10-21-2025

Examining the Relationship Between Technology Acceptance Model (TAM) Factors and AI Adoption in Financial Industry's Nontechnical Staff

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This is to certify that the doctoral study by

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Walden University
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Abstract

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MS, University of Texas, 2022

BS, University of Houston, 2004

Doctoral Study Submitted in Partial Fulfillment

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Abstract

The rapid integration of artificial intelligence (AI) into the financial services industry has created a need for financial services managers to understand which factors drive AI adoption among non-technical staff, because shortfalls in AI adoption can erode efficiency gains and competitive advantage. Grounded in the Technology Acceptance Model (TAM), the purpose of this quantitative correlational study was to examine the relationship between perceived usefulness (PU) of AI, perceived ease of use (PEOU) of AI, and AI adoption among non-technical employees in the financial services industry. The research questions focused on whether PU and PEOU were significantly related to AI adoption and whether one was a stronger predictor than the other. A convenience sample of 81 non-technical financial services professionals from LinkedIn met the inclusion criteria and completed a SurveyMonkey questionnaire. Data were analyzed using the Statistical Package for the Social Sciences (SPSS). Results of the multiple linear regression were significant, with $F(2, 78) = 46.469$, $p < .001$ and $R^2 = .544$. Notably, both PU (B = 0.723, $p < .001$) and PEOU (B = 0.355, $p = .008$) significantly predicted adoption, with PU being the stronger predictor. The model explained 54.4% of the variance in adoption, indicating a large effect size. Findings suggest that organizations can increase AI adoption by emphasizing productivity benefits while reducing complexity barriers. The implications for positive social change include the potential for employees to experience increased efficiency and reduced work complexity, enabling financial institutions to operate more effectively and contributing to the economic resilience of local communities.

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Dedication

I dedicate this work to my wife, whose unwavering love, patience, and encouragement sustained me through the most challenging moments of this journey. To my children, whose understanding and joy inspire me to push beyond my limits, and to my mother, whose lifelong nurturing has been a steady source of strength. I also dedicate this to my father, whose brilliance and determination taught me to reach for more than I thought possible.

Acknowledgments

I extend my deepest gratitude to my chair and committee members for their continued support, thoughtful feedback, and personalized guidance throughout the doctoral process. Their commitment to excellence and attention to detail challenged me to refine my thinking and strengthened the quality of this research. I also wish to acknowledge those in my professional network who participated in my study and who energized their own networks to help me find participants; I am grateful for the time and insight you contributed.

I am profoundly thankful to my wife, who not only supported me emotionally but also carried the extra responsibilities at home so I could focus on completing this study. Her belief in me, even during my most difficult days, gave me the determination to press forward. To my children, thank you for your patience and for reminding me of the importance of balance and joy, even in the midst of intense work.

Finally, I thank God for providing to me the wisdom, perseverance, and opportunities that allowed me to complete this doctoral journey. Every step of the way, I have been reminded of His blessings and provision, far beyond what I could have imagined or deserved.

Table of Contents

List of Tables

List of Figures

Section 1: Foundation of the Study

In this study, I examined the significance of artificial intelligence (AI) adoption within the financial services industry, emphasizing the role of non-technical staff perceptions in driving or hindering this adoption, and established the foundational elements in Section 1. By addressing the study's problem, purpose, research design, and theoretical framework, I laid the groundwork for understanding the critical factors influencing AI adoption and set the stage for subsequent analysis and discussions. Finally, in Section 1, I included a comprehensive literature review, exploring the theoretical framework used to examine technology adoption and analyzing relevant scholarly works on AI adoption.

Background of the Problem

A large portion of economic growth in the near term will be driven by businesses that are able to adopt AI for productivity growth, using it for increased automation and integration with current processes and technology (Nortje & Grobbelaar, 2020; Czarnitzki et al., 2023). According to Fraunhofer and Forbes (n.d., as cited in Nortje & Grobbelaar, 2020), increasing AI development and adoption will result in a 14% increase in global GDP by 2030, an approximate $15.7 trillion increase; however, in their study, Nortje and Grobbelaar (2020) found that many companies lacked readiness to participate in these benefits. The difficulty for some leaders in the financial industry to understand nontechnical staff's reluctance to adopt AI leads to business problems discussed in this study, which are found in the following section.

Researchers who have conducted the vast majority of research related to AI impacts on productivity have shown a positive correlation (Ismatullaev & Kim, 2024). As such, it is important for researchers and practitioners to better understand how to achieve the outcome of greater AI usage at companies. Towards this end, researchers in some articles, such as Gupta et al. (2022), discuss external factors needed by companies to achieve successful implementation; however, even successful implementation in companies does not lead to adoption at the individual level, and their research called for additional studies that looked at AI adoption individually. This call for additional research was echoed by Ismatullaev and Kim (2024), who conducted a meta-analysis of AI adoption, where they called for research on AI adoption in different application areas and to validate current qualitative findings through experiments and surveys.

Problem and Purpose

The specific business problem is that some managers in the financial services industry lack an understanding of the relationship between non-technical staff's perception of artificial intelligence (AI) usefulness (PU), their perception of AI ease of use (PEOU), and the adoption of AI. Therefore, the purpose of this quantitative correlational study is to examine the relationship between the independent variables (a) employees' perceptions of AI usefulness and (b) perceptions of AI ease of use, and the dependent variable of AI adoption by non-technical staff in the financial services industry.

Population and Sampling

For this study, I needed information from the targeted population consisting of employees in non-technical (non-IT) positions at companies in the financial services industry of the United States. The strategy for gaining access to participants was the use of social media, specifically LinkedIn. A survey for the study was created based on the survey produced and validated by Davis (1989) on the technology acceptance model (TAM), and was created in SurveyMonkey® and distributed on LinkedIn to a wide variety of professionals who are in functions not considered IT. The new survey was based on the Davis (1989) survey, but included modifications to align the questions to artificial intelligence and enable the measurement of the dependent variable, adoption. I collected survey data from the participants through the use of a Likert scale. I used convenience sampling due to its speed, ease of access, and affordability.

Due to the variables of my study all being constructs of a theory that has undergone a large variety of testing, a large effect size was likely; however, to be conservative, I chose a medium effect size ($f^2 = 0.15$). I used a common significance test of 0.05, a common target power of 0.80, and had two independent variables; using G*Power (version 3.1.9.7), I calculated a needed sample size of 68 participants. A power of 0.80 is a standard target for power in many fields, including social sciences. If I adjusted my target to 0.95, I would reduce my type II errors but increase the number of participants I needed to 107. I ended up using 80 participants, overcoming the benchmark of 0.80 power, while not adding significant costs of finding more participants.

Nature of the Study

In his study, I employed a quantitative methodology, which is most appropriate for examining the relationships between constructs of TAM as they relate to the adoption of AI. This approach was ideal because it allows for the precise measurement and statistical analysis of the relationships between the variables of interest, employees' perceptions of AI usefulness, their perceptions of AI ease of use, and the adoption of AI. By utilizing a quantitative methodology, I could systematically test hypotheses appropriate for examining these relationships. The justification for this method stems from the necessity to empirically evaluate the efficacy of TAM components from Davis (1989) within a specific population, which in this study is non-technical employees in the financial services industry. Additionally, the nature of the study should be one that is appropriate for the research questions of the study; since the research questions for this study were related to the correlation between constructs of TAM, a quantitative methodology was the most appropriate. Given the focus on examining relationships between specific variables, a quantitative methodology was more suitable than a qualitative one, as it enabled the use of inferential statistics to draw conclusions from the data (Saunders et al., 2019).

To address the research questions in this quantitative study, the specific research design was a correlational design through multiple linear regression. The correlational design was appropriate for this research because the purpose of the study was to examine the relationship between factors associated with technology adoption and the adoption of an emerging technology, in this case, artificial intelligence, within a specific population.

As I wanted to assess the degree and direction of the relationship, correlation was the most appropriate design. This design was more appropriate than experimental designs because I was not seeking information on cause-and-effect relationships or a longitudinal design, as I was not examining variables over an extended period of time. Using a correlational design was expected to enable me to examine the relationships of my variables in a real-world setting (Saunders, 2019).

Research Question

RQ: What is the relationship between an employee's PEOU in AI, PU in AI, and AI adoption within non-technical staff?

Hypotheses

Null Hypothesis

H_0: There is not a statistically significant relationship between PEOU, PU, and AI adoption in non-technical staff.

Alternative Hypothesis

H_a: A statistically significant correlation exists between PEOU, PU, and AI adoption in non-technical staff.

Theoretical Framework

TAM was first published by Davis (1989) to explain and predict users' acceptance and use of technology based on perceptions of usefulness and ease of use. Although the framework was first proposed by Davis (1986) through a dissertation, it was refined and published by Davis (1989) along with a validated survey. Since its inception, researchers have used TAM as a foundational model in many other theories focused on the acceptance and adoption of technology, such as Venkatesh (2003), which combined TAM with seven other models to create the unified theory of acceptance and use of technology (UTAUT).

In his theory, Davis (1989) posited that two primary factors influence an individual to adopt new technology, which is their PU and PEOU of that technology. The first construct, PU, refers to the degree to which a person believes that using a particular technology would enhance their performance; the other construct, PEOU, refers to the degree to which a person believes that using a specific technology would have low effort. Belief and perceptions are important to the theory, with Davis stating that, related to TAM, beliefs are meaningful variables, making participants' subjective appraisal of performance an acceptable behavioral determinant (1989).

Davis (1986) suggested that perceptions related to these constructs lead to an individual's attitude towards using and accepting the technology, which in turn influences their behavioral intentions. Over time, other researchers have expanded TAM by adding additional constructs, but PU and PEOU remain central to all expanded models. In my study, I leveraged the traditional constructs of TAM, consisting of PU and PEOU, which I used to examine the relationship between non-technical staff's perceptions of AI's usefulness, ease of use, and adoption in the financial services industry. I applied TAM to better understand influences towards acceptance and adoption of AI technologies, which is important towards implementation and garnering usage.

Operational Definitions

Adoption: The process by which users begin to accept and integrate a new technology into their daily routines or business practices; in TAM, adoption is correlated to PEOU and PU (Davis, 1989).

Artificial Intelligence (AI): Computer systems capable of performing tasks that typically require human intelligence, often in an automated manner, such as learning, reasoning, problem-solving, and decision-making (Haenlein & Kaplan, 2019).

Generative AI (GenAI): This subset of AI focuses on creating new content and information, such as text, images, music, or movies, by learning patterns from existing data and generating outputs that resemble them, in real time; the output of AI systems is a mimic of human processes frequently indeterminable from human output (Chakraborty et al., 2023).

Machine learning (ML): This subset of AI focuses on training algorithms to recognize patterns in data and make decisions or predictions based on that data; these systems can frequently improve their performance over time without additional programming (Chakraborty et al., 2023).

Natural language processing (NLP): This subset of AI focuses on computer systems that understand, interpret, and generate human language, creating enhanced communications between humans and technology systems (Lyu et al., 2024).

Financial Services Industry (FI): This industry encompasses businesses that provide financial products and services, including banking, insurance, investment management, payments processing, and Fintech (Gomber et al., 2017).

Financial Technology Company (Fintech): This subset of FI uses technology to offer innovative financial services and products; in recent history, other subsets of FI have frequently been disrupted due to Fintech efficiencies and accessibility (Gomber et al., 2017).

Technology acceptance model (TAM): TAM is a theoretical framework published by Davis (1989) that is used to explain how users come to accept, adopt, and use technology based on their perceptions of that technology's ease of use (PEOU) and usefulness (PU).

Perceived ease of use (PEOU): This construct of TAM refers to the degree to which a person believes that using a specific technology would have low effort (Venkatesh, 2003).

Perceived usefulness (PU): This construct of TAM refers to the degree to which a person believes that using a particular technology would enhance their performance (Venkatesh, 2003).

User Experience (UX): The overall experience a person has when interacting with a technology or system, encompassing factors like usability, accessibility, and satisfaction, offering a holistic perspective on users' interactions with technology (Marques, 2024).

Assumptions, Limitations, and Delimitations

In this subsection, I outline the foundational assumptions, inherent limitations, and boundaries of this study. Assumptions address the accepted truths that guide the research process, while limitations identify potential weaknesses beyond the researcher's control. Delimitations define the scope of the study, specifying what is included and excluded to ensure the research remains focused and aligned with its objectives.

Assumptions

According to Saunders et al. (2019), assumptions are information accepted as true for the purposes of the study, such as the honesty of survey participants or the suitability of the methods used. They are found in sections dealing with either research philosophy or approaches to executing the research. As such, the assumptions in this research are related to the usage of TAM as a viable framework, the tactical gathering of data, and the underlying premise of AI's positive role in business organizations.

A primary assumption of this research was that using AI is a worthwhile activity for users; while ample literature exists that finds AI usage leading to productivity, there is no generally accepted increase in efficiency, effectiveness, or productivity in general across any specific industry or case. Some articles exist that point to the ethical dilemmas of AI usage; my research assumed that the benefits of AI usage outweigh the disadvantages, making the adoption of the technology a worthy topic to develop for practitioners and academia.

Next, it was assumed that TAM is an appropriate theoretical framework for this study. Alternative theories were considered and are discussed in greater detail in the literature review, and while there were constructive reasons for choosing TAM over the alternatives, an exhaustive examination of all adoption-related theories was not conducted.

