed by Davis (1989) and grew to impact in explaining the decision to adopt a technology in the business environment by focusing on perceived usefulness and ease of use.

Cultural and social factors also have had an impact on the fraud detection strategy. The change in the reliance of consumers on digital financial services particularly after the Covid-19 pandemic has put in place a new normal where financial security has become one of the top priorities. Economic instability in the process and aftermath of the pandemic also gave further impetus to fraudsters and there was an increase in phishing, identity theft, and synthetic fraud generation. McKinsey & Company (2022) said that more than 75% of banking leaders recognised the need for improved fraud detection systems in place but did not have a clear roadmap to strategic implementation. The CIO (2024) reported that although various banks had piloted tools that use AI, less than 30% of them have succeeded in operationalizing them because of misalignment in their organization.

The historical and technological situation reveals that there has been a definite change in both the nature of frauds and the capabilities in the fight against frauds. The key problem is not in lack of technology, but in the disparity in strategy between the available technology and strategy execution. Chenguel (2020) and Hariyani et al. (2024) concluded that leadership needs to change to facilitate innovation and frameworks to integrate machine learning into basic operational practices. The significance of the shift comes through: The financial and reputational risks of not modernizing fraud detection methods. In an economy of high risk for digital transformation, strategic leadership and organizational alignment are not only enablers of innovativeness but requirements for getting institutional integrity (Rahman et al., 2024). The evolution of the topic for last two decade represents an increased awareness that to detect advanced fraud more advanced tools are not sufficient, and leadership transformation is required based on strategic vision, collaboration and operational excellence.

Current Trends

Current trends in adoption of machine learning in fraud detection in the financial industry in the U.S. find a rising interest in the use of artificial intelligence in the fight against the complexity of emerging fraud schemes (Bello & Olufemi, 2024). Since 2020, the financial institutions have accelerated the effort of digital transformation which has created both opportunities and problems in managing fraud risk (Wang et al., 2025). The increase in the amount of real-time payments, mobile banking, and contactless transactions has resulted in the increase of being more susceptible to fraud, which is undertaken to introduce advanced methods of detection to curb the danger. The developments emphasize the weaknesses of the traditional fraud detection systems and support the need for more dynamic and responsive).

Machine learning has become a backbone in fraud prevention, but there is equal amounts of hope and doubts from the academic and professional sides. Pattnaik et al. (2024) mention the technical benefits of the models of anomaly detection that are technically better than rule-based systems in the sense that they detect the outliers in real-time. While this proves that there is definite technical potential of machine learning, the story is not that simple, according to Afjal et al. (2023), where less than 50% of financial organizations have operationalized these tools. What they found is that there is a disconnect that is not technological capacity, but organizational alignment that is a challenge. Such tension suggests that while often the scholars focus on the importance of accurate models, practitioners are more interested in integration barriers, such as fragmented leadership and poor interdepartmental coordination.

Consulting agencies and research with a governance orientation only confirm this perception. McKinsey & Company (2022), claims that machine learning cannot be ignored as a strategic enterprise priority, and neither can it be considered a technical enhancement. Similarly, Ahmed et al (2024) and Bevilacqua et al. (2025) refer to the presence of governance and managerial capability as decisive factors, with a powerful governance structure in organizations with fraud incidents reduced to as much as 30%. McKinsey places emphasis on the executive vision while Bevilacqua et al. stress on organizational preparedness on a managerial and operational level. This is part of an emerging trend in fraud prevention becoming more of a challenge in leadership and culture and not just a challenge in data science.

The stress test of the pandemic of Covid-19 has found the deficiencies of legacy fraud detection systems. Zhu et al. (2021) reported the emergence of fraud due to the explosion of digital transactions and Hariyani et al. (2024) reported the sophistication of emerging threats, for example, synthetic identity fraud. Odufisan et al. (2025) said that such pressures hastened the adoption of machine learning by the financial institutions. Here, the difference between the underutilization by pre-pandemic (Afjal et al., 2023) and the urgency by pandemic is the ability of outside shocks to force organizations to close the gap between the potential and the practice. This modification also represents a trend, because fraud detection no longer acts reactively but is rather proactive, so machine learning is a strategic measure in the protection against ever-changing threats.

