

Original Research Article

Artificial Intelligence and the Future of Finance: An Empirical Study of Adoption, Benefits and Challenges

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Abstract

The rapid integration of artificial intelligence (AI) into the financial sector has fundamentally transformed the way financial institutions operate, manage risk, and deliver services to customers. Despite the growing adoption of AI technologies across banking, insurance, and investment management, there remains a limited understanding of how the perceived benefits and perceived challenges of AI collectively shape the adoption behavior of finance professionals and organizations. This study addresses this gap by developing and empirically testing a conceptual model that examines the influence of perceived benefits (PB) and perceived challenges (PC) on AI adoption (AD) in the financial services industry.

Drawing on the Technology Acceptance Model (TAM), the Diffusion of Innovations (DOI) theory, and the Unified Theory of Acceptance and Use of Technology (UTAUT), this research employs a quantitative survey methodology. A structured questionnaire was administered to 100 respondents working in or associated with the financial sector. The instrument comprised 24 items distributed across three constructs: Perceived Benefits of AI (8 items, $\alpha = 0.922$), Perceived Challenges of AI (8 items, $\alpha = 0.931$), and AI Adoption in Finance (8 items, $\alpha = 0.911$). Data were analyzed using descriptive statistics, Pearson correlation analysis, and multiple linear regression.

The results of the multiple linear regression analysis revealed that the model explained 38.9% of the variance in AI adoption ($R^2 = 0.389$, $F(2,97) = 30.87$, $p < .001$). Perceived benefits emerged as a strong and statistically

significant positive predictor of AI adoption ($\beta = 0.580$, $p < .001$), while perceived challenges had a statistically significant but weaker negative effect ($\beta = -0.162$, $p < .05$). The regression equation was: AI Adoption = $0.884 + 0.617(\text{PB}) - 0.162(\text{PC})$. These findings underscore that while perceived benefits are the primary driver of AI adoption, perceived challenges exert a modest inhibiting effect, suggesting that organizations can accelerate AI adoption by strategically emphasizing tangible benefits while proactively addressing recognized challenges.

Keywords: artificial intelligence, AI adoption, financial services, perceived benefits, perceived challenges, Technology Acceptance Model, multiple linear regression

1. Introduction

1.1 Background of the Study

The financial services industry has long been at the forefront of technological innovation, driven by the imperative to improve operational efficiency, enhance customer experience, and maintain competitive advantage in an increasingly digital global economy. In recent years, artificial intelligence (AI) has emerged as one of the most transformative technologies reshaping the financial landscape, with applications spanning credit scoring, fraud detection, algorithmic trading, risk management, customer service automation, and regulatory compliance (Vukovic, 2025; Ahmed et al., 2022). The global AI in financial services market has grown exponentially, with industry reports indicating that financial services represent one of the highest-adopting sectors for AI technologies, second only to the technology and software industry itself (McKinsey & Company, 2024; Deloitte, 2026).

The adoption of AI in finance has been accelerated by several converging factors, including the exponential growth in data availability, dramatic reductions in computing costs, significant advancements in machine learning algorithms, and increasing pressure from digital-native competitors such as fintech startups and challenger banks (Pattnaik et al., 2024). Financial institutions ranging from global investment banks to community credit unions are deploying AI-powered solutions to automate routine processes, generate predictive insights, personalize financial products, and detect anomalous patterns that may indicate fraudulent activity (Ridzuan et al., 2024). According to the World Economic Forum and the Cambridge Centre for Alternative Finance (2025), AI is fundamentally altering the nature of financial intermediation, risk assessment, and customer engagement, creating both unprecedented opportunities and novel risks for market participants, regulators, and consumers alike.

However, despite the considerable enthusiasm surrounding AI in finance, the adoption process is far from straightforward. Financial institutions face a complex array of challenges, including concerns about algorithmic transparency and bias, data privacy and cybersecurity vulnerabilities, regulatory uncertainty across jurisdictions, the shortage of AI-savvy talent, and the ethical implications of delegating consequential financial decisions to automated systems (Fundira et al., 2025; Wang et al., 2024; CFA Institute, 2025). The Financial Stability Board (2024) has highlighted that while AI may improve efficiency and risk management, it may also amplify certain financial sector vulnerabilities and thereby pose risks to financial stability, particularly if many institutions rely on similar AI models or data sources, potentially creating herding behavior and systemic correlations.