Other assumptions for the research were more tactically focused on the gathering of data. It was assumed that participants met the selection criteria to be surveyed and provide accurate information related to their positions and perspectives. It was assumed that surveyed participants were a true representation of nontechnical staff in the financial services industry, and that they understood the scope of the survey as well as the language and context used in the questions.

Limitations

According to Saunders et al. (2019), limitations refer to potential weaknesses in the study that are beyond the control of the researcher, which often are related to research design, data access, and population sampling. These limitations often pose a risk to validity or research scope. In this study, the limitations are associated with research design, including framework, scope, and population sampling.

One limitation of this study was that the survey used to measure the constructs of TAM within participants is, by standard, without a measurement for adoption. Furthermore, this study was not longitudinal, and I did not observe the adoption of AI within the participants over a period of time. As a result, this study leveraged a participant's self-evaluation of their intention to leverage AI in their nontechnical position.

Another limitation was related to achieving a statistical representation of all nontechnical staff in the financial services industry. Reaching out to individuals via social media and other digital channels stressed this limitation due to the nontechnical requirement for participants, increasing the chance that they were unreachable via modern technology and communication structures. As a result, respondents could have been biased more towards younger professionals who are more likely to participate in social media channels. Future researchers could validate the strength of the study by gathering data with communication structures that are not dependent upon social media or computer usage.

Another limitation was that this study considered only the perspective of individuals without exploring how external factors might influence these perspectives. The technological, operational, and environmental (TOE) framework from Tornatzky and Fleischer (1990) postulates these external factors and how they impact implementation, and the level at which, in turn, they impact an individual's perspectives is not covered in this study. As a result, there could be unknown biases where the presence of external factors important to AI adoption permeates into the individual contributor's perspectives of usefulness and ease of use. For example, it is unknown to what level of impact an organization's readiness to implement AI has on an individual's perspective of its ease of use; poor technology stacks could disrupt AI implementation, which could, in turn, negatively impact a user's perspective.

Delimitations

According to Saunders et al. (2019), delimitations are boundaries the researcher sets to narrow the scope of the research, often focusing on specifications of populations and research and survey questions. Delimitations are often related to the researcher's specific decisions on what the study will and will not cover, and are reflective of the research objectives. In this study, the delimitations focus on both the constructs examined and the specifications of the population.

This study was conducted to understand the correlations between the constructs of TAM within the context of nontechnical staff in the financial services industry. As a result, the constructs examined were exclusively PU, PEOU, and the adoption of AI. Constructs such as attitude toward use, behavioral intention, or external variables are part of extended versions of TAM and related frameworks but are intentionally excluded from this study to maintain focus and alignment with the core TAM components most relevant to early-stage adoption behaviors. I recognize that other psychological, organizational, and environmental factors may also correlate with AI adoption; however, their examination falls outside the scope and objectives of this research.

Additionally, this study's delimitations restricted participants to those who occupied nontechnical roles at the time of survey distribution and were sourced from the financial services industry. While both concepts (a nontechnical role and working in financial services) are broad, more precise restrictions (e.g., by organization type, job title, or company size) were not applied in order to enable a more generalized understanding within this sector. These boundaries reflect intentional decisions to focus the study on the intersection of core TAM constructs and the experiences of nontechnical employees, where research is limited and further understanding is needed.

Significance of the Study

AI has rapidly become a critical driver of economic growth, with projections indicating that AI could contribute up to $15.7 trillion to the global GDP by 2030, representing a significant portion of economic expansion across industries (PwC, 2017). One of the industries that stands to gain from increased AI usage is the financial services industry, where the adoption of AI technologies has the potential to revolutionize operational efficiency, customer service, and risk management. Given that the financial services sector accounts for a large amount of GDP in developed countries, the implications of AI adoption extend beyond individual firms, influencing broader economic stability and growth.

Efficiency ratios, such as the cost-to-income ratio, are critical metrics in the financial services sector, reflecting how effectively institutions manage resources to generate revenue. Small improvements in these ratios can lead to substantial increases in profitability, underscoring the importance of optimizing these measures (Mehzabin et al., 2023). Understanding the factors influencing AI adoption, especially from the perspective of non-technical staff operating these technologies, is therefore crucial. This study provides insights into how perceptions of AI usefulness and ease of use affect adoption rates, contributing to the financial sector's growth and productivity and, by extension, global economic expansion.

Contribution to Business Practice

This research contributes to business practices by illuminating the drivers of AI adoption, enabling more organizations to achieve enhanced productivity through wider AI adoption. While there is abundant evidence of AI's positive impact on productivity, adoption remains uneven, particularly among non-technical staff in the financial services industry (Czarnitzki, 2023). Generically and at a high level, the factors leading to the adoption of AI at an individual level have been explored in other literature, but even those highlight the need to explore those factors more deeply and within more specific scenarios, such as with non-technical staff (Maragno et al., 2023). By addressing this gap, this study yielded new insights into increasing AI adoption among a substantial but under-reported segment of the workforce.

At the individual level, increased AI adoption could lead to workforce reskilling and upskilling. Understanding how non-technical staff perceive AI usefulness and ease of use can help develop stronger training programs. At the organizational level, increased AI adoption could enhance decision-making, boost productivity, and generate novel ideas, ultimately strengthening competitive positioning. Understanding AI adoption among non-technical staff can lead to the development of tools and platforms that are more intuitive and aligned with employees' daily tasks, leading to the improved efficiencies described above.

Implications for Social Change

This study could also have significant implications for social change. By understanding the constructs that influence AI adoption among non-technical staff, interventions can be developed to improve job satisfaction and well-being. On a broader scale, widespread AI adoption could stimulate economic growth, create jobs, and increase income in communities where adoption occurs. More efficient productivity associated with AI use can lead to higher GDP, improved quality of life, and poverty reduction. Additionally, the increased revenue from higher productivity could generate taxes that fund social programs, further benefiting communities. Furthermore, understanding the perceptions of non-technical staff can also inform the development of AI systems that are not only efficient but also ethical and aligned with human values, contributing to ethical development in a technology where ethics is frequently cited as a high concern.

Moreover, as Luke and Chu (2013) suggest, innovative thinking is essential for addressing complex social issues. While their discussion focused on entrepreneurship, the principle applies to AI adoption as well. As companies reap financial benefits from AI, further research and development could lead to more advanced AI systems, generating novel ideas that drive social change beyond initial expectations.

A Review of the Professional and Academic Literature

This section contains a comprehensive review of the literature relevant to this quantitative correlational study. The specific business problem addressed in this study is the lack of understanding among managers in the financial services industry regarding the relationship between non-technical staff's perceptions of AI usefulness, their perceptions of AI ease of use, and the adoption of AI. The purpose of this literature review is to provide a foundation for understanding the constructs central to TAM and how these relate to AI adoption within financial institutions.

This literature review is organized into several key sections. In the first section, I cover the importance of AI and its impact on productivity, with a focus on how AI technologies are transforming operational efficiency and decision-making processes. This section includes the role of AI within financial institutions, examining current trends, challenges, and the potential for AI to reshape the industry. This section also contains subjects related to other considerations regarding AI usage in business, such as ethics and job displacement.

The review then moves into a detailed examination of TAM, where I highlight its relevance to technology adoption with a focus on AI adoption. In this section, I include a discussion on the relationship between the TAM constructs of PU and PEOU and their influence on AI adoption. An examination of how the correlational strength to adoption changes for each construct depending on differing cases is covered in this section. Additionally, alternative theories to TAM are presented and evaluated for use over TAM, providing alternative perspectives on technology adoption.

In the final section, I discuss the adoption of AI in business. This section contains environmental and external factors affecting AI adoption, considering how these broader influences might impact the relationship between non-technical staff's perceptions and AI adoption. Following this, I explore the adoption of AI, analyzing factors that influence adoption decisions, particularly among non-technical staff.

The literature for this review was sourced from a variety of databases, including Google Scholar, ProQuest Central, and the Walden University Library. Search keywords included *AI adoption, financial services, technology acceptance model, artificial intelligence, AI productivity, AI integration*, and *non-technical staff*. For the selection criteria, I focused on peer-reviewed articles published within the past 5 years to ensure the relevance and currency of the research. Older, seminal works related to TAM and AI were also included to provide a comprehensive theoretical foundation. Of the 57 references contained in this section, 40 are from journal articles, 14 from conferences (primarily from IEEE), and three come from academic textbooks. Of the 40 journal articles, 38 are peer-reviewed, comprising 95% of that subtotal. Of the full selection of reference material, 50 come from articles published in 2019 or later; however, of the remaining seven, four are considered seminal works. Excluding the seminal works, 94.3% are from 2019 or later; the remaining three articles are all related to TAM or alternative theories and models. This chapter concludes with a summary and transition to the methodology chapter, where the research design and approach are detailed.

The Importance of AI

AI is becoming relevant across industries due to its transformative potential in enabling the handling of vast amounts of data, solving complex problems, and assisting in being creative and driving innovation. One of its most notable impacts is on productivity, demonstrated by automating repetitive tasks and streamlining workflows (Babashahi et al., 2024). This increased efficiency enables businesses to respond faster to changes and make data-driven decisions that enhance overall performance. To demonstrate this, Aishwarya et al. (2023) used a simple description of AI that focused on adding productivity in their article, which focused on increasing productivity in workers through the use of AI. Beyond productivity, AI plays a critical role in improving accuracy in sectors like healthcare, financial services, and manufacturing, where precision can lead to better outcomes and potential cost savings. This section explores this critical area of importance, productivity, as well as one of those industries that will be important to this study, the financial services industry.

AI and Its Related Impacts on Productivity

There are many ways that the usage of artificial intelligence improves productivity; Aishwarya et al. (2023) described productivity using a standard productivity formula of the ratio of output for a given amount of input; they found that using a model that enabled ML to support decision-making and NLP to deliver consumable results resulted in increased productivity. They outlined several ways AI improves this formula, such as automating repetitive and mundane tasks, providing personalized recommendations, and augmenting decision-making capabilities. Each of these productivity-improving categories, and more, are explored in this section, which helps describe the value-added reason for wanting to improve AI adoption within businesses (Aishwarya et al., 2023).

Many researchers study how AI helps improve efficiency through automation across a variety of industries and settings in their articles. Greiner et al. (2023), for example, studied how AI can be used to help automate grading and grading dissemination in academia. Choudhary and Pandita (2023) studied how AI increases efficiency in HR through automating tasks and streamlining processes. Rukadikar et al. (2023), also examining AI in HR, found that AI increased efficiency in HR, focusing on how it reduced the workload of talent acquisition. This automation occurs across a multitude of business functions and tasks; some of the tasks outlined by Aishwarya et al. (2023) related to automation include performing data entry, generating reports, and scheduling meetings. For example, AI can evaluate attendee availability and suggest the best time to schedule meetings; it can even help prioritize discussion items for that meeting based on deadlines, gravity, and other criteria.

Related to personalized recommendations, AI can improve productivity by giving tips on how to manage workloads based on the characteristics of a worker and create virtual sales assistants with individualized recommendations (Gupta et al., 2024). There are several reasons why AI is adept at personalization, and one of them, creativity, is enhanced by its ability to analyze large amounts of data. The ability of GenAI to produce creative outputs is particularly useful in increasing productivity in some specific industries. For example, Gupta et al. (2024) explored the implications of the adoption of large language models (LLMs), with a focus on ChatGPT, in the marketing industry; they found that LLMs have had a significant impact because of their ability to quickly create compelling and relevant content and integrate it into existing systems.

Next, AI can assist in productivity by augmenting decision-making to make it more effective and efficient. Some of the ways outlined by Aishwarya et al. (2023) that AI can assist in decision-making are by conducting predictive analysis and trend analysis, and suggesting ways to avoid or overcome potential roadblocks and mitigate risk. It can also provide quick access to information and even support through virtual assistants. Rukadikar et al. (2023) found similar results in the HR industry, finding that AI usage increased the accuracy of talent acquisitions.

While many researchers exploring the impact of AI on productivity used some sort of productivity function in their analysis, other innovative ways to measure productivity have also concluded that AI drives productivity. Although the causal direction was not tested, Damioli et al. (2021) found an extra-positive effect on a company's labor productivity related to the existence of AI patents from that company. Regardless of whether having AI patents leads to productivity or whether companies considered more productive are also ones more likely to submit AI-related patents, their study found a clear correlation.

AI Usage in Financial Institutions

There are several perspectives when it comes to exploring AI usage in the financial services industry, including those of customer-focused and employee-focused perspectives. When research focused on the customer perspective, the AI-enabled tools most frequently helped customers more effectively communicate with the company, learn about a part of the industry where their knowledge may be lacking, or have more efficient interactions with the services of that company. Fraderic et al. (2024), for example, found that when customers in the Indonesian banking industry adopted digital banking technologies, important constructs of adoption were ease of use, perceived usefulness, security, perceived self-efficacy, and awareness. Mondego et al. (2023), on the other hand, found that banking customers in Australia have been slower in adopting AI because of the importance they place on security, but AI was still seen as a significant tool to reduce fraud.

AI applications in financial services industry that are employee-focused are diverse, ranging from improving operational efficiency to enhancing decision-making and risk management. Olasiuk et al. (2023) provided an overview of key AI applications, identifying areas like customer management, fraud detection, and risk management as pivotal. Furthermore, Rahman et al. (2023) emphasized AI's role in fraud prevention and risk analysis in Malaysian banks, highlighting how these applications enhance operational efficiency. These are common AI-focused use cases in financial services industries, and fraud detection, risk assessment, and customer experience enhancement are specifically identified in several articles (Mehndiratta et al., 2023; Rana et al., 2023).

Outside these common nexus points between AI and the financial services industry employees, AI is already found in nearly every business function in large companies in this industry. For example, Mogaji and Nguyen (2022) found that marketing managers effectively leveraged AI for marketing purposes, making modeling and targeting more efficient. In addition to marketing, AI is found in other important business functions in the financial industry, such as risk management, investment management, compliance, cybersecurity, and operations. In each of these, the usage of AI mirrors that of the previous section, being used in automation, personalization, and even creativity.

Other Considerations Regarding AI Usage in Business

In addition to productivity and operational efficiency, the adoption and integration of AI into business practices raises broader considerations that extend beyond technical functionality. Among these, and covered in the following section, are the ethical implications and societal impacts of AI, which have a significant influence on both the organizational and individual perceptions of its use. Ethical considerations, such as transparency, fairness, and data privacy, shape trust and acceptance of AI systems. Similarly, the potential for job displacement influences a critical tension between technological progress and workforce stability. Understanding these interconnected dimensions is important when examining AI adoption, as they relate to the challenges and opportunities businesses face in balancing innovation with ethical and social responsibility.

Ethics. Although the productivity value of AI is rarely questioned in practice or in academia, researchers frequently consider cost/benefit analysis, and ethical considerations are weighed against the productivity value. For example, Choudhary and Pandita (2023) found that AI can be used in the workplace to create opportunities for promoting diversity, equity, and inclusion, including reducing bias in important human-focused decisions. While touting the benefits of AI, they also discussed several risks that could impact perceptions and ethics, such as the use of employee data in training and how private information could be used; additionally, results could contain bias if not carefully handled during model training. This idea that new technology lacks controls around privacy is not new when it comes to technology with novel input mechanisms and is echoed as an ethical concern in earlier emerging technologies, such as smart speakers (Manis, 2020). While AI could incorrectly use private data, it can also use that data to create incorrect results. The tradeoff related to accuracy was further described by Damiano et al. (2024), who acknowledged the added productivity of students using GenAI in higher education but found concern from students accepting incorrect results as correct.

Another subcomponent that loosely falls under the umbrella of ethics is transparency. Greiner et al. (2023) found that a lack of transparency in how an AI grades papers led to a large number of appeals when it was used for grading in academia. This is similar to the argument that the usage of AI has dilemmas in settings where accountability is held at the individual level; in this case, errors in grading were due to the tool of the instructor rather than an error by the instructor. More specifically, however, AI lacks transparency in how it creates decisions, especially in individuals with less technical knowledge and who do not understand the system's algorithms. Marco-Ruiz et al. (2024) identified trust and explainability as significant barriers, albeit less impactful than they expected, in clinical AI adoption. Similarly, Shao et al. (2024) found that perceived ethics mediate user attitudes toward AI, linking these to self-efficacy and trust. These findings suggest that ethical considerations significantly shape perceptions of AI.

The way that some AI, such as GenAI, consume existing creative expressions as inputs creates ethical concerns that its usage can be plagiaristic. Interestingly, Damiano et al. (2024), which explored the perceptions of ChatGPT usage in higher education among students and faculty, found that students generally claimed they would not use GenAI to plagiarize but felt others would. Concerns surrounding plagiarism also extend to the ethics of originality, as GenAI tools are frequently critiqued for drawing upon existing content without clear attribution, with discussions on the moral responsibility of developers and users alike to ensure ethical usage of AI systems (Al-kfairy et al., 2024; Gupta et al., 2024).

Societal Impacts. AI's integration into businesses brings societal impacts as well, particularly in the areas of workforce transformation, organizational culture, and economic inequality. One of the more commonly discussed societal effects is that of job displacement. Automation has already replaced many repetitive and low-skill tasks, particularly in industries like manufacturing, customer service, and even financial services (Sachdeva et al., 2024). While this displacement is often framed as a cost of progress, it also creates opportunities for reskilling and upskilling employees to transition into new and higher-skilled roles. Studies show that organizations investing in workforce development programs not only mitigate the risks of displacement but also improve employee morale and productivity (Babashahi et al., 2024).

Beyond job displacement, AI adoption also affects organizational hierarchies and employee autonomy. As AI systems increasingly fill complex business functions such as fraud detection and customer segmentation modeling, employees may experience shifts in their decision-making authority. Sachdeva et al. (2024) noted that such shifts can result in cognitive dissonance for employees, creating barriers to AI adoption due to fears of redundancy or loss of influence.

Another societal impact is the potential to increase or even cause economic inequalities. Businesses with greater access to AI technologies, especially with patent protection, can achieve significant productivity gains and competitive advantages, widening the gap between larger enterprises and smaller businesses that may lack the resources to adopt such technologies (Damioli et al., 2021). This disparity can extend to employees, with lower-skilled workers bearing the brunt of job displacement while those in more technical or creative fields benefit from the transformation.

The Technology Acceptance Model (TAM)

For this study, TAM formed the theoretical framework used to examine the adoption of AI at an individual employee level. This theory is appropriate for this study because, as its founder stated in Davis (1989), the model predicts how individuals adopt and use technology. TAM contains two predictor variables, PU and PEOU, and both constructs are covered in greater detail later in this section. These constructs drive a person's behavioral intention to use a technology system, which creates the dependent variable of adoption (Vankatesh et al., 2003). This model has been applied across various industries to assess how people perceive and ultimately accept or reject emerging technologies, ranging from information systems to more complex systems such as AI. One of the strengths of TAM is that it is generalized to fit a multitude of technology systems in a variety of situations and across any type of population; it, therefore, is valuable in understanding how non-technical users engage with technology, making it well-suited for this study.

The Development of the Model (Origins)

The development of TAM is rooted in the need to provide a simplified yet robust framework for predicting user acceptance of technology. Originating with Davis (1989), TAM was designed to measure the influence of PU and PEOU on behavioral intention, ultimately shaping technology adoption. TAM is grounded in the theory of reasoned action (TRA) and posits that these PU and PEOU constructs influence users' attitudes toward technology, affecting their behavioral intentions and actual system use. Over the years, this foundational model has been expanded to incorporate additional constructs and applied to various emerging technologies, including AI. Understanding the origins of TAM not only provides context for its application but also highlights the adaptability of its constructs in addressing the complexities of recent and modern technological innovations, such as AI, within a multitude of industries, such as the financial services sector.

Davis (1989) described perceived usefulness as the degree to which a person believes that using a particular system would enhance their job performance. This construct reflects the extent to which individuals perceive that utilizing a specific technology will improve their work efficiency and productivity. Davis's seminal work established PU as a critical determinant of user acceptance, highlighting that users are more likely to adopt a technology if they believe it offers substantial performance benefits.

Davis (1989) described perceived ease of use as the degree to which a person believes that using a particular system would be free from effort. This construct reflects how effortless and straightforward users perceive the interaction with the technology to be. Davis's research demonstrated that PEOU significantly influences user acceptance, as technologies perceived as easier to use are more likely to be embraced by users, and thus adopted into regular use.

While adoption is a product of PU and PEOU, not all technologies are influenced in the same way by these constructs. Ismatullaev and Kim (2024) contained examples where PU had a greater impact while showing PEOU had a greater impact on other technologies. In early TAM development, Davis (1989) found that the adoption of most technologies received a greater influence from the PU construct, which he articulated was justified due to the expectation that new technology served a purpose, and if that purpose was not filled, then no level of PEOU could overcome that shortfall. When reviewing the literature related to TAM, most recent articles did, in fact, stress PU as having the most correlation (Lewis & Sauro, 2023; Pan et al., 2023). In these situations, users are more inclined to adopt a technology if they believe it will enhance their performance, even if it is not particularly easy to use. There are other articles, however, that found PEOU had a greater correlation to adoption, such as from Rahmawati et al. (2019), which examined a new E-Report educational technology. The fact that different technologies contain differing levels of strength from the constructs supports the need for a closer examination of AI adoption through the TAM lens.

Over the past couple of decades, TAM has been used continuously in literature to examine the behavioral traits of individuals adopting technology systems. This examination has looked at everything from UIs facing individual consumers, such as Ahmeti and Bajrami (2024), who examined user behaviors and satisfaction with web-based designs, to emerging technologies, such as VR, ML, AI, and blockchain (Hayek et al., 2022; Olasiuk et al., 2023; Pan et al., 2023; Priya & Sharma, 2023).

Widespread Usage of TAM in Emerging Technologies

TAM has become one of the most widely applied frameworks for studying user acceptance of new technologies. Although it was originally created in the 1980s to describe computer-related technology systems, it continues to be used today for emerging technology. Pan et al. (2023), for example, used TAM to measure adoption of Metaverse platforms. Chaudry et al. (2023) used TAM in conjunction with other frameworks to examine the acceptance or rejection of human implantable technologies; they studied how well the models addressed the attributes of embeddable technologies. Chen (2023) used TAM to examine the adoption of blockchain technology.

While the majority of researchers focused their articles on the correlation of TAM constructs regarding specific cases for specific technologies, this is not the only way TAM has been used in reporting on emerging technologies. For example, Hayek et al. (2022) used TAM to examine the differences in perceptions of usefulness and ease of use of ML technology for two different populations (internal and external auditors in the UAE) in their research; this type of TAM application is useful in validation of alternative approaches, such as choosing internal or external auditors.

Widespread Usage of TAM for AI

The TAM constructs PU and PEOU are frequently applied to AI adoption. Panagoulias et al. (2023) used TAM to study AI adoption among healthcare professionals, identifying varying impacts of PEOU on different clusters of users. Ma et al. (2024) explored ChatGPT adoption, finding significant correlations between TAM constructs and behavioral intention. These studies provide examples that demonstrate TAM’s relevance in explaining adoption behaviors.

Rarely does new technology become a staple in consumer usage that does not make an end user more effective or more efficient at a given task; AI is no exception, targeting both effectiveness (doing the task better) and efficiency (doing the task with less effort). As a result, it is logical that TAM is a frequent theory used to examine AI adoption because it measures both perceived usefulness and perceived ease of use, which align with effectiveness and efficiency. The previous section contained specific areas where users experience increased productivity when using AI, which also aligns with the constructs. When a user is enabled to make more rigorous business decisions because AI quickly provides insightful analytics to the situation, they may find it useful; alternatively, usefulness can be experienced when a user gains more time to execute high-value tasks because AI automates the more mundane scheduling or other repetitive tasks.

There is a wide variety of recent academic reports where the researchers have used TAM to evaluate AI adoption in various populations and situations. For example, Ismatullaev and Kim (2024) conducted a meta-analysis of literature aimed at providing a comprehensive overview of the factors impacting AI adoption and found TAM widely used. Hussein (2022) studied the drivers for the adoption of AI assistants, and Geddam and Gowd (2023) examined the acceptance of human augmentation with AI, both using TAM.

Some researchers have even examined AI in financial industries using TAM, as is the intention of my research, with varying cases and situations. For example, Rahman et al. (2023) used a mixed-methods methodology to examine AI adoption in banks in Malaysia. In their quantitative section, which focused on TAM, they found significant influences from each construct in extended TAM (which, in addition to PU and PEOU, included perceived risk, perceived trust, and subjective norms) except for PEOU. In this research, I will examine AI adoption in a different geographic region, the US, but in a specific subset of the population, non-technical staff, and the results could be compared to Rahman et al. (2023) to gain insights into the differences in the relationships between the variables across different regions and populations. Further supporting the need for my research, Ma et al. (2024) found that demographics impacted the correlation between TAM constructs related to the usage of ChatGPT and behavioral intentions.

Limitations of TAM

One of the limitations of TAM is that it relies on just two constructs, that being PU and PEOU, which potentially only partially represent the behavioral aspects of an individual that contribute to their intention to adopt. To overcome this limitation, some researchers have used TAM as a base theory and added other constructs to supplement PU and PEOU. For example, Hussein (2022), who studied the reasons driving the demand for AI assistants leveraging TAM, added constructs of perceived affordability and perceived risk. Pan et al. (2023), who studied the adoption of Metaverse, added subjective norms, perceived enjoyment, and external regulations. Geddam and Gowd (2023) added image, self-efficacy, external control, anxiety, and playfulness when they used TAM to examine adoption of human augmentation. Çelik and Özköse (2023) expanded TAM with trust and perceived risk to examine mobile banking adoption, finding that PEOU had little effect, highlighting potential contextual and explanative limitations. Fraderic et al. (2024) further emphasized the need to integrate additional constructs, such as security and self-efficacy, to enhance TAM's applicability.

However, it is important to note that PU and PEOU already encompass broader elements of perception and behavior and often overlap with other constructs found in adoption models. Venkatesh and Davis (2000) suggested that these core constructs, while limited, capture key dimensions of user attitudes and are adaptable enough to coexist with additional factors such as perceived risk or social influence. This overlap does not diminish the value of TAM but instead highlights its versatility in incorporating new dimensions without negating the relevance of its original framework.

Flexibility of TAM

The flexibility of TAM is well demonstrated in its ability to adapt to various contexts, including emerging technologies like AI. Greiner et al. (2023) illustrated this adaptability by applying TAM to a specific use case, AI as a sender in grading dissertations. The researchers found that acceptance of AI interactions was closely tied to the transparency of its role, a factor that influenced user trust and acceptance. This finding indirectly reinforces TAM's core constructs of PU and PEOU, while also showcasing its limitations in fully capturing the complexity of AI adoption. To address this, the authors combined TAM with Schulz von Thun's four-sides communication model, allowing them to account for the complexities of human-AI interaction. This demonstrated how TAM can work in conjunction with other models to offer a more comprehensive view of AI adoption in specialized settings.

Other researchers have examples in the literature that highlight the flexibility of TAM by combining the framework with other theories. For example, Damiano et al. (2024) used TAM in combination with the diffusion of innovation theory to explore AI adoption in combination with ethics in education. Zou et al. (2023) used an integrated model of TAM to examine language learning AI adoption, demonstrating TAM's foundational influence on extended theories. Shao et al. (2024) combined TAM with self-efficacy theory to demonstrate how the use of AI technologies are influenced by self-efficacy along with other technological factors. Liu and Huang (2024) combined TAM with the expectation confirmation model (ECM) to create a theoretical model in their effort to examine AI-driven visual synthesis in design ideation. Zeng et al. (2024) created a model to assist in the development of technology products like smartphones using DEMATEL and TOPSIS, but used TAM to ground their framework and establish evaluation criteria, integrating TAM with the other models.

Alternative Theories

There is a myriad of theories that provide lenses into the likelihood of AI being used in order to increase productivity. Some frameworks examine technology implementation at the organizational level, such as the technological, organizational, and the TOE framework by Tornatzky and Fleischer (1990). Other theories, such as the unified theory of acceptance and use of technology (UTAUT), examine adoption at the individual level. Some theories even provide a framework that considers both the individual level and organizational, such as the diffusion of innovations (DOI) theory from Rogers (2003). As TAM examines technology adoption at the individual level, which aligns with the research question for my research, those theories also examining technology adoption at the individual level will be discussed below as potential alternative theories. When examining the adoption of AI, Ismatullaev and Kim (2024) found that behavioral factors have the greatest impact on adoption, supporting the usage of TAM or behavioral-focused alternative theories.

UTAUT: The Unified Theory of Acceptance and Use of Technology (UTAUT) is a technology acceptance framework introduced by Venkatesh, Morris, Davis, and Davis in Vanketesh et al. (2003), which integrated eight prominent acceptance models to better understand the constructs influencing behavior intention. Two of their constructs, performance expectancy and effort expectancy are similar to TAM constructs of PU and PEOU, respectively. They added social influence, which is the degree to which an individual perceives that important and connected others believe they should use the new system, and facilitating conditions, which is the degree to which an individual believes that organizational and technical infrastructure support the system's use. Additionally, they stated gender, age, experience, and voluntariness of use were moderators affecting the relationship between the constructs and the intention to use the technology.

Sánchez-Holgado and Arcila-Calderón (2024) applied UTAUT to study big data adoption, finding parallels with TAM's PU construct. This was most evident in their findings that performance expectancy is the strongest predictor of intention to use and leading to greater adoption, with effort expectancy being an indirect determinant mediated by the intention to use. Their findings make the similarities between UTAUT and TAM apparent, with usefulness and performance expectancy being closely aligned, and effort and ease of use being aligned.

Although UTAUT incorporates TAM in a more comprehensive framework, there are several reasons why researchers would use TAM over UTAUT. Perhaps the most prevalent reason in the context of my research was expressed by King & He (2006), which is that TAM is often preferred when exploring the basic determinants of technology acceptance in the initial phase of adoption studies. Additionally, in a related reason, TAM is ideal when studies focus on individual-level adoption and when the social factors are not central concerns. Alternatively, UTAUT would have been more ideal if the research used a more complex organizational setting and when moderators were more important to answering the research question, such as if they were focused on demographics (Venkatesh et al., 2003).

TRA. The theory of reasoned action (TRA) is a foundational framework for understanding human behavior and is helpful in examining technology adoption; in fact, TRA is a foundational theory used to ground TAM (Davis, 1989). Fishbein and Ajzen (1975) originated TRA, which posited that a person's behavior is determined by their behavioral intention, which in turn is influenced by the attitude toward the behavior and subjective norms. It is these intentions that are the immediate precursors of specific behavior. Within the attitude toward the behavior construct, personal positive or negative evaluations of performing the behavior are evaluated within the individual. Within the subjective norm construct, perceived social pressures to perform or not perform the behavior are evaluated within the individual. For TRA to be relevant, the behavior needs to be under volitional control.

The TRA is very generalized and can be used to examine any number of different behaviors and behavior intentions, making it useful in a wider breadth of research than TAM, which is focused on technology adoption behaviors. Even though it is more generalized and offers the ability to examine a wider range of behaviors, TRA can also be used in examining technology adoption. Some examples of TRA being used in technology acceptance research include the adoption of e-pharmacy, Fintech usage in China, and vaccination against Covid-19 (Hwang et al., 2024; Fan & Ukaegbu, 2024; Roh et al., 2024). The TRA has also been used in a predictive manner in recent reporting, such as with David and Roberts (2024), who used TRA, along with TAM, to predict cell phone usage in church services.

If TRA were used in this research, the behavior to examine would still be adoption, and PU and PEOU would fit into the construct of attitude toward the behavior. In this regard, TRA could potentially be used to answer the research questions; however, TAM contains constructs more precisely aligned with answering the research questions, whereas TRA is more generalized, and not specifically designed with adoption in mind. TRA also contains social norms, which would entail a more complex examination of AI adoption than this initial research seeks to accomplish. As such, TAM is a more appropriate framework than TRA.

TPB. The theory of planned behavior (TPB), which originated in Ajzen (1991), is an extension of TRA that adds a new construct; in addition to attitude toward the behavior and subjective norm, TPB adds perceived behavioral control. This additional construct is related to the perceived ease or difficulty of performing the behavior and is shaped by an individual's past experiences and anticipated obstacles. The extension enables researchers to examine behaviors that are less under volitional control. Like the theories that support it, TPB influences both behavioral intention and actual behavior.

Due to the ability of TPB to layer in external constraints and subjective norms, it may be a more appropriate framework for follow-up research, where additional complexity can be examined that builds upon the findings in this research. For example, attitudes toward AI adoption under TPB could include not only perceptions of AI's usefulness and ease of use but also broader considerations, such as ethical concerns, job security, or alignment with organizational values. Subjective norms would allow an exploration of how social influences such as management expectations, coworker opinions, or industry trends impact employees' willingness to adopt. However, for an initial examination of AI adoption, TAM satisfies the requirements associated with the research questions.

In several articles, Venkatesh compared these alternative theories to TAM; Venkatesh and Davis (2000) stated that TAM outperformed TRA and TPB when it came to usage intentions and behavior. Furthermore, Greiner et al. (2023) argued that TAM remains highly relevant for analyzing AI adoption despite its critiques, such as Venkatesh's release of the UTAUT as a refined alternative. The authors specifically chose TAM over UTAUT due to its broader application to the AI context they were studying. This flexibility in applying TAM across various fields, such as academia, further supports its adaptability and continued importance in technology adoption research. By adjusting and supplementing TAM with additional constructs or integrating it with other models, researchers can tailor the framework to better capture the nuances of adoption in various domains, including AI in educational settings, but TAM itself frequently remains the preferred model to study adoption.

Even when TAM is not used as the primary framework to examine technology adoption, the findings using other frameworks often still align with the constructs of

TAM. For example, Nazri et al. (2023) examined key factors influencing student acceptance of AI, and found the most important criteria were learning outcomes, cost-effectiveness, and accessibility. These findings are similar to constructs of TAM, where learning outcomes maps to PU and accessibility maps to PEOU. In another example, Chan and Zhou (2023) examined the intention to use GenAI in higher education using the expectancy-value theory (EVT) and found that perceived value had a strong correlation; other constructs in their examination included familiarity and cost. Each of these constructs are similar to those in TAM, and EVT is even cited as foundational in its development (Davis, 1989). The frequent similarities in findings that do not use TAM to the expectation when using TAM constructs when examining acceptance and adoption are further indications of the strength of the theory.

Adoption of AI

With the growing importance of AI due to its ability to increase productivity through automation and execution of advanced problem-solving and its ability to streamline, articulate, and create communications, a large body of literature exists to examine the adoption of AI. In fact, Olasiuk et al. (2023) conducted bibliometric structural topic modeling on 378 academic articles related to AI in financial services and found that adoption was a primary research point alongside regulation and management services. This highlights the importance of exploring the multifaceted drivers of AI adoption, including its role as a dependent variable and the broader technological, organizational, and environmental factors influencing its implementation across industries.

Adoption as a Dependent Variable

Many researchers have examined the adoption of AI using a multitude of frameworks and cases. A commonality in these examinations is to better understand what factors and constructs are correlated to AI adoption, making adoption a common dependent variable across these various studies. Some researchers, such as Priya and Sharma (2023), focused on the qualities of AI that lead to adoption, such as strong anthropomorphism and perceived intelligence of the tool; many others focused on the perceptions of individuals towards the general technology rather than relationship with a specific quality of the technology. Chan and Zhou (2023), for example, examined correlations of perceived value, perceived cost, and knowledge to the intention to use AI. Rahman et al. (2023) explored AI adoption in banking, identifying PU, trust, and other factors as critical for adoption. Other times, adoption is examined by studying directly related constructs; for example, Liu and Huang (2024) investigated adoption through TAM constructs, finding PU significantly influences satisfaction and, thus, adoption.

Ismatullaev and Kim (2024) found that user's attitudes, trust, and perceptions about AI can be improved by increasing transparency, compatibility, and reliability, as well as simplifying the tasks. In this finding, the development of AI over time impacts adoption by way of PEOU. They also found that technological factors, discussed in the next section, can further enhance that development and contribute to increasing the PEOU in users with lower trust in AI-infused systems.

In some cases, researchers examined the acceptance of new technologies rather than the adoption. For example, Geddam and Gowd (2023) explored the acceptance of human augmentation through AI, also using the lens of TAM. Nazri et al. (2023) also examined AI acceptance in the context of education and had several findings related to adoption. Acceptance, as was used in these cases, could logically be considered a precursor to adoption. The factors they found to be related to image, self-efficacy, and anxiety, therefore, play a role in acceptance, which would directly influence how and when employees move to full-scale adoption. Regardless, the premise Geddam and Gowd (2023) took when examining adoption using TAM was that the behaviors of individuals could be influenced, which could increase the chance for adoption.

Some researchers, when studying adoption as a dependent variable, have had findings that support the use of TAM in examining this dependent variable. For example, Kim et al. (2023) found that ethical concerns about the quality of recommendations lowered ChatGPT's acceptance and satisfaction. If results cannot be accepted, users may have a decreased perceived usefulness. This idea is supported by Damiano et al. (2024), who found ethical concerns reduced acceptance, which could logically be drawn to perceived usefulness in the same way.

Environmental and External Factors Affecting AI Adoption

In addition to the individual characteristics of employees that impact their willingness to adopt AI, external factors at the companies, in their societies, and from their regulations also impact their ability to adopt the technology. Yang et al. (2024), for example, showed how external factors, such as regulatory environments and competitive pressures, play crucial roles in AI adoption, and Batani et al. (2024) highlighted challenges like the lack of regulation and financial constraints, which limit adoption in digital marketing. One framework frequently used to explore these factors comes from Tornatzky and Fleischer (1990), which introduced the technological, operational, and environmental (TOE) framework. It suggests that the three key areas of technological factors (the characteristics of the technology), organizational factors (the internal processes, structure, and resources of the organization), and environmental factors (external influences such as competition, regulations, and industry trends) work together to shape how and why new technologies are adopted. This framework helps researchers systematically explore the various pressures and enablers that affect adoption decisions.

One of the most prevalent external factors impacting AI adoption is regulation. This idea is controversial in reporting, with some research stating that a lack of regulation is cause for concern, while other articles highlight how regulation prevents wider adoption, such as with marketing and customer targeting in the banking industry (Mogaji & Nguyen, 2022). Regardless of the perspective that regulation helps or hinders AI adoption, its examination is covered in the use of TOE.

There are many other examples of how TOE describes the external factors that contribute to AI adoption outside of individual characteristics. For example, Gupta et al. (2022) found that the technological and environmental factors of relative advantage, complexity, market dynamics, regulatory support, and competitive pressures all had a significant relationship with AI adoption, as well as some operational factors, including top management support and financial readiness. Top management support and financial readiness are both important to be present at a company for successful AI implementation, and their absence could negatively impact adoption. Maragno et al.

(2023) leveraged TOE to explore AI implementation in the public sector, leaning on the framework's strength in dividing important factors towards AI implementation into the categories of TOE.

Additionally, some of the factors external to an individual may impact adoption through their influence on behavioral intentions in addition to barriers they may erect in businesses. For example, Hussein (2022) found that although AI assistants have been widely adopted, many users recognize privacy risks and are not prepared to handle them. These privacy risks could cause organizations to place restrictions on AI usage, limiting adoption externally, or could impact an individual's perception of the technology itself.

Transition

In Section 1, I provided the foundational context for this study, including an overview of the research problem, the significance of AI adoption in the financial services industry, and the theoretical framework guiding the inquiry. A specific gap in the literature was identified: the need to better understand how PU and PEOU influence AI adoption among non-technical staff. To address this, the study is grounded in TAM, which offers a validated structure for exploring individual-level technology adoption. It also included a comprehensive review of relevant literature, highlighting key findings and gaps that demonstrate the importance of this research. I build on this foundation in Section 2 by outlining the research design and methodology, detailing the quantitative approach, sampling strategies, data collection instruments, and analytical techniques employed to investigate the relationships between perceptions of AI usefulness, ease of use, and adoption among non-technical staff. These two sections provide the foundations under which the study will be built, with the findings of that research being presented in the third and final section.

Section 2: The Project

In this section of the study, I outline the key components necessary to conduct a rigorous and valid research project that is methodologically sound and aligned with my study's purpose of examining factors influencing AI adoption. It begins with the purpose statement, clearly defining the study's objectives and aligning them with the research problem. The role of the researcher section highlights ethical considerations and measures to maintain objectivity, integrity, and adherence to established research standards. The participants section identifies the target population and sampling strategies, emphasizing the importance of selecting a representative sample to achieve meaningful results.

Following this, I explain the rationale for employing a quantitative methodology and a correlational research design using multiple linear regression in the research method and design section. These methodological choices align with the study's objectives to explore relationships between theoretical constructs, which are specifically PU, PEOU, and AI adoption. In the data collection instruments section, I detail the instrument used, including psychometric properties, scales, and scoring processes. In the data collection technique subsection, I discuss how data were gathered, emphasizing efficiency, confidentiality, and accessibility. Finally, I describe the statistical methods, assumption testing, and procedures to ensure the reliability and validity of the findings in the data analysis and study validity sections.

Purpose Statement

The specific business problem is that some managers in the financial services industry lack an understanding of the relationship between non-technical staff's perception of artificial intelligence (AI) usefulness, their perception of AI ease of use, and the adoption of AI. Therefore, the purpose of this quantitative correlational study was to examine the relationship between the independent variables (a) employees' perceptions of AI usefulness and (b) perceptions of AI ease of use, and the dependent variable of AI adoption by non-technical staff in the financial services industry.

Role of the Researcher

The role of the researcher in business-focused doctoral studies is to study business phenomena by collecting data, ensuring objectivity, and organizing, analyzing, and interpreting results with rigor and integrity (Saunders et al., 2019; Creswell & Creswell, 2018). As outlined in Saunders et al. (2019), rigor and integrity include reducing bias, including methodological soundness, using correct instruments, having honest reporting, and ensuring the study measures what it claims to measure. Additionally, it is the responsibility of the researcher to adhere to any ethical guidelines; adherence includes following guidelines determined through governing organizations, such as IRB, and following the ethical principles and guidelines outlined in the Belmont Report (U.S. Department of Health, Education, and Welfare, 1979). The Belmont Report remains the foundational document for ethical guidelines in research involving human subjects in the United States, which makes it appropriate for this study.

As an analyst in the financial services industry, I may have had past contact with participants in my study due to the extended length of time I have worked in the industry. In fact, I leveraged my financial services industry network in order to find additional participants, leveraging a snowball sampling in order to achieve an adequate sampling size. As a result, there is an increased risk of biased responses from participants that I may have crossed paths with in the past. To mitigate the risk, an introductory letter that clearly states participation is voluntary and anonymous was disseminated, along with contact information for Walden University.

Participants

The participants for this study were employees working in non-technical roles within financial institutions. These individuals were not directly involved in the development, implementation, or maintenance of artificial intelligence systems but are end-users or decision-makers who may engage with AI tools in their daily tasks. The participants' characteristics aligned with the study's focus on understanding how non-technical staff perceive the ease of use and usefulness of AI. Since these employees may have had less technical knowledge of AI systems, their perceptions of AI ease of use and usefulness are distinct from their technical counterparts, providing valuable insight into factors that influence adoption.

To gain access to participants, I leveraged my professional LinkedIn network to identify potential candidates who fit the eligibility criteria and were active in the financial services sector; I also encouraged my network to share the link with others in similar non-technical roles within financial institutions, supplementing my convenience sampling with a snowball technique. The use of snowball and self-selection sampling is supported by the work of Saunders et al. (2019), who highlight these methods as efficient for accessing hard-to-reach populations. The survey was created in SurveyMonkey® and was based on the validated TAM survey developed by Davis (1989), with modifications to tailor the questions to AI adoption. The survey used a Likert scale to measure participants' perceptions of AI ease of use, usefulness, and overall adoption.

To build trust with participants, confidentiality and anonymity were emphasized throughout the recruitment process. Clear communication regarding the study's goals, the voluntary nature of participation, and the anonymity of responses was provided through informed consent forms. Regular follow-ups via LinkedIn or email ensured that participants felt engaged and valued. Open lines of communication were maintained, allowing participants to ask questions or seek clarification on any part of the process.

Research Method and Design

In this section, I provide an overview of the research method and design chosen for this study, explaining the rationale behind selecting a quantitative methodology and a correlational analysis design using multiple linear regression. It outlines how these choices align with the research questions, the theoretical framework, and the nature of the data to be collected. By grounding these decisions in academic literature and methodological principles, I established a solid foundation for the study to examine AI adoption through the constructs of TAM.

Research Method

In the nature of the study section, I identified a quantitative methodology as the most appropriate for this study because the research questions are related to the correlation between variables in TAM as it relates to AI. Based on the definitions of quantitative and qualitative research found in Saunders et al. (2019), and due to their explanation of when to use each methodology, the quantitative approach was chosen over the qualitative approach. In addition to these definitions and explanations, the decision to use a quantitative approach is supported by numerous academic writings, several of which are found later in this section. In examining the decision criteria more closely, academic research supports my decision for a quantitative methodology specifically due to the questions asked, the types of variables, the relationship between the variables, and the philosophical foundations of my research topic.

First, the research questions dictate which methodology to choose, and the chosen methodology must be matched to the research questions and justified to better defend the process and outcomes that result from the research (Jackson, 2013). Jackson supported the idea that questions drive the choice for methodology, with the examination of relationships and correlations again being the key determinant of the methodology. It is important to note, however, that researchers using quantitative approaches are not the only ones able to research relationships. As pointed out in Walker (1997), researchers conducting qualitative phenomenography also examine relationships. In that case, however, the relationships are between people and their experiences, which is more interpretive. As the relationship I examined was between variables and not from a subjective perspective, the qualitative methodologies he described were not as appropriate, and a quantitative approach was more appropriate based on the research questions relating to the relationship between variables.

Near the same time that Davis was releasing TAM, the theory used in this study, Galliers and Land (1987) contributed to ongoing academic discussions related to which methodology was most appropriate for information systems (IS); they stated that 85% of studies at that time followed the traditional empirical methodologies, which supports the use of a qualitative methodology for this study. However, they stated that IS research was frequently just as focused on the human interaction of information systems and that the topic examined and the philosophical underpinnings should be taken into consideration (Galliers & Land, 1987). Jackson (2013) added that ontological and epistemological positions also play a role in the decision on methodology. Since my study assumed that an objective reality can be measured (an individual’s perceptions of ease of use and usefulness of a technology), a quantitative study remained appropriate.

Research Design

In the nature of the study section, I identified a correlational analysis design through multiple linear regression because it was the most appropriate design based on the purpose of my research, which examined the relationship between constructs of a theoretical framework as it related to AI adoption. A correlational design is appropriate for this study because it allows for the exploration of relationships between variables without manipulating them, and is ideal for examining constructs in natural, real-world settings (Creswell & Creswell, 2018).

Multiple linear regression was chosen because it is the most effective design when seeking to understand the correlations between constructs where there are multiple independent variables and a dependent variable, when those variables are observed in real-world settings, and when the data types match what I received through my intended Likert scales (Green & Saulkind, 2017; Saunders et al., 2019). Given these characteristics, a correlational research design using multiple linear regression was not only aligned with the purpose of this study but is also validated by its frequent use in similar studies involving TAM constructs and Likert-scale data; for example, Shresth (2020) discussed the appropriateness of multiple regression analysis in examining relationships between multiple predictors and an outcome variable in real-world settings in an article addressing the challenges and techniques of overcoming the challenges of multicollinearity. Even though it is considered a challenge, multicollinearity was less of a concern for my study, as Davis (1989) found the constructs to be without levels of concern. Furthermore, Variyath and Brobbey (2020) demonstrated the application of multiple regression models in analyzing relationships, specifically in observational studies, which further aligned that technique with my study.

Although the specific statistical technique I used is multiple linear regression, I considered other correlational techniques, such as Pearson's product-moment correlation; however, I found multiple linear regression best suited to this study. In using Pearson's, it would be possible to run a series of simple regressions or correlations on this data, but it would not provide as strong of a prediction or correlation; this is because instead of yielding just one prediction on a series of predictors, it would yield multiple predictions, with none of them being as strong; through multiple regression, my model predicted the outcome of AI adoption to include any interactions or combined effects of the independent variables.

Population and Sampling

The population for this study consisted of non-technical employees working in financial institutions across a range of departments, such as customer service, finance, and operations. These employees may use AI systems as part of their regular tasks, but are not involved in the technical aspects of AI development or deployment. The focus on non-technical staff aligns with the study's goal of understanding AI adoption from the perspective of end-users who may use AI but do not possess the technical expertise related to AI's inner workings. Furthermore, the population was directly aligned with the research question, which sought to understand the factors influencing AI adoption among non-technical staff in financial institutions. These employees' perceptions of AI's ease of use and usefulness are important in determining adoption rates, particularly given their less specialized knowledge of the underlying AI algorithms.

Financial institutions constitute a large amount of business across the globe, and as such, there is a naturally wide variety of characteristics across the whole population. In order to reach an acceptable sample size, I primarily employed convenience sampling, leveraged my LinkedIn network, and used snowball and self-selection techniques to reach employees outside my network when possible. Convenience sampling, which Saunders et al. (2019) described as the selection of cases that are most available, is both cost-efficient and time-efficient, making it ideal for doctoral studies and dissertations (Saunders et al., 2019). Convenience sampling is more frequently used in quantitative studies and is useful when more robust sampling methods like random sampling are impractical (Lee-Jen et al., 2014). As I asked for my network to extend the reach of my survey by commenting on my survey post, there are elements of the snowball technique, where participants help connect the questionnaire to other participants, and self-selection sampling, as the participants had to choose to participate when they saw the survey post (Saunders et al., 2019).

While convenience sampling is efficient, a potential limitation was that the sample may not fully represent the broader population of non-technical employees. However, the combination of snowball sampling and a diverse LinkedIn network helped mitigate this risk by reaching participants across different regions and financial institutions. The use of convenience sampling was justified by the need for quick and easy access to participants, as supported by the work of Saunders et al. (2019), while the application of snowball sampling helps expand the sample reach. Furthermore, the decision to adapt the TAM survey as the basis for AI-related questions was consistent with prior studies on technology adoption (Davis, 1989).

Due to the variables of my study all being constructs of a theory that has undergone a large variety of testing, there is likely a large effect size; however, to be conservative, I chose a medium effect size ($f^2 = 0.15$). I used a common significance test of 0.05, a common target power of 0.80, and had two independent variables; using G*Power (version 3.1.9.7), I calculated a needed sample size of 68 participants. A power of 0.80 is a standard target for power in many fields, including social sciences. If I adjusted my target to 0.95, I would reduce my type II errors but increase the number of participants I needed to 107.

Ethical Research

Ensuring the ethical protection of participants was a critical aspect of this and any research. The research execution and procedures were designed to comply with the ethical standards set forth by Walden University's Institutional Review Board (IRB). The proposal for this study included a copy of the informed consent form, which was removed for the final stage of this study. Participants were fully informed of their rights and the nature of the study through an informed consent process. The consent form outlined the purpose of the study, the voluntary nature of participation, and the right of participants to withdraw at any time without any consequences. Prior to commencing the study, I obtained IRB approval; the IRB approval number for this study is 05-16-25-1197479.

Participants were not offered any incentives to participate in the study, ensuring that their involvement was entirely voluntary. If participants chose to withdraw, clear procedures were in place to ensure their data would be excluded from further analysis, and they would not be pressured to remain in the study. An email, notification through LinkedIn, or communication through any other platform used to disseminate the survey from a participant on their desire to withdraw would have been considered an official request and would have begun the withdrawal procedures. To safeguard the ethical protection of participants, all data collected is stored in a secure location, ensuring confidentiality. The data will be retained for five years, after which it will be securely destroyed. Any withdrawn participant who had provided data would have that data segregated from the rest of the data. During the study and in this final report, no names or other identifying information of individuals or organizations were included, ensuring the privacy and anonymity of participants. Additionally, all agreement documents related to participant involvement, confidentiality, and withdrawal were listed in the text of the study, the appendices, and the Table of Contents.

Data Collection Instruments

In this quantitative study, I adopted the TAM survey instrument designed and used by Davis (1989) with slight modifications by adding a question related to the dependent variable. I chose to include all the questions from the finished and validated study of Davis (1989) and chose only to add a question because of the importance of measuring the dependent variable. I also replaced the placeholder technology with artificial intelligence to make it relevant to my study. This made the final survey used in my study consistent with other studies frequently referenced in TAM-specific literature (Davis, 1989; Venkatesh et al., 2003). Appendix A contains the survey distributed through LinkedIn called Attitudes Toward AI in the Workplace.

Purpose of the Instrument

The TAM survey was developed to measure the constructs of PU and PEOU, which are central to TAM, and the independent variables in my study. Also in my study, the instrument included items designed to measure the dependent variable, AI adoption. The survey assessed participants' perceptions of AI and how those perceptions influence their willingness to adopt AI in their work environment. This instrument was appropriate for the intended population, non-technical staff in the financial services industry. A sample of these individuals was ideal for this study because they represent the target population whose perceptions of AI adoption are being explored.

Scales and Scoring Process

The TAM survey entailed a 7-point Likert scale that ranged from 1 = "Strongly Disagree" to 7 = "Strongly Agree." Each question was scored individually, and composite scores were calculated for each construct (PU, PEOU, and AI adoption). Higher scores indicated stronger agreement or more positive perceptions of the measured construct. The scoring process involved computing mean scores for each construct based on participants' responses. For example, I included a mean PU construct score to represent the responses to all PU-related items. This approach ensured consistency with previous research utilizing the TAM survey.

Time to Complete

The survey was designed to be completed within 10 to 15 minutes and contained 15 items, including the additional question on AI adoption, as well as instructions on withdrawing and ethics information described in the Ethics section. This time frame included reviewing those instructions, while remaining brief enough to minimize participant fatigue while allowing for comprehensive data collection.

Psychometric Properties

The TAM instrument has demonstrated high reliability in prior studies. Davis (1989) reported Cronbach's alpha coefficients of 0.97 for perceived usefulness and 0.94 for perceived ease of use, indicating excellent internal consistency. Similarly, Venkatesh and Bala (2008) confirmed the reliability of the TAM instrument across various contexts, with Cronbach's alpha values consistently exceeding the acceptable threshold of 0.70.

For this study, reliability was reassessed using Cronbach's alpha, calculated with the study's data. This ensured that the instrument was reliable for the specific sample of non-technical staff in the financial services industry. Content validity was assumed through the expert review process during the base instrument's development by Davis (1989). Items were carefully constructed to capture the theoretical constructs of PU and PEOU. Criterion-related validity was demonstrated by significant correlations between TAM constructs and actual technology usage in previous studies (Davis, 1989; Venkatesh & Davis, 2000). Finally, construct validity was confirmed in past usage through factor analysis, which consistently identifies PU and PEOU as distinct but correlated factors (Venkatesh et al., 2003). Intercorrelation coefficients for these constructs typically range between 0.50 and 0.70, supporting their validity as separate but related dimensions. Davis (1989) was able to rule out multicollinearity.

Data Collection Technique

For this study, data was collected using an online survey distributed via LinkedIn and hosted on SurveyMonkey. After IRB approval, the survey link was shared through professional connections on LinkedIn and targeted non-technical staff within the financial services industry. LinkedIn was chosen for its professional network reach, allowing the survey to efficiently target the desired population and reach the needed sample size. The survey was available for four weeks, and no reminders were necessary to reach the needed sample size; had the needed sample size remained unreached after four weeks, a plan was in place to spend a few weeks expanding the LinkedIn network before the survey would have been posted for a second period of time, but that additional effort was not necessary. Using SurveyMonkey enabled data security, easy export to SPSS, and anonymity.

There were several advantages and disadvantages to this collection technique, with the advantages outweighing the disadvantages and making this approach appropriate for this study. From the advantages perspective, because LinkedIn is both professional and an online community, it created a broad reach and allowed access to a large professional population (Wright, 2005). It provided convenience and flexibility to the respondents who could complete the survey at their convenience; this was important to achieve higher response rates since no compensation for participation was offered. This method was also cost-effective, with LinkedIn being free and the survey portion containing minimal cost and maximum automation (Ward et al., 2014). According to Saunders et al. (2019), online surveys are particularly useful for reaching a geographically dispersed audience and allow for efficient data collection with lower costs compared to traditional methods. From a disadvantage perspective, the self-selection aspect of voluntary participation created a risk for self-selection bias, and potentially, only highly motivated individuals would respond. Additionally, respondents were unable to ask questions that might arise while taking the survey, and respondents without internet access were not able to participate at all.

Although pilot studies can be beneficial in refining survey questions, they were not used in this study for several reasons. First, SurveyMonkey contains tools for reviewing and testing the survey to identify technical issues prior to distribution. Next, from a non-technical perspective, the survey questions were based on a preestablished and validated survey, increasing the likelihood that comprehension and relevance were not issues. Finally, AI and the TAM constructs of usefulness and ease of use are widely understood. As a result, the added time to conduct a pilot study would have created more cost than benefit towards achieving the final results.

Data Analysis

In this section, I describe the statistical methods, data management procedures, assumptions, and software that were used to analyze the data collected for this study. The data analysis process was designed to ensure that each research question was addressed appropriately, using statistical techniques suited to the data type and study design. The reasoning for test selection, inferential statistic processes, and assumption handling (each covered below) was taken from Green and Salkind (2017). My goal was to provide a clear and transparent process for analyzing data in a way that accurately reflects the relationships between the variables of PU, PEOU, and adoption and is aligned with the study's objectives and purpose.

The following research questions and hypotheses guided the selected statistical test selection and resulting analyses:

Research Question

RQ: What is the relationship between an employee's perception of the ease of use (PEOU) in artificial intelligence (AI), perception of usefulness (PU) in AI, and AI adoption within non-technical staff?

Null Hypothesis

H_0: There is not a statistically significant relationship between PEOU, PU, and AI adoption in non-technical staff.

Alternative Hypothesis

H_a: A statistically significant correlation exists between PEOU, PU, and AI adoption in non-technical staff.

A multiple linear regression analysis was conducted to address the research questions. This method was appropriate because researchers use it to examine the relationships between multiple independent variables (PEOU and PU) and the dependent variable (AI adoption) while controlling for other potential variables. Regression analysis was also appropriate given the continuous (interval scale) nature of the variables resulting from using Likert scales in my survey, which was consistent with other research using TAM. Multiple linear regression also enabled simultaneous analysis of the variables, which was more appropriate than other correlational analyses that only compare two variables at once, such as a T-test. It was also more appropriate than an ANOVA test because of the continuous nature of the variables. Finally, chi-square tests would have been less appropriate because the variables were not categorical.

The multiple linear regression was conducted using SPSS, which is a standard software package frequently used for this type of analysis. The regression coefficients for PU and PEOU were interpreted to assess the strength and direction of their relationship with AI adoption. Effect size was calculated to measure the magnitude of relationships, and confidence intervals for regression coefficients were reported to demonstrate the precision of the estimates. All p-values used a threshold of .05 for the hypothesis testing.

Due to the automated nature of using SurveyMonkey, I anticipated that a low amount of data cleaning would be necessary. All data entries were reviewed for accuracy and consistency, and incomplete surveys were discarded. Although I tested for outliers using boxplots and z-scores due to their usefulness in analysis, no changes were made to the data, as Likert scales represent the true opinions and perceptions of respondents.

All usual assumption tests for multiple linear regression were conducted, including linearity, independence, homoscedasticity, and normality. Scatterplots were used to assist in testing for linearity. Independence was tested, and no issue was expected since each response represents an individual's perception. I would have conducted data transformations had any residual plots indicated a failure of the homoscedasticity assumption. Finally, normality was tested with a histogram and probability plots.

Study Validity

As per the Walden University quantitative doctoral capstone handbook, studies that are observational, such as correlational designs, do not include a relevance from internal validity. As a result, the eight threats to internal validity, selection, selection by maturation, statistical regression, morality, maturation, history, testing, and instrumentation were not further evaluated. However, threats to statistical conclusion validity were a concern, and threats that inflated Type I error rates (a rejecting of the null hypothesis when it is true) and Type II error rates (accepting the null hypothesis when it is false) are covered next.

Reliability of the Instrument

One threat to reliability is that the instrument may not perform consistently across different populations, which could introduce measurement errors (Bougie & Sekaran, 2019). I built my survey using the technology acceptance model survey (TAMS) as the foundation, and TAMS has been previously validated and demonstrated acceptable reliability in prior studies, with a Cronbach's alpha coefficient of .98 for PU and .94 for PEOU (Davis, 1989; Venkatesh & Bala, 2008). For this specific study, reliability was assessed by also calculating Cronbach's alpha for the collected data using SPSS. An acceptable threshold for internal consistency is $\alpha \geq 0.70$. The results of this reliability analysis are presented in Section 3, "Presentation of Findings." This analysis compared the reported reliability coefficient with the calculated coefficient to ensure consistency.

Data Assumptions

Statistical tests are based on assumptions that, if violated, can compromise the validity of the results. Green and Salkind (2017) laid out the assumptions for multiple linear regression, which include:

- Normality: The residuals of the regression model should be approximately normally distributed. The distribution of residuals will be assessed using a Shapiro-Wilk test and Q-Q plots.
- Linearity: The relationship between the independent variables and the dependent variable is linear. Scatterplots of predictor variables versus the dependent variable will be used to verify linearity.

- Homoscedasticity: The residuals have constant variance across all levels of the independent variables. An initial review of residuals vs. fitted values plot will be used to evaluate homoscedasticity, and if the variance does not appear constant, Levene's test or Breusch-Pagan test will evaluate the equality of variances.
- Multicollinearity: The independent variables are not highly correlated with one another. Variance Inflation Factors (VIF) will be used, with VIF > 10 indicating problematic multicollinearity.

A violation of the normality assumption, for example, can lead to biased estimates and reduced statistical power (Bougie & Sekaran, 2019; Green & Salkind, 2017). Necessary adjustments or alternative statistical methods would have been applied if any assumptions were violated to a point where the study was no longer considered valid. It was expected that assumptions related to the specific constructs would not be violated, as a multitude of academic literature has used TAM in multiple linear regression in the past.

Sample Size

Sample size affects the statistical power of the study, which is the ability to detect true relationships between variables. Due to the variables of my study all being constructs of a theory that has undergone a large variety of testing, there is likely a large effect size; however, to be conservative, I chose a medium effect size ($f^2 = 0.15$). I used a common significance test of 0.05, a common target power of 0.80, and had two independent variables; using G*Power (version 3.1.9.7), I calculated a needed sample size of 68 participants. A power of 0.80 is a standard target for power in many fields, including social sciences. If I adjusted my target to 0.95, I would reduce my type II errors but increase the number of participants I needed to 107. Using an inadequate sample size would have threatened the study's statistical power, increasing the likelihood of failing to detect a significant relationship when one exists (Cohen, 1992). Recruiting an adequate sample size mitigated the risk of Type II errors, ensuring sufficient power to detect significant effects.

Transition and Summary

In this section, I outlined the components of this study, including the purpose statement, the role of the researcher, participant selection and sampling strategies, the research method and design, the data collection instruments and techniques, and the planned data analysis methods. These elements collectively established the foundation for examining the relationships between non-technical staff's perceptions of AI usefulness, PU, ease of use, PEOU, and AI adoption in the financial services industry. Ethical considerations and strategies for ensuring the validity and reliability of the findings were also addressed, demonstrating a commitment to rigor and integrity throughout the research process.

In the following section, I shift the focus to presenting the findings of the study, including the results of the data analysis and their alignment with the research questions and hypotheses. In this section, I also explore the practical applications of the findings for professional practice, discuss their implications for social change, and provide actionable recommendations for industry professionals and future researchers. Also included are reflections on the research process and a concluding summary.

Section 3: Application to Professional Practice and Implications for Change

Introduction

The purpose of this quantitative correlational study was to examine the relationship between the independent variables (a) employees' perceptions of AI usefulness and (b) perceptions of AI ease of use, and the dependent variable of AI adoption by non-technical staff in the financial services industry. As a result, the primary goal was to determine whether the independent variables of PU and PEOU were determinants of the decision by non-technical employees in the financial service industry to adopt AI. Previous research using TAM has frequently demonstrated that PU and PEOU are associated with technology adoption, providing a theoretical basis for examining these relationships in the context of AI.

The null hypothesis in this study was rejected because the results confirmed the positive relationship between PU and PEOU with the dependent variable of AI Adoption for the studied population, non-technical staff in the financial services industry. Furthermore, PU was the stronger predictor of adoption, which was the result most commonly found in the literature review. The statistical analysis indicated that both predictors accounted for a substantial proportion of the variance in AI adoption, highlighting the continued relevance of TAM in explaining adoption behaviors in emerging technologies, and specifically in AI adoption. Overall, the model explained 54.4% of the variance in AI adoption, indicating a strong predictive relationship and providing actionable insight for practitioners seeking to improve AI integration among non-technical staff in the financial services industry.

Presentation of the Findings

In this section, I will present descriptive statistics, discuss testing of the assumptions, present inferential statistics results, address implications of my research, and conclude with a concise summary. I used multiple regression analysis to test the hypothesis in this study. The independent variables were PU and PEOU, and the dependent variable was the intent to adopt AI. As I had two independent variables as determinants for my one dependent variable, multiple linear regression was appropriate; using this technique, I was able to establish the linear relationship between these independent variables and the dependent variable, and was able to reject the null hypothesis.

Descriptive Statistics

A total of 81 respondents participated in the study. Participants responded to a survey using a 7-point Likert scale ranging from 1 (Strongly Disagree) to 7 (Strongly Agree); higher mean values indicate stronger agreement with the measured construct. A summary of the resulting descriptive statistics can be found in Table 1. The descriptive statistics indicate that participants, on average, perceived AI systems as both useful (M = 5.78, SD = 1.08) and easy to use (M = 5.43, SD = 1.15). The mean score for AI Adoption (M = 5.75, SD = 1.48) suggests a favorable inclination towards adopting AI within the sample. Thus, the values reflect a perception of the technology’s utility and usability, as reflected by the values in PEOU and PU, respectively. These statistics are consistent with patterns found in the literature review for adoption behaviors within the financial services industry.

Table 1

Descriptive Statistics Regression

Construct	Mean	Std. deviation	N
PU(MEAN)	5.7835	1.0774	81
PEOU(MEAN)	5.4280	1.1508	81
Intent to Adopt	5.7531	1.4793	81

Note. N represents the total number of responses per variable. Due to missing data, only 80 valid cases were included in the regression analysis.

Correlation Matrix and Interpretation

Pearson correlation analysis showed statistically significant positive relationships among all the variables in the study. Table 2 depicts the relationships between these variables. The correlation between PU and AI adoption was strong ($r = .707$, $p < .001$), indicating that higher perceptions of usefulness are associated with a greater likelihood of AI adoption. Similarly, the correlation between PEOU and AI Adoption was also fairly strong ($r = .621$, $p < .001$), suggesting that ease of use is also important to AI Adoption.

The correlation between PU and PEOU was also moderate to strong ($r = .655$, $p < .001$), reflecting a positive relationship between the independent variables; this relationship is consistent with TAM, which posits that these constructs are interrelated. These correlation coefficients demonstrate adequate inter-variable relationships for regression analysis while avoiding multicollinearity concerns, as none of the coefficients approach the threshold of $r > .80$ that might indicate redundancy.

Table 2

Correlation Matrix

	PU(MEAN)	PEOU(MEAN)	AI Adoption
PU(MEAN)	1.000	.655**	.707**
PEOU(MEAN)	.655**	1.000	.621**
AI Adoption	.707**	.621**	1.000

Note. ** Correlation is significant at the 0.01 level (2-tailed).

Linearity and Residual Normality Assumptions Assessment

I assessed linearity by visually inspecting scatterplots for each independent variable plotted against the dependent variable, AI Adoption. The scatterplot for PU is in Figure 1, and indicates a positive linear relationship, with higher PU scores associated with higher AI Adoption scores and no substantial curvature. The scatterplot for PEOU is in Figure 2, and also shows a positive linear relationship, though the pattern was slightly less tightly clustered than for PU, still without signs of non-linearity. Additionally, an examination of a related matrix to evaluate bivariate relationships between each of the variables further showed the presence of linear associations appropriate for regression analysis.

I assessed normality of residuals through visual inspection of a histogram, found in Figure 3, and normal probability plot (P-Plot) of the standardized residuals. The histogram displayed an approximately normal distribution centered near zero, with most residuals falling between -2 and +2 standard deviations; the P-P plot showed points near the diagonal line, showing that residuals met the assumption of normality. No significant deviations from normality were observed.

Figure 1

Scatterplot of AI Adoption by PU

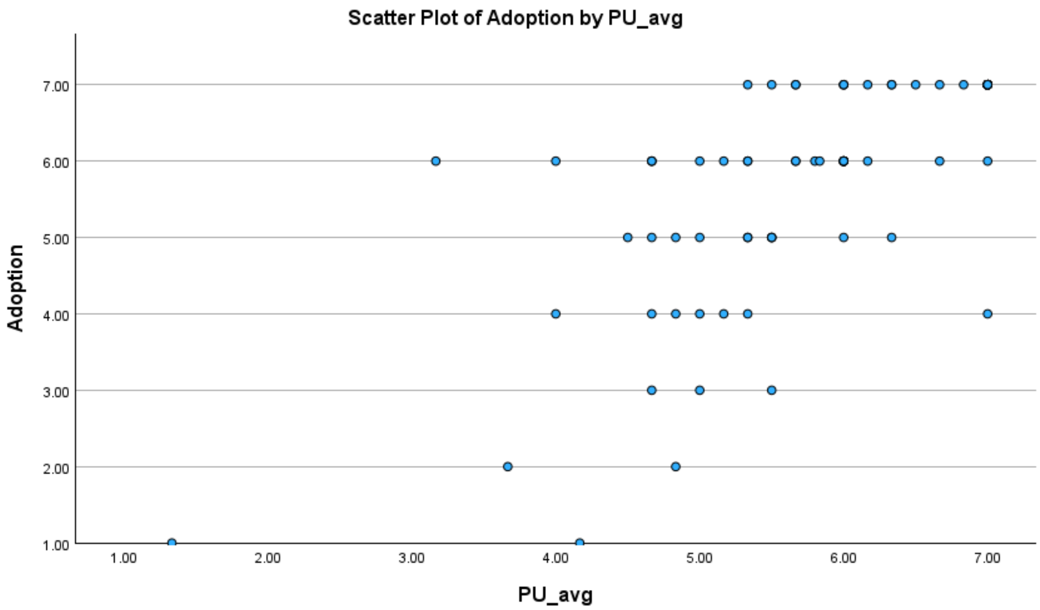


Figure 2

Scatterplot of AI Adoption by PEOU

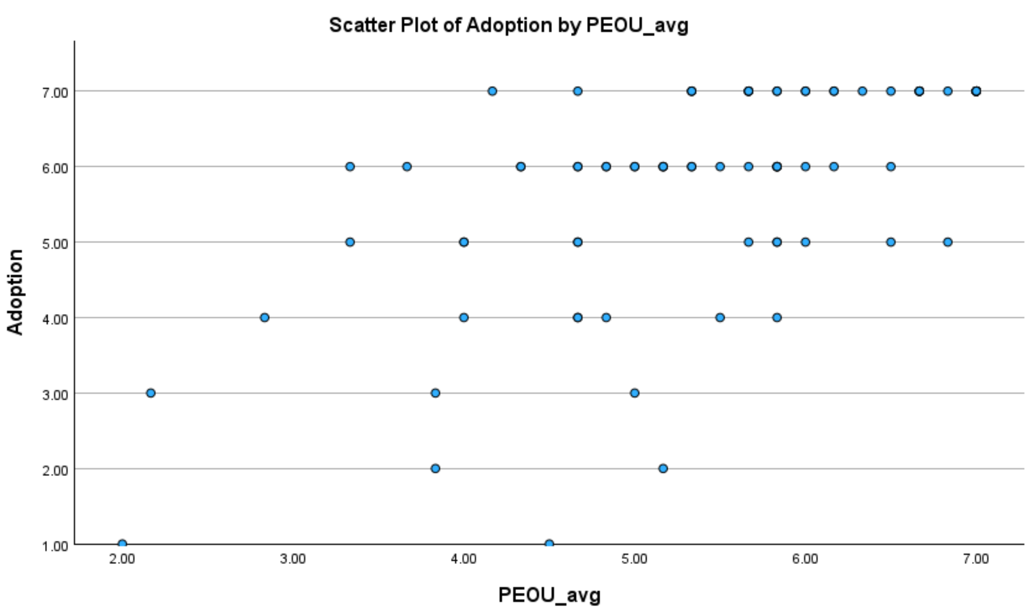
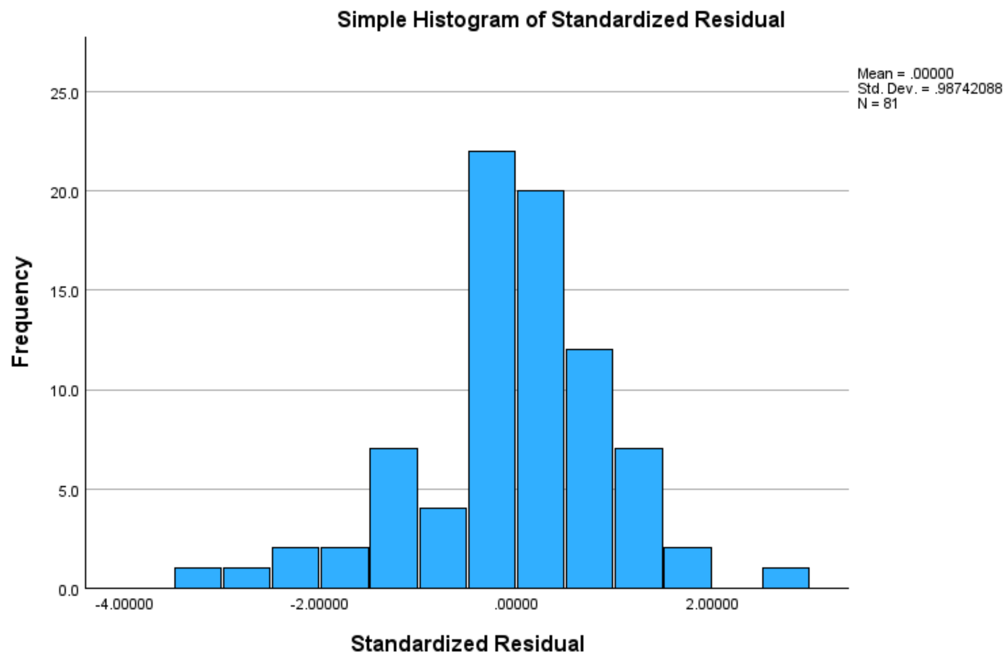


Figure 3

Histogram of Standardized Residuals



Reliability Statistics

Reliability analysis showed high internal consistency for both measurement scales, which can be found summarized in Table 3. The PU construct yielded a Cronbach's Alpha of 0.955, demonstrating a very high level of internal consistency among its six items. Similarly, the PEOU scale produced a Cronbach's Alpha of 0.941, demonstrating that the questions within this construct consistently measure the intended concept. The values for each item making up the constructs can be found in Table 4.

These values exceed the commonly accepted threshold of 0.70 for acceptable reliability; these coefficients exceed 0.90, demonstrating excellent reliability. The high alpha values suggest that the survey items within each construct are highly correlated and measure a cohesive underlying concept, which is not surprising since they were taken directly from the original instrument. This high reliability shows that the survey questions worked well together, which means the average scores I used in the regression are dependable and not distorted by inconsistent responses. I also created composite variables by averaging the individual items for each construct. This practice is consistent with prior TAM research and ensures that each composite reflects the intended latent variable while minimizing measurement error. The AI Adoption variable was measured using a single Likert-scale item, and therefore, no reliability analysis was necessary.

Table 3

Reliability Statistics Summary

Construct	Cronbach's Alpha	N
PU	0.955	6
PEOU	0.941	6

Table 4

Cronbach's Alpha Item-Total Statistics

Variable and Question	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
PUQ1	28.7089	29.183	.849	.948
PUQ2	28.9367	29.675	.869	.946
PUQ3	28.7848	29.735	.894	.943
PUQ4	29.0633	28.778	.856	.948
PUQ5	28.9114	29.031	.855	.948
PUQ6	28.6329	30.851	.852	.948
PEOUQ1	26.9500	33.846	.788	.934
PEOUQ2	27.4500	32.175	.808	.932
PEOUQ3	27.1000	32.294	.863	.924
PEOUQ4	27.1625	34.011	.744	.939
PEOUQ5	26.6875	33.711	.857	.926
PEOUQ6	26.9000	32.699	.881	.922

Validity Justification

As I used established constructs from TAM and a previously validated survey for the questions for PU and PEOU, exploratory and confirmatory factor analysis were not necessary. Instead, reliability was assessed using Cronbach's Alpha to confirm the internal consistency of the constructs in this study and is outlined in the reliability section. Additionally, I did not include Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy or Bartlett's Test of Sphericity because the study focused on regression analysis and not exploratory factor validation. The high Cronbach's Alpha values for PU (0.955) and PEOU (0.941) provide enough evidence of measurement reliability. As a result, no further factor structure testing was conducted.

Model Summary for AI Adoption Regression

A multiple regression analysis was conducted to evaluate how well PU and PEOU predicted AI adoption. The model summary results found in Table 5 show that the model was statistically significant, $R^2 = .544$, $F(2,78) = 46.469$, $p < 0.001$. The R^2_{adj} is .532, meaning this model explains 53.2% of the variance in intention to adopt AI after adjusting for the number of predictors. The ANOVA results presented in Table 6 confirm the statistical significance of the regression model.

Both independent variables were statistically significant predictors, with PU ($B = 0.723$, $p < .001$) and PEOU ($B = 0.355$, $p = .008$) contributing to the model. Among these, PU demonstrated a stronger influence on AI adoption, as indicated by its higher standardized coefficient ($\beta = .526$) compared to PEOU ($\beta = .276$).

Table 5

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	F	Sig. F
1	0.737	0.544	0.532	1.012	46.469	<.001

Note. Dependent Variable: AI Adoption.

Table 6

ANOVA Table for AI Adoption Regression

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	95.180	2	47.590	46.469	<.001
Residual	79.881	78	1.024		
Total	175.062	80			

Note. Dependent Variable: AI Adoption.

Coefficients and Collinearity Diagnostics

The regression coefficients, presented in Table 7, showed that both PU and PEOU significantly predict AI Adoption. PU had a standardized beta coefficient of 0.526 ($t = 5.200$, $p < .001$), demonstrating a strong and statistically significant positive influence on AI Adoption. PEOU also exhibited a statistically significant effect with a beta coefficient of 0.276 ($t = 2.727$, $p = .008$), though it had a smaller magnitude compared to PU. The higher standardized coefficient of PU ($\beta = .526$) compared to PEOU ($\beta = .276$) suggests that PU had nearly double the influence on adoption intentions for this sample.

Collinearity diagnostics, also shown in Table 7, revealed Tolerance values of 0.571 and corresponding Variance Inflation Factor (VIF) values of 1.752 for both PU and PEOU. These statistics fall within the acceptable thresholds (Tolerance > 0.2 and VIF <

5), indicating that multicollinearity is not a concern in the model. The predictors maintain sufficient independence, ensuring stable and reliable coefficient estimates.

Table 7

Coefficients and Collinearity Diagnostics

Predictor	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
(Constant)	-0.353	0.643	-	-0.549	0.584	-	-
PU	0.723	0.139	0.526	5.200	<.001	0.571	1.752
PEOU	0.355	0.130	0.276	2.727	0.008	0.571	1.752

Note. Collinearity statistics indicate acceptable levels of multicollinearity, as tolerance values are above 0.2 and VIF values are below 5.

Final Predictive Equation

The final regression equation derived from the analysis is as follows:

AI Adoption = -0.353 + 0.723*(PU) + 0.355*(PEOU)

This equation indicates that for each one-unit increase in PU, AI Adoption increases by 0.723 units, holding PEOU constant. Similarly, a one-unit increase in PEOU results in a 0.355 unit increase in AI Adoption, holding PU constant. Based on these results, I reject the null hypothesis and confirm that both PU and PEOU significantly predict AI adoption intentions among non-technical staff in the financial services industry.

Discussion

I conducted a multiple linear regression analysis to examine the influence of PU and PEOU on AI Adoption among non-technical staff in the financial services industry. The overall regression model was statistically significant, $F(2, 78) = 46.47$, $p < .001$, indicating that the model explains a significant proportion of variance in AI Adoption. The model accounted for approximately 54.4% of the variance ($R^2 = .544$), with an adjusted R^2 of .532, demonstrating a strong explanatory power.

PU emerged as the stronger predictor ($\beta = .526$, $t = 5.20$, $p < .001$), indicating that higher perceptions of usefulness significantly increase AI Adoption. PEOU was also a significant predictor ($\beta = .276$, $t = 2.73$, $p = .008$), suggesting that ease of use, while having a lesser effect compared to usefulness, still contributes positively to adoption levels.

The unstandardized regression equation derived from the analysis is:

AI Adoption = -0.353 + 0.723*(Perceived Usefulness) + 0.355*(Perceived Ease of Use)

These results align with the TAM framework, reinforcing the importance of both PU and PEOU in influencing adoption behaviors. The stronger effect of usefulness implies that employees are more likely to adopt AI technologies if they perceive a direct benefit to their work performance. PEOU still remains an important factor, potentially enhancing adoption by reducing learning barriers and facilitating smoother integration into existing workflows. These findings support a strategic focus on demonstrating practical benefits of AI applications while ensuring user-friendly interfaces to maximize adoption rates among non-technical staff.

The findings of this study corroborate existing literature on TAM, particularly emphasizing the dominant role of perceived usefulness in driving AI adoption (Davis, 1989; Venkatesh & Davis, 2000). The significant beta coefficient for PU shows its predictive strength, aligning with research suggesting that employees are more inclined to embrace AI technologies when they perceive clear improvements in task performance or efficiency for productivity gains (Aishwarya et al., 2023).

Similarly, PEOU was also a statistically significant factor, though with a smaller standardized beta. This result aligns with prior studies indicating that while ease of use facilitates initial acceptance, its impact is secondary to usefulness in determining sustained adoption behavior (Venkatesh & Bala, 2008). This means that creating more intuitive or easier to use AI solutions, whether through minimizing complexity or enhancing user experience, is still essential for creating a positive adoption.

The high R^2 value (.544) observed in this study indicates that TAM constructs explain a substantial portion of the variance in AI Adoption among non-technical staff, which is in line with expectations based on prior TAM research frameworks (Davis, 1989; Venkatesh & Davis, 2000). These results indicate that organizations seeking to increase AI adoption should prioritize showcasing tangible benefits of AI systems in enhancing job performance, while concurrently reducing perceived barriers related to complexity. Training programs, user-friendly interfaces, and clear communication of AI’s value proposition are actionable strategies that can be derived from these findings.

Applications to Professional Practice

The findings of this study provide actionable insights for professionals responsible for implementing and managing AI initiatives in the financial services industry. By identifying PU and PEOU as significant predictors of AI adoption, my research offers guidance on where leaders should focus their efforts to maximize adoption outcomes. For managers, technology leaders, and change management practitioners, the results demonstrate the importance of aligning AI tools with employees' core work objectives and clearly communicating the productivity gains these tools can deliver. Translating these findings into practical strategies can help organizations overcome adoption barriers, accelerate the integration of AI into daily workflows, and ultimately improve operational efficiency across non-technical teams.

The finding that PU was the dominant driver in the regression model is consistent with other TAM-based studies. The influence of PU on adoption could come from a variety of reasons, such as the professional setting lending to the need for outcomes that matter more than usability. Additionally, people using AI are often attempting to accomplish tasks that could be difficult, time-consuming, or otherwise complicated, and the benefits of having a tool to accomplish the task likely outweigh the desire for the tool's use to be easy. Regardless of the reason, with PU being the dominant driver to adoption, leaders in the financial services industry should stress the ability of AI to increase productivity when attempting to garner adoption of AI tools among their staff.

The practical implications of this study are usable by managers across many business functions, such as managers in learning and training, technology leaders, and change management practitioners in the financial services industry; each of the leaders play a role explaining the usefulness of AI towards productivity, which will lead to wider adoption. The results highlight the necessity of framing AI initiatives in terms of their direct utility to employees' roles. Additionally, investments in intuitive user interfaces and comprehensive training programs can help address concerns around ease of use, particularly among non-technical personnel who may be apprehensive about adopting new technologies. Further, organizations should consider deploying targeted communication strategies that highlight success stories and practical benefits experienced by early adopters, thereby enhancing perceived usefulness organization-wide.

Implications for Social Change

The findings of this study have the potential to contribute to positive social change by leading to greater organizational efficiency, which in turn can translate into tangible benefits for individuals and communities. Increased productivity can stimulate economic growth, create new job opportunities, and potentially lead to higher wages. Improved resource efficiency through automation can also reduce waste and lower costs, freeing organizational resources for reinvestment in employee development and community initiatives. At the societal level, higher productivity and profitability can expand the tax base, enabling greater funding for public services and social programs.

This change may occur because the study's results identify clear strategies for increasing AI adoption among non-technical staff in the financial services industry, which is a group that represents a substantial portion of the workforce but is often overlooked in technology adoption research. By showing that PU and PEOU significantly influence adoption, with PU emerging as the stronger driver, the findings equip organizations to target adoption barriers more effectively. This can lead to more rapid integration of AI tools into everyday workflows, enabling non-technical employees to complete tasks with greater accuracy, speed, and adaptability. Over time, these improvements can make the workforce more resilient to evolving technologies and market demands, helping organizations maintain competitiveness while empowering employees with new capabilities.

Beyond direct economic effects, the integration of AI into broader segments of the workforce can foster innovation by encouraging the development of more advanced AI tools tailored to diverse user needs. As organizations realize greater returns from AI adoption, reinvestment in research and development can accelerate the creation of systems capable of addressing complex challenges in novel ways, including those beyond the scope of the original business use. In this way, improved AI adoption strategies not only enhance organizational performance but may also contribute to transformative solutions that promote long-term social and cultural advancement.

Recommendations for Action

The findings of this study are relevant to individuals who have roles in influencing the adoption of AI technologies among non-technical staff, and include organizational leaders, technology implementation teams, human resource managers, and change management professionals within the financial services industry. When organizational leaders are disseminating information and actions based on the findings, they could do it via internal strategic meetings and AI implementation workshops; when technology implementation teams are involved, cross-department briefings and demos of tools might be necessary, where usefulness can be shown and demonstrations make tools easier to use.

Outside of direct communication in business structures, the results could be presented in professional industry forums or published in white papers that reach decision-makers at all organizational levels across industry. In these communications, it would be important to stress the factors influencing AI adoption to equip leaders with practical strategies to drive adoption.

Based on the study findings, PU and PEOU were both significant predictors of AI adoption among non-technical staff in the financial services industry, with PU being identified as the stronger driver. Therefore, organizations aiming to enhance AI adoption among non-technical staff should stress the usefulness of AI in increasing productivity as well as make it easy to use; consider the following actionable strategies:

- Emphasize Usefulness in Communications: Highlight how AI tools directly improve employee productivity and task performance.
- Invest in User-Friendly Interfaces: Simplify AI system interfaces to minimize learning curves and reduce adoption resistance.
- Develop Comprehensive Training Programs: Provide hands-on training to boost user confidence and proficiency.
- Showcase Early Adopter Success Stories: Share case studies or testimonials demonstrating tangible benefits from peers.
- Maintain Ongoing Support Structures: Establish accessible support resources to assist employees' growth in AI capabilities post-implementation.
- Address Perceived Complexity Early: Identify and mitigate perceived barriers related to system complexity during the planning phase.
- Align AI Features with Employee Needs: Conduct user feedback sessions to ensure AI applications meet actual workflow requirements.

Recommendations for Further Research

Future research could expand upon these findings by examining the moderating and influencing effects of demographic factors such as age, tenure, or prior technology experience on AI adoption behavior. Additionally, longitudinal studies could provide deeper insights into how perceptions of usefulness and ease of use evolve over time as employees gain familiarity with AI tools. Exploring external factors such as organizational culture, leadership support, and perceived trust in AI systems could also offer a more holistic understanding of adoption dynamics beyond the scope of TAM constructs.

One of the limitations discussed in Section 1 involved the unknown biases that may be present at the individual level related to the constructs of TAM and the adoption of AI that result from the influences of external factors. These external factors are outlined in TOE and discussed in greater detail in the literature review. For example, Gupta et al. (2022) found a significant correlation between many factors related to technological and environmental influences at a company. Future research could address the level of influence the TOE factors have on individual perspectives of usefulness and ease of use.

Another notable limitation of this study is the reliance on self-reported survey data, which may be subject to response bias. Additionally, the study sample was limited to non-technical staff within the financial services industry, which may limit the generalizability of findings to other sectors or to technical users. Future research should aim to include a more diverse participant pool and consider incorporating objective usage data where feasible.

Reflections

Entering this doctoral study, my professional background as an analyst strongly shaped my approach to research. My tendency was to focus on measurable outcomes, statistical validity, and actionable insights, often emphasizing efficiency and productivity as primary goals. While I maintained these values throughout the process, I recognized the potential for personal bias in interpreting findings primarily through an operational or financial lens. As such, I appreciate the research processes shaped through the doctoral program that helped me to minimize this bias, enabling me to rely on established methodological rigor.

Through the DBA process, my perspective broadened. The program's emphasis on the social implications of research added a dimension to my thinking that was less prominent in my prior work. Considering the potential for AI adoption to impact not only organizational performance but also workforce development, job quality, and community well-being prompted me to approach analysis with a wider lens. This expanded focus led me to balance operational efficiency with broader societal outcomes.

Additionally, the extensive review of academic literature, much of which spanned disciplines beyond my core expertise, helped integrate concepts that might otherwise have remained separate in my mind. Exposure to theories, frameworks, and empirical studies in fields such as organizational behavior, change management, and technology adoption increased my ability to connect analytical findings with strategic and human-centered considerations. Ultimately, the doctoral study process strengthened my capacity to evaluate complex business problems not only as data-driven challenges but also as opportunities to create value across multiple dimensions.

Conclusion

This study examined the relationship between PU, PEOU, and AI Adoption among non-technical staff in the financial services industry using TAM as the theoretical framework. The regression analysis demonstrated that both PU and PEOU significantly influence AI adoption, with PU emerging as the stronger predictor. The model accounted for 54.4% of the variance in AI adoption, highlighting the explanatory power of TAM constructs in this context. These findings demonstrate the importance of emphasizing practical benefits and usability in AI implementation strategies.

While this study provided valuable insights into the adoption behaviors of non-technical staff, future research should explore additional factors such as organizational culture, trust in AI, and demographic variables to gain a more comprehensive understanding of adoption dynamics. Addressing the identified limitations through broader and more diverse sampling will further strengthen the applicability of these findings across industries. A longitudinal study could help practitioners to understand if the importance of these variables are changing as the population becomes more comfortable with AI over time.

In conclusion, this study contributes to the growing body of knowledge on AI adoption by validating the relevance of TAM in a financial services context and offering actionable insights for practitioners seeking to drive successful AI integration among non-technical employees.

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Appendix: Survey for Attitudes Towards AI in the Workplace

1. Using artificial intelligence in my job would enable me to accomplish tasks more quickly.
2. Using artificial intelligence would improve my job performance.
3. Using artificial intelligence in my job would increase my productivity.
4. Using artificial intelligence would enhance my effectiveness on the job.
5. Using artificial intelligence would make it easier to do my job.
6. I would find artificial intelligence useful in my job.
7. Learning to operate artificial intelligence would be easy for me.
8. I would find it easy to get artificial intelligence to do what I want it to do.
9. My interaction with artificial intelligence would be clear and understandable.
10. I would find artificial intelligence to be flexible to interact with.
11. It would be easy for me to become skillful at using artificial intelligence.
12. I would find artificial intelligence easy to use.
13. I intend to use artificial intelligence in my current role in the future.