Thought leaders in artificial intelligence and finance, including the Federal Reserve and the Financial Industry Regulatory Authority (FINRA), have been clamoring for better implementation of intelligent fraud detection systems. A study by Dama et al (2024) indicated that the use of machine learning solutions for better risk management is being encouraged by regulatory bodies, who have witnessed an increase in financial frauds with increasingly sophisticated attacks. In response, CIOs and compliance leaders have begun searching for frameworks that blend technology implementation with a larger risk governance structure (Ejiga et al., 2024).

From 2020, the path followed by machine learning in the detection of fraud has been characterised by events beyond the organisation as well as by the dynamics within the organisation. The literature strongly suggests that there is a strong correlation between successful implementation and strategic leadership, organizational culture, and cross-functional collaboration. The trend today reflects a reasonable awareness that machine learning is not only a technical solution but a strategic tool that must be led in a suitable manner to achieve its potential (Bello & Olufemi, 2024). Financial institutions adopting a holistic approach to enhancing their capacity to identify fraud activity, minimize their losses, and build consumer trust in a rapidly digitized financial economy.

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

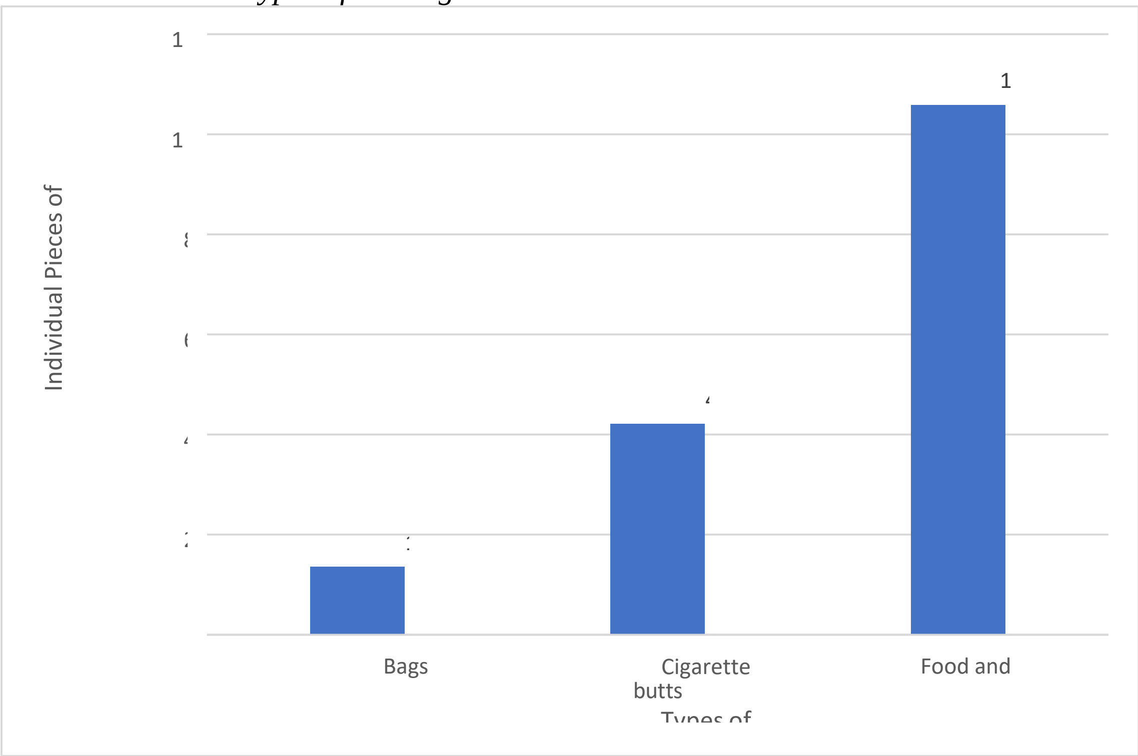
Data Collection

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

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APPENDIX A. TITLE OF APPENDIX A

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