1.2 Statement of the Problem

While existing literature has extensively documented the technical capabilities and potential applications of AI in finance, there remains a significant gap in understanding the perceptual and attitudinal factors that drive or hinder AI adoption among finance professionals and organizations. Most prior studies have focused either on the

technological aspects of AI implementation or on specific use cases such as robo-advisory services and algorithmic trading (Zhu et al., 2024; Sabir et al., 2023). Less attention has been paid to the holistic assessment of how finance professionals perceive the benefits and challenges of AI and how these perceptions collectively influence their adoption decisions. This study addresses this gap by empirically examining the relative influence of perceived benefits and perceived challenges on AI adoption in the financial sector, providing actionable insights for practitioners, policymakers, and technology providers.

1.3 Research Objectives

The primary objective of this study is to examine the influence of perceived benefits and perceived challenges of artificial intelligence on AI adoption in the financial services industry. Specifically, this study aims to: (a) assess the level of perceived benefits of AI among finance professionals; (b) evaluate the level of perceived challenges associated with AI adoption; (c) determine the extent of AI adoption in financial services; (d) analyze the relationship between perceived benefits, perceived challenges, and AI adoption; and (e) identify which factor, perceived benefits or perceived challenges, exerts a stronger influence on AI adoption behavior.

1.4 Significance of the Study

This study makes several important contributions to both academic knowledge and professional practice. From a theoretical perspective, it integrates constructs from the Technology Acceptance Model (Davis, 1989), the Diffusion of Innovations theory (Rogers, 2003), and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) into a unified framework specifically adapted for the AI-in-finance context. This integration extends the applicability of these well-established theories to an emerging and critically important domain. From a practical perspective, the findings provide evidence-based guidance for financial institution leaders, technology vendors, and regulators seeking to promote responsible AI adoption while mitigating potential risks. Understanding the relative strength of benefits versus challenges as drivers of adoption enables more targeted intervention strategies, resource allocation decisions, and policy frameworks.

1.5 Scope and Delimitation

This study focuses specifically on the perceptions of individuals working in or associated with the financial services industry regarding AI adoption. The research is delimited to three core constructs: perceived benefits of AI, perceived challenges of AI, and AI adoption behavior. While the study acknowledges the broader ecosystem of factors that may influence AI adoption, such as organizational culture, regulatory environment, and technological infrastructure, these factors are not directly measured. The sample consists of 100 respondents, which, while adequate for the statistical analyses employed, limits the generalizability of findings to broader populations. The study employs a cross-sectional survey design, capturing perceptions at a single point in time, and therefore cannot establish causal relationships or track changes in perceptions over time.

2. Literature Review

2.1 Theoretical Framework

This study draws on three well-established theoretical frameworks that provide complementary lenses for understanding technology adoption: the Technology Acceptance Model (TAM), the Diffusion of Innovations (DOI) theory, and the Unified Theory of Acceptance and Use of Technology (UTAUT). Together, these theories inform the development of the conceptual model and the hypotheses tested in this research.

2.1.1 Technology Acceptance Model (TAM)

The Technology Acceptance Model, originally proposed by Davis (1989), is one of the most widely applied theoretical frameworks for explaining and predicting user acceptance of information technology. TAM posits that two primary beliefs, perceived usefulness and perceived ease of use, are the fundamental determinants of user attitudes toward using a technology, which in turn influence behavioral intention and actual usage. Perceived usefulness is defined as the degree to which a person believes that using a particular system would enhance their job performance, while perceived ease of use refers to the degree to which a person believes that using a system would be free from effort (Davis, 1989). TAM has been extensively validated across diverse technology contexts, from early computer systems to contemporary AI applications, and continues to serve as a foundational theory in technology adoption research (Lee, 2025; Fel et al., 2025).

In the context of AI in finance, TAM provides a particularly relevant framework because the decision to adopt AI technologies is heavily influenced by whether finance professionals perceive these technologies as genuinely useful for improving their work outcomes and whether they believe the technologies are sufficiently user-friendly to be practically implemented. Recent empirical studies have confirmed that perceived usefulness significantly influences AI adoption in banking contexts, with Ikhsan et al. (2025) demonstrating that conceptual perceived usefulness among bank customers strongly predicts AI acceptance, and Papathomas et al. (2025) finding that perceived usefulness remains a central driver of AI adoption behavior among banking professionals in semi-urban settings. Furthermore, Nyanga et al. (2025) provided evidence that both perceived usefulness and perceived ease of use significantly affect FinTech adoption, reinforcing TAM's continued relevance in the financial technology domain.

2.1.2 Diffusion of Innovations (DOI) Theory

The Diffusion of Innovations theory, developed by Everett M. Rogers (2003) in its fifth edition, provides a comprehensive framework for understanding how, why, and at what rate new ideas and technologies spread through social systems. According to DOI, the adoption of an innovation is influenced by five key attributes: relative advantage (the degree to which an innovation is perceived as better than what it replaces), compatibility (how well the innovation aligns with existing values, experiences, and needs), complexity (the perceived difficulty of understanding and using the innovation), trialability (the opportunity to experiment with the innovation on a limited basis), and observability (the visibility of the innovation's results to others). These attributes collectively determine the rate at which an innovation is adopted across different categories of adopters, ranging from innovators and early adopters to the late majority and laggards (Rogers, 2003).

In the context of AI adoption in finance, DOI theory is particularly instructive because it highlights the importance of perceived relative advantage, which aligns closely with the concept of perceived benefits in this study. Financial professionals are more likely to adopt AI technologies when they perceive clear advantages over existing methods, such as improved accuracy, faster processing times, and enhanced decision-making capabilities. Simultaneously, the complexity attribute of DOI corresponds to perceived challenges, as technologies that are perceived as difficult to understand, implement, or integrate into existing workflows face slower adoption rates. Recent research has applied DOI theory to understand the adoption of AI-driven technologies in financial contexts, with scholars noting that the perceived attributes of AI innovations significantly predict adoption intentions among financial services professionals (SUERF, 2024).

2.1.3 Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology, proposed by Venkatesh, Morris, Davis, and Davis (2003), was developed to integrate the fragmented landscape of technology acceptance models into a single, comprehensive framework. UTAUT identifies four core determinants of behavioral intention and use behavior: performance expectancy (the degree to which an individual believes that using the system will help attain gains in job performance), effort expectancy (the degree of ease associated with the use of the system), social influence (the degree to which an individual perceives that important others believe they should use the system), and facilitating conditions (the degree to which an individual believes that organizational and technical infrastructure exists to support the use of the system). UTAUT has been shown to explain approximately 70% of the variance in behavioral intention, substantially outperforming any of the eight individual models on which it was based (Venkatesh et al., 2003).

For this study, UTAUT contributes the concept of performance expectancy, which closely parallels the perceived benefits construct, and facilitating conditions, which relates inversely to perceived challenges. The theory's emphasis on the interplay between individual beliefs and organizational support structures is particularly relevant in the financial services context, where AI adoption decisions are shaped not only by individual perceptions but also by organizational readiness, regulatory frameworks, and institutional support mechanisms. Beraducci (2025) recently examined the relationship between TAM constructs and AI adoption in professional settings, finding that technology acceptance models continue to provide robust explanatory power for understanding AI adoption behavior, even as the technology itself evolves rapidly.

2.2 AI in the Financial Sector

2.2.1 Applications of AI in Finance

Artificial intelligence has found diverse and increasingly sophisticated applications across the financial services industry. One of the most prominent applications is in fraud detection and prevention, where machine learning algorithms analyze vast quantities of transactional data in real time to identify patterns indicative of fraudulent activity, achieving accuracy rates that substantially exceed those of traditional rule-based systems (Pattnaik et al., 2024). Credit scoring represents another critical application area, with AI-powered models incorporating a broader range of data points, including non-traditional data sources, to produce more nuanced and inclusive credit assessments (Vukovic, 2025). In investment management, algorithmic trading systems powered by AI execute trades at speeds and frequencies impossible for human traders, while robo-advisory platforms use AI algorithms to provide automated, personalized investment advice at a fraction of the cost of traditional financial advisors (Zhu et al., 2024; Sabir et al., 2023).

Beyond these well-established applications, AI is increasingly being deployed in regulatory compliance and risk management, where natural language processing systems automate the monitoring of regulatory changes and the detection of potential compliance violations. Customer service has been transformed by AI-powered chatbots and virtual assistants that handle routine inquiries, process transactions, and provide personalized product recommendations, significantly improving service availability and reducing operational costs (Alnaser et al., 2023). The Boukherouaa et al. (2021) has documented how AI and machine learning are being adopted across a wide range of financial sector activities, from asset management and insurance underwriting to payment processing and anti-money laundering efforts, noting that the pace of adoption has accelerated markedly since the onset of the COVID-19 pandemic.

2.2.2 Benefits of AI Adoption in Finance

The perceived benefits of AI adoption in the financial sector are manifold and well-documented in the literature. Operational efficiency gains represent perhaps the most immediately tangible benefit, as AI systems automate repetitive tasks, reduce processing times, and minimize human error across a range of back-office and front-office functions (Ridzuan et al., 2024). Enhanced decision-making capability is another frequently cited benefit, with AI's ability to process and analyze large volumes of structured and unstructured data enabling more informed, timely, and evidence-based decisions in areas such as lending, investment, and risk assessment (Ahmed et al., 2022). Cost reduction is a significant driver, as financial institutions seek to leverage AI to reduce labor costs, improve resource allocation, and achieve economies of scale in service delivery (McKinsey & Company, 2024).

Customer experience improvement is an increasingly important benefit, as AI enables the delivery of personalized financial products and services tailored to individual customer needs, preferences, and risk profiles. The emergence of AI-powered robo-advisors has democratized access to investment advisory services, making sophisticated portfolio management available to a broader segment of the population (Senteio, 2024). Furthermore, AI enhances risk management capabilities by improving the accuracy of risk models, enabling real-time monitoring of risk exposures, and facilitating more effective stress testing and scenario analysis. The European Central Bank (2024) has noted that AI adoption may increase the efficiency and resilience of financial intermediation, while the World Economic Forum (2025) has highlighted AI's potential to promote financial inclusion by extending services to underserved populations through innovative digital channels.

2.3 Perceived Challenges of AI in Finance

Despite the substantial benefits, the adoption of AI in finance is accompanied by significant challenges that may inhibit or slow the pace of implementation. Data privacy and security concerns are among the most pressing challenges, as AI systems require access to vast quantities of sensitive financial data, creating potential vulnerabilities that could be exploited by malicious actors (Wang et al., 2024). The concentration of data and the opacity of AI decision-making processes raise fundamental questions about individual privacy rights and the adequacy of existing data protection frameworks in an AI-driven financial landscape. Regulatory uncertainty represents another major challenge, as the rapid evolution of AI technologies has outpaced the development of comprehensive regulatory frameworks, creating an environment of ambiguity and potential compliance risk for financial institutions seeking to adopt AI solutions (FSB, 2024).

Ethical considerations, including algorithmic bias, fairness, and accountability, constitute a growing area of concern. AI systems trained on historical data may perpetuate or amplify existing biases in lending, insurance pricing, and other financial decisions, raising questions about discriminatory outcomes and the equitable treatment of customers (Fundira et al., 2025; CFA Institute, 2025). The black-box nature of many AI models, particularly deep learning systems, creates transparency challenges that may conflict with regulatory requirements for explainability in financial decision-making. Talent scarcity is another significant barrier, as the demand for professionals with expertise in both AI and finance substantially exceeds the available supply, creating a competitive labor market that disadvantages smaller institutions (World Economic Forum, 2025). Additionally, the cost of implementing and maintaining AI infrastructure, the risk of technological obsolescence, and potential resistance from employees concerned about job displacement all contribute to the complex landscape of challenges facing AI adoption in finance (Ridzuan et al., 2024).

2.4 Conceptual Framework and Hypotheses

Based on the theoretical foundations and empirical evidence reviewed above, this study proposes a conceptual framework in which perceived benefits (PB) and perceived challenges (PC) of AI are modeled as independent variables influencing AI adoption (AD) as the dependent variable. The framework integrates elements from TAM (perceived usefulness as a benefit construct), DOI (relative advantage as a benefit and complexity as a challenge), and UTAUT (performance expectancy as a benefit and facilitating conditions as inversely related to challenges). The conceptual framework is presented in Figure 1.

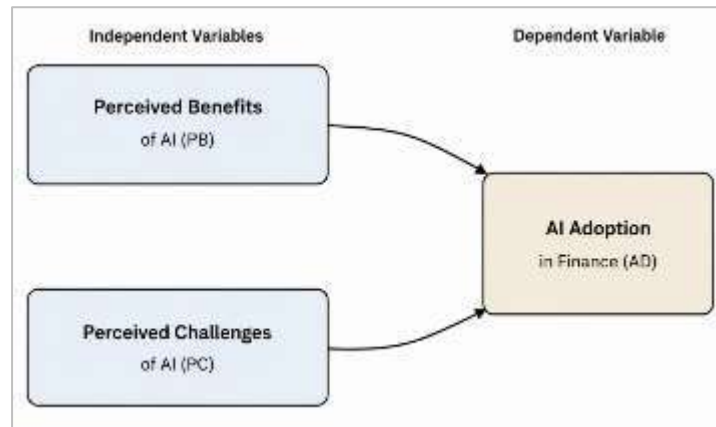


Figure 1. Conceptual Framework: Perceived Benefits and Perceived Challenges as Predictors of AI Adoption

The following hypotheses are proposed and tested in this study:

H₁: There is a significant positive relationship between perceived benefits of AI and AI adoption in the financial sector.

H₂: There is a significant negative relationship between perceived challenges of AI and AI adoption in the financial sector.

3. Research Methodology

3.1 Research Design

This study employed a quantitative research design using a cross-sectional survey methodology to collect data from individuals working in or associated with the financial services industry. The quantitative approach was selected because it enables the systematic collection of numerical data that can be analyzed using inferential statistical techniques, specifically multiple linear regression, to test the hypothesized relationships between the independent variables (perceived benefits and perceived challenges) and the dependent variable (AI adoption). The cross-sectional design provides a snapshot of perceptions at a single point in time, which is appropriate for establishing the strength and direction of relationships among the study variables. This research design is consistent with established practices in technology adoption research, where survey-based quantitative methods are widely employed to test theoretical models and hypotheses (Venkatesh et al., 2003; Davis, 1989).

3.2 Population and Sample

The target population for this study comprised professionals working in the financial services industry, including banking, insurance, investment management, and financial technology sectors. A convenience sampling technique was employed to recruit 100 respondents who had knowledge of or experience with AI applications in their respective organizations. While convenience sampling has inherent limitations regarding representativeness, it was

deemed appropriate for this exploratory study given the practical constraints of accessing a diverse pool of finance professionals across multiple organizations and geographic locations. The sample size of 100 respondents exceeds the minimum threshold recommended for multiple regression analysis, which typically requires at least 50 observations plus 8 observations for each independent variable (Tabachnick & Fidell, 2013), and is consistent with similar empirical studies on technology adoption in finance (Papathomas et al., 2025; Sabir et al., 2023).

3.3 Instrument Development

The research instrument was a structured self-administered questionnaire comprising three sections corresponding to the three constructs of the study: Perceived Benefits of AI (PB), Perceived Challenges of AI (PC), and AI Adoption in Finance (AD). Each construct was measured using eight items, resulting in a total of 24 items. All items were measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The items for each construct were adapted from established scales in the technology adoption literature, modified to suit the specific context of AI in the financial services industry.

The Perceived Benefits scale measured respondents' perceptions of the advantages and positive outcomes associated with AI adoption, including improved efficiency, enhanced decision-making, cost reduction, customer satisfaction, competitive advantage, innovation capability, risk management improvement, and overall organizational performance. The Perceived Challenges scale assessed respondents' perceptions of the obstacles and risks associated with AI, including data privacy concerns, cybersecurity risks, regulatory uncertainty, ethical considerations, implementation costs, talent shortages, job displacement fears, and technological complexity. The AI Adoption scale measured the extent to which respondents' organizations had adopted or were in the process of adopting AI technologies across various financial service functions.

3.4 Validity and Reliability

Content validity was established through a comprehensive review of the relevant literature and existing validated instruments. The items were derived from established scales in the TAM, UTAUT, and DOI research traditions, adapted for the AI-in-finance context. Prior to data collection, the instrument was reviewed by subject matter experts to ensure clarity, relevance, and appropriateness of the items. Construct validity was assessed through confirmatory factor analysis and evaluation of the reliability coefficients. The reliability of each construct was assessed using Cronbach's alpha coefficient, with all three constructs demonstrating excellent internal consistency: Perceived Benefits ($\alpha = 0.922$), Perceived Challenges ($\alpha = 0.931$), and AI Adoption ($\alpha = 0.911$). These values substantially exceed the commonly accepted threshold of 0.70 (Nunnally & Bernstein, 1994), indicating high reliability of the measurement instrument.

3.5 Data Collection Procedure

Data were collected through a combination of online and paper-based survey administration. The online questionnaire was distributed via professional networks, industry forums, and financial services associations, while paper-based questionnaires were administered to selected organizations that preferred in-person data collection. Respondents were provided with a brief overview of the study's purpose and assured of the anonymity and confidentiality of their responses. A total of 120 questionnaires were distributed, of which 100 were returned complete and usable, yielding a response rate of 83.3%. Data collection took place over a period of four weeks, and all responses were compiled into a single dataset for analysis.

3.6 Data Analysis Techniques

Data were analyzed using Statistical Package for the Social Sciences (SPSS) version 26.0. The analysis proceeded in several stages. First, descriptive statistics (means, standard deviations, frequencies, and percentages) were computed to characterize the sample and provide an overview of the distribution of responses across all three constructs. Second, reliability analysis was conducted using Cronbach's alpha to assess the internal consistency of each construct. Third, Pearson correlation analysis was performed to examine the bivariate relationships among the three variables. Fourth, multiple linear regression analysis was conducted to test the hypothesized relationships, with AI Adoption as the dependent variable and Perceived Benefits and Perceived Challenges as independent variables. Prior to conducting the regression analysis, several diagnostic tests were performed, including tests for normality, multicollinearity (using variance inflation factors), and autocorrelation (using the Durbin-Watson statistic), to ensure that the assumptions underlying multiple linear regression were satisfied.

4. Results and Analysis

4.1 Response Rate and Demographic Profile

Out of 120 questionnaires distributed, 100 were returned complete and usable, representing a response rate of 83.3%. This response rate is considered excellent for survey-based research in the financial services domain and exceeds the minimum threshold required for the statistical analyses employed in this study. The demographic analysis of the respondents revealed a diverse sample in terms of age, gender, educational background, and professional experience. The majority of respondents were between 26 and 45 years of age, held at least a bachelor's degree, and had more than five years of professional experience in the financial sector. Respondents represented a range of organizational roles, including management, operations, technology, and customer service functions across banking, insurance, investment, and fintech sectors.

4.2 Descriptive Statistics

Descriptive statistics were computed for all three constructs to provide an overview of the distribution of responses. The results are presented in Table 1. The mean scores for all three constructs were above the midpoint of the scale (3.00), indicating generally positive perceptions of AI benefits, moderate awareness of challenges, and a reasonable level of AI adoption among the respondents and their organizations. Perceived Benefits recorded the highest mean score ($M = 3.92$, $SD = 0.74$), followed by AI Adoption ($M = 3.65$, $SD = 0.81$), and Perceived Challenges ($M = 3.41$, $SD = 0.88$).

Table 1. Descriptive Statistics of Study Variables (N = 100)

Variable	No. of Items	Mean	Std. Deviation	Interpretation
Perceived Benefits (PB)	8	3.92	0.74	High
Perceived Challenges (PC)	8	3.41	0.88	Moderate
AI Adoption (AD)	8	3.65	0.81	Moderate to High

4.3 Reliability Analysis

The internal consistency reliability of each construct was assessed using Cronbach's alpha coefficient. As presented in Table 2, all three constructs demonstrated excellent reliability, with alpha values ranging from 0.911 to 0.931, well above the commonly accepted threshold of 0.70 (Nunnally & Bernstein, 1994). The Perceived Challenges construct exhibited the highest reliability ($\alpha = 0.931$), followed by Perceived Benefits ($\alpha = 0.922$) and AI Adoption

($\alpha = 0.911$). These results confirm that the measurement instrument used in this study possesses high internal consistency and that the items within each construct are measuring the same underlying latent variable.

Table 2. Reliability Analysis Results (N = 100)

Construct	No. of Items	Cronbach's Alpha	Interpretation
Perceived Benefits (PB)	8	0.922	Excellent
Perceived Challenges (PC)	8	0.931	Excellent
AI Adoption (AD)	8	0.911	Excellent

4.4 Normality Test

The assumption of normality was assessed using both graphical methods (histograms and normal probability plots) and statistical tests (Kolmogorov-Smirnov and Shapiro-Wilk tests). The results indicated that the data for all three constructs were approximately normally distributed, with skewness and kurtosis values falling within the acceptable range of -1 to +1. While the Kolmogorov-Smirnov test was statistically significant for some variables (which is common with larger sample sizes), the visual inspection of histograms and Q-Q plots confirmed that the distributions were reasonably symmetric and bell-shaped, satisfying the normality assumption required for parametric statistical analysis.

4.5 Pearson Correlation Analysis

Pearson product-moment correlation coefficients were computed to examine the bivariate relationships among the three study variables. The results, presented in Table 3, reveal several important findings. There is a strong, positive, and statistically significant correlation between Perceived Benefits and AI Adoption ($r = 0.601$, $p < .01$), suggesting that respondents who perceive greater benefits from AI also report higher levels of AI adoption. The correlation between Perceived Challenges and AI Adoption is weak, negative, and statistically significant ($r = -0.189$, $p < .05$), indicating that higher perceived challenges are associated with somewhat lower levels of adoption, though the relationship is notably weaker than that of perceived benefits. Additionally, there is a weak positive correlation between Perceived Benefits and Perceived Challenges ($r = 0.175$, $p < .05$), suggesting that respondents who are more aware of AI's benefits also tend to be somewhat more aware of its challenges, likely reflecting greater overall familiarity with AI technologies.

Table 3. Pearson Correlation Matrix (N = 100)

Variable	1. PB	2. PC	3. AD
1. Perceived Benefits	1.000	0.175*	0.601**
2. Perceived Challenges	0.175*	1.000	-0.189*
3. AI Adoption	0.601**	-0.189*	1.000

Note. * $p < .05$, ** $p < .01$ (two-tailed).

4.6 Multicollinearity Diagnostics

Multicollinearity was assessed using the variance inflation factor (VIF) to ensure that the independent variables were not excessively correlated with each other, which would compromise the stability and interpretability of the regression coefficients. As presented in Table 4, the VIF values for both independent variables were well below the commonly accepted threshold of 10.0 (and even the more conservative threshold of 5.0), with Perceived Benefits showing a VIF of 1.031 and Perceived Challenges a VIF of 1.031. The tolerance values for both predictors were

approximately 0.970, well above the minimum acceptable value of 0.10. These results confirm that multicollinearity is not a concern in this study, and the regression coefficients can be interpreted with confidence.

Table 4. Collinearity Diagnostics

Variable	Tolerance	VIF	Collinearity Status
Perceived Benefits (PB)	0.970	1.031	No concern
Perceived Challenges (PC)	0.970	1.031	No concern

4.7 Autocorrelation Test

The Durbin-Watson statistic was computed to test for the presence of autocorrelation in the residuals of the regression model. The obtained Durbin-Watson value of 1.987 falls within the acceptable range of 1.5 to 2.5, and is very close to the ideal value of 2.0, which indicates the complete absence of autocorrelation. This result confirms that the residuals are independent of each other, satisfying one of the key assumptions of ordinary least squares (OLS) regression. The absence of autocorrelation suggests that there is no systematic pattern in the residuals that could bias the regression estimates, and the standard errors of the regression coefficients are not inflated by serial correlation among the error terms.

4.8 Multiple Linear Regression Analysis

Multiple linear regression analysis was conducted to test the hypothesized relationships between the independent variables (Perceived Benefits and Perceived Challenges) and the dependent variable (AI Adoption). The summary of the regression model is presented in Table 5. The overall model was statistically significant, $F(2, 97) = 30.87$, $p < .001$, indicating that the combination of perceived benefits and perceived challenges significantly predicts AI adoption. The coefficient of determination (R^2) was 0.389, indicating that the two independent variables collectively explain 38.9% of the variance in AI adoption. The adjusted R^2 of 0.376 accounts for the number of predictors in the model and provides a more conservative estimate of the explained variance. While 38.9% of variance explained is meaningful and statistically significant, it also indicates that approximately 61.1% of the variance in AