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

by

Name

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Professor

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School of Business, Technology, and Healthcare Administration

A Capstone Work Presented in Partial Fulfillment

Of the Requirements for the Degree

Doctor of Business Administration

Capella University

Month & year of dean's approval

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.

Tips for Developing a Quality Abstract. (a) The abstract is representative of your work. Researchers will review your abstract to determine whether your manuscript is worthy of reading and relevant to their literature review. Those in your field will review your abstract to learn more about the nature and quality of your doctoral work. Thus, the abstract stands as a record of your doctoral-level work. (b) Additional guidelines for development of an abstract are in section 3.3 of the *APA Publication Manual*, 7th edition, or on Campus at Academic Writer, https://academicwriter-apa-org.library.capella.edu/learn/browse/QG-59?group=All&view=list&term=abstract&sort=asc (c) References are generally not used in the abstract, as the focus is the study, the research, and the findings.

Formatting for the Abstract. Format the abstract as one double-spaced block-style paragraph (i.e., do not indent the first line). Set the text flush left, ragged right. Do not justify the right margin. Do not use headings, bullets, or bold. The Abstract page is not numbered, and "Abstract" does not appear in the Table of Contents.

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This dedication page is optional. It is your acknowledgment indicating your appreciation and respect for significant individuals in your life. The dedication is personal; thus, any individuals named are frequently unrelated to the topic of the capstone.

Typically, learners dedicate the work to the one or two individuals who instilled the value of education and the drive to succeed in educational pursuits. Learners often dedicate capstones to relatives, immediate family, or significant individuals who have supported them or played a role in their lives.

Avoid identifying participants or anyone connected with the research site. You may use individuals' titles with no name (e.g., "Thanks to the research director and site proctor for their help"). Or you may name individuals without connecting them to the site (e.g., "Thanks to Abdul Ibrahim and Mary Carson for their help"). Typically, avoid naming the site.

Note: if the Abstract runs onto a second page, change the page number of the Dedication to 4.

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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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Table of Contents

Acknowledgments 4

List of Tables 7

List of Figures 8

SECTION 1. PROJECT DESCRIPTION 9

Overview of the Project 9

Problem Statement and Purpose ..... **Error! Bookmark not defined.**

Theoretical Framework 13

Project Context 18

- Historical Background and Current Trends 18
- Synthesis of the Scholarly Literature 18
- Synthesis of the Practitioner Literature 18
- Alignment of the Project With the Literature and Discipline 19

SECTION 2. PROCESS 20

Project Questions 20

Project Design/Method 20

Stakeholders, Participants, and Target Audience 20

Role of the Researcher 20

Project Study Protocol 20

- Sample 20
- Data Collection 20

Ethical Considerations 20

Data Analysis 20

SECTION 3. FINDINGS AND APPLICATION 22

Relevant Outcomes and Findings 22

Application and Benefits..... 22

Implications..... 22

Recommendations for Policy.....22

Recommendations for Practice 22

Recommendations for Future Work.....22

Conclusion 22

REFERENCES 23

APPENDIX A. TITLE OF APPENDIX A 26

APPENDIX B. TITLE OF APPENDIX B 27

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List of Tables

Table 1. Set Table and Figure Titles in Title Case xx

Table 2. Title xx

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List of Figures

Figure 1. Set Table and Figure Titles in Title Case xx

Figure 2. Title xx

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AND UPDATE THE PAGE NUMBERS.

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SECTION 1. PROJECT DESCRIPTION

Overview of the Project

The digital age has been followed by an age of unprecedented convenience in financial transactions, but it has also increased the scale of financial fraud in the United States. The financial sector is constantly battling increasingly complex fraud schemes, ranging from credit card scams to identity theft to wire transfer fraud and account takeovers (Afjal et al., 2023). Furthermore, American consumers reported approximately $58 million in credit card fraud in the third quarter of 2024, the lowest amount reported that year (Statista, 2025). The need is for smarter, more responsive fraud detection systems that can detect and prevent illegal activities in real time.

Existing fraud detection approaches often rely on human judgment and pre-programmed rules, which may fail to respond to emerging fraud threats in financial organisations. Emerging technologies, such as artificial intelligence (AI) and machine learning (ML) algorithms, offer opportunities to develop more advanced and responsive algorithmic fraud-detection approaches (Pattnaik et al., 2024). Some financial institutions are not fully leveraging AI for fraud detection. As fraud schemes continue to become more sophisticated, organizational leaders need to look beyond technological solutions and adopt a management-driven approach to innovation (McKinsey & Company, 2022). Despite advances in technology, organizational resistance, leadership uncertainty, and poor cross-functional alignment often lead to underutilization of fraud detection tools. The challenges point to a lack of practice, as many general managers do not have a clear roadmap for integrating AI strategic and operational frameworks within institutions.

The US financial industry, including banks and fintech companies, is especially prone to fraud due to the high volume and velocity of digital transactions (Brogi & Lagasio, 2024). Real-time payment systems, while convenient, have little time allotment for manual fraud intervention (Vanini et al., 2023). There is strong pressure on institutions to have a working fraud detection system in place that can identify anomalies, flag suspicious behavior, and trigger automated responses within milliseconds. Abikoye et al. (2024) stated that strategically aligning ML capabilities with organizational objectives significantly reduces fraud in financial institutions. Bevilacqua et al. (2025) emphasised the importance of managerial capability and organisational preparedness in realising the business value of ML initiatives. The organizational efforts are critical to ensuring the long-term success of fraud detection initiatives and minimizing risk exposure.

The objective of the project is to use ML algorithms to reduce fraudulent activity at financial institutions in the United States. The abilities of ML on anomaly detection offer great support to the leaders to use an efficient fraud prevention system to stop the fraudulent activities (Dama et al., 2024). The root problem identified is the lack of leadership strategies for implementing ML technology to combat fraud in financial institutions. (Gupta et al., 2025) The problem is that management in financial institutions often lacks the strategic thinking and operating models needed to adopt advanced technologies, such as ML, to combat financial fraud effectively (Chenguel, 2020). In cases where solutions (technological solutions) are available, the disconnect in practice lies in the managerial capacity to implement them within organizational practices and decision-making systems. The project aims to deliver significant benefits to financial organizations and to create a safer financial system for consumers by actively identifying and stopping fraudulent transactions.

The significance of this project may provide new insights for financial institution leaders on how to reduce financial losses by enabling faster, more accurate fraud detection. Effective leadership strategies enable the implementation of ML technology, which helps minimize fraud events through proactive detection (Bevilacqua et al., 2025). Thus, promoting a culture of innovation by leveraging ML would help address emerging fraud threats and make the organization's financial establishment more stable. Therefore, the project aims to address a general management business problem: the ineffective use and administration of smart fraud detection systems (Chenguel, 2020). Focusing on the managerial aspects of integrating ML technology, the data from this project may provide a way forward for financial institutions seeking to update fraud prevention measures to ensure long-term security and confidence in the digital world.

Problem Statement and Purpose

The general business problem is the loss of profitability and decreased customer satisfaction resulting from fraud (Feingold & Wood, 2024). Traditional fraud detection systems are ineffective at detecting fraud and can impact the organization's performance. According to the Federal Trade Commission (FTC), U.S. consumers lost $90 to $501 million due to fraudulent activities (FTC, 2025). The increasing losses suggest that not only is fraud persistent, but it is also becoming more complex and a major, ongoing threat to consumer trust and organizational stability.

The particular business problem is that some technology managers in the U.S. financial industry lack the resources and technology strategies to implement ML fraud protection (Lamey et al., 2024). However, financial institutions have access to these technologies; however, leadership incompetence and a lack of strategic support have often led to the failed

implementation of fraud detection systems, affecting organizational performance. Weak leadership in adopting the latest technology has been identified as a key issue, with roughly 2.6 million consumers reporting fraud due to misaligned strategies (FTC, 2025). The issue has several adverse effects, including customers remaining vulnerable to fraud for an extended period, which in turn erodes customer confidence and results in financial losses (Afjal et al., 2023). The disconnection between technological capability and strategic management is a critical concern across general management in the financial industry.

Alignment with Program

The project on leveraging ML technology through strategic leadership in financial institutions is an excellent fit for a Doctor of Business Administration (DBA) program because it aims to tackle a high-impact business problem in the finance industry. Financial fraud is one of the most expensive and complex issues in the banking and financial services industry. Thus, the project focuses on the role of strategic management failures in unsuccessful ML adoption, leading to financial losses, regulatory risks, and reputational damage. The issue highlighted the importance of leadership in improving financial operations through the integration of ML technology (Pattnaik et al., 2024). Thus, the project is a perfect fit with the DBA's focus on interdisciplinary leadership and strategic management. Exploring financial leaders' ability to make decisions to implement advanced technology provides valuable insights into improving an organization's financial operations and reducing fraud risk. The project under the DBA aims to solve complex business problems through applied research.

Purpose Statement

The purpose of this generic qualitative inquiry project is to explore managers' perspectives in the US financial industry on resource and technology strategies for implementing

ML-based fraud detection and protection. The project will delve into the concepts of leadership strategy on the adoption of ML technology for fraud detection (Dama et al., 2024). The target population will be US financial leaders and executives within institutions that do business in the banking and financial services industry throughout the United States.

Gap in Practice

The gap in practice is that some U.S. financial leaders have not implemented effective strategies to reduce fraud detection in financial institutions (Chenguel, 2020). Using standard fraud detection systems is not keeping pace with fraudsters' evolving methods and can lead to fraudulent activity. The practice gap is not due to the unavailability of fraud detection technologies but to a lack of a strategic leadership approach to implementing ML technologies (Hariyani et al., 2024). The gap translates into the specific problem that financial institutions face: complex fraud that escapes detection systems available and results in monetary losses. An ideal state is one in which leaders of financial institutions actively use ML's predictive power to detect and prevent fraud in real time with high accuracy (Pattnaik et al., 2024). Project findings can be useful for practitioners seeking to fill gaps by demonstrating the potential value of adopting more sophisticated analytical methods to prevent fraud. In addition, results must be considered in the context of a company's overall strategic plan.

Theoretical Framework

The research aims to examine the perspectives of US financial-sector technology managers who have adopted machine learning (ML)- based fraud detection and protection systems, using resources and technology measures. The qualitative research study was grounded in the Technology Acceptance Model (TAM), which was first developed by Davis (1989). TAM has become very popular as an explanation for the technology adoption of new and exciting

technologies. It remains a powerful tool for studying the strategic, behavioral, and managerial aspects of ML adoption in financial institutions (Davis & Granić, 2024). The theoretical basis offers important insights into the complex decision-making processes that lead to successful technology integration in high-stakes financial environments.

At the manager level, perceived usefulness refers to what managers believe ML systems can do to enhance fraud detection results and add strategic value to the organization. Perceived ease of use refers to the extent to which managers believe that implementing an ML system will not require excessive effort or complexity for financial organizations (Joseph & Eaw, 2023). High perceived ease of use affects managers' attitudes toward adopting ML, especially among decision-makers who may oppose technology adoption due to perceived implementation challenges. The sequential technology acceptance model constructs, attitude towards use, intention to use behavior, and actual system use, offer a systematic framework for understanding how the technology adoption proved effective for managing the fraudulent activities in the financial sector.

The specific problem under exploration concerns the usability of ML technology within the TAM framework. The research questions are intended to address how perceived usefulness and perceived ease of use influence ML technology adoption, which factors influence behavioral intentions, and the barriers to actual system implementation. In this project, the TAM, as defined by Davis, is the conceptual framework used to understand how financial institution managers' attitudes toward ML technology for fraud detection are shaped. According to Thathsarani & Jianguo (2022), TAM is directly linked to the project questions by providing constructs (perceived usefulness and perceived ease of use) that help explore the usefulness of technology adoption. In financial services, TAM and extended constructs have been used to measure

technology adoption and to assess the effectiveness of fraud prevention. For example, the TAM model is applied with 487 participants of Small and Medium Enterprises (SMEs) in Sri Lanka. Findings showed that TAM-based views of digital adoption in financial contexts significantly impact SME performance. TAM is especially suited to the investigation because the framework focuses on user acceptance views, which are critical to understanding the challenges of adopting strategic ML initiatives in financial institutions.

The TAM is based on five constructs, of which perceived usefulness and perceived ease of use are the most important for ascertaining technology acceptance. Perceived usefulness measures how users believe a system will improve their job performance. Perceived usefulness is associated with the development of ideas for improving fraud detection accuracy, operational efficiency, and competitive advantage among managers and senior management (Ayodeji, 2024). These constructs affect users' attitudes towards the technology, their intention to use it, and their actual use of the system.

Using TAM, the study analyzes the relationships among ML technology use, successful strategy implementation, organizational support, and the TAM constructs in ML technology adoption. The framework supports the project's aim of exploring the usefulness of organizing ML technology adoption (Borhani et al., 2021). The TAM is a theoretical lens that fuses the worlds of finance, technology, and management, implying that the framework is also relevant to DBA-level research on technology adoption decision-making.

Although the main model used in the project is the original TAM, its extension includes additional variables, such as subjective norms, and elaborates on perceived usefulness through social influence and cognitive instrumental action, thereby improving understanding of organizational technology adoption perspectives (Granić, 2024). Similarly, the unified theory of

acceptance and use of technology (UTAUT) integrates the constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. The model presumably has a broader reach into the influences of organizational and environmental factors that perspectives on adoption rely on (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 the thematic coding procedures during data analysis.

The TAM's relevance to understanding slow ML technology adoption in financial institutions stems from its ability to predict key factors in technology adoption. By researching TAM elements, the project can determine why some financial institutions have more positive views of ML-based fraud detection systems than others (Masumbuko & Phiri, 2024). The findings can be used directly to develop more effective ML implementation strategies based on managerial views and organizational contexts. The TAM's core constructs are implemented to help organizations enhance fraud detection and avoid financial loss.

TAM provides a structural basis for a literature review that uses a systematic approach to structure and assess research related to perspectives on technology adoption in the financial sector. Masumbuko and Phiri (2024) illustrated the application of TAM and argued for using the framework to address efficient strategic management, technological capability, and user acceptance. By applying TAM to fraud detection systems in financial industries, the project extends the model's relevance to high-risk, high-compliance industries, where perspectives on the use of AI and ML are both critical and complex. The project contributes to the literature by providing context-specific knowledge on executive views and ML integration readiness.

Expanding the application of TAM from user-level technology acceptance to strategic analysis of adoption perspectives fills gaps in how technological capability and adoption

decision-making frameworks are constructed. The project will provide actionable strategies for fraud reduction by better aligning financial operations with technology utilization. The TAM will be used to derive semi-structured interview questions to solicit rich, qualitative responses from financial executives about their perspectives on ML adoption (Ebot, 2024). Questions will seek attitudes toward ML utility for fraud detection, beliefs about integration complexity or simplicity, and other contextual factors, such as regulatory pressure and organizational culture, regarding adoption perspectives. While insights from models such as TAM2 or UTAUT may enhance the analysis, the project maintains theoretical consistency by basing constructs on the original TAM framework.

During data analysis, the results from the financial institution manager's interview will be coded using a qualitative thematic approach. While TAM constructs won't be explicitly informing initial coding frameworks, they will serve as conceptual models for interpreting emergent themes related to adoption perspectives. The project will examine recurring patterns in managerial attitudes towards the adoption and strategic integration of ML systems for fraud detection (Masumbuko & Phiri, 2024). The TAM was selected for its relevance to views on technology adoption in the organizational context, particularly among financial organization managers who make strategic technology decisions. Financial organizations face strict regulatory scrutiny, aggressive digital transformation, and increasing customer security demands; these factors are affecting how managers assess the potential to adopt emerging technologies (Rodrigues et al., 2023). TAM constructs provide structured frameworks for understanding ML adoption drivers at the executive level of decision-making.

Project data can contribute to the literature in several ways. First, the information obtained from the study will reflect the views of financial managers on ML adoption strategies

for fraud detection and risk management. Second, the research will examine the influence of organizational factors, such as risk tolerance, regulatory compliance, technological infrastructure, and managerial readiness, on ML adoption perspectives. Third, the project will examine the correspondence between TAM constructs and real challenges of ML implementation in financial fraud prevention scenarios (Gupta et al., 2025). Study data may provide information to help practitioners and policymakers make better ML adoption decisions. By examining the intersections of technology acceptance and strategic management perspectives, the project may help bridge the theory-practice gap in financial management, contributing to improved organizational performance through more effective integration of technology through managerial adoption.

Project Context

Historical Background and Current Trends

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

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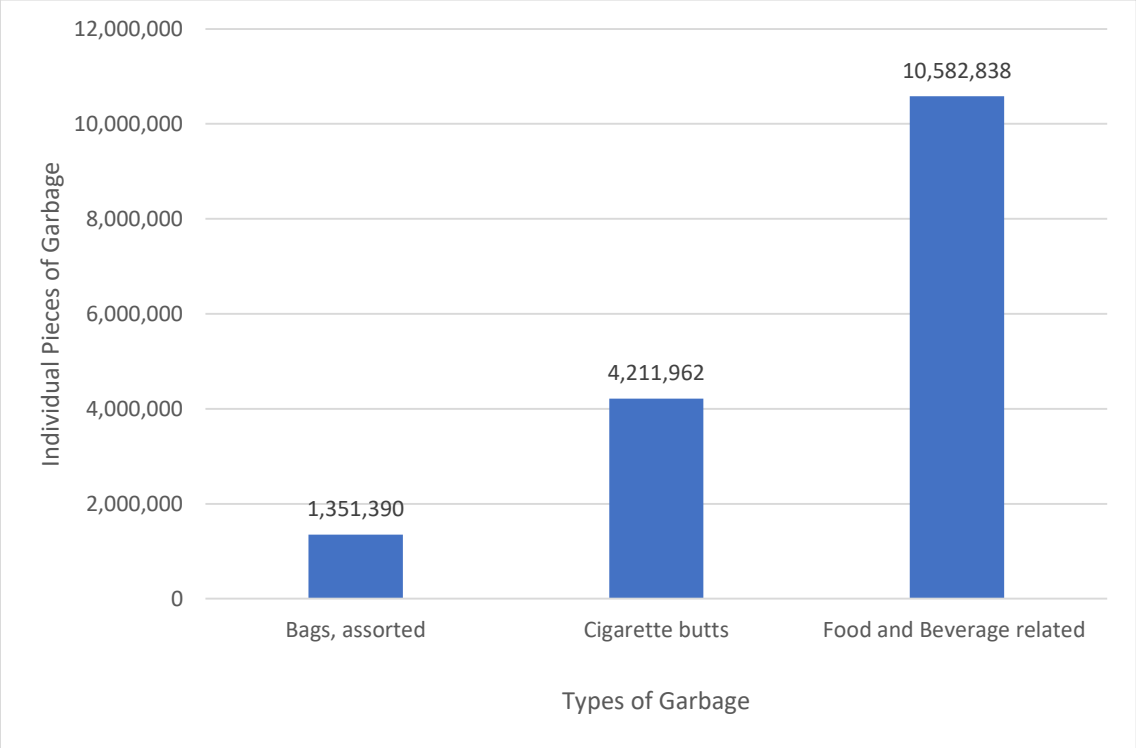

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Table 1

Demographic Information

Participant	Age	Sex	Position	Years in position
P1	25-30	Male	Chairman	10-15
P2	41-45	Female	CEO	6-10

Note. Potential participants under age 16 were omitted from the sample. Only essential notes need to be included. See Table setup (apa.org) and https://academicwriter-apa-org.library.capella.edu/learn/browse/QG-44?group=All&view=list&term=tables&sort=asc. The Doctoral Publications Guidebook also addresses tables and figures.

SECTION 3. FINDINGS AND APPLICATION

Relevant Outcomes and Findings

Application and Benefits

Implications

Recommendations for Policy

Recommendations for Practice

Recommendations for Future Work

Conclusion

References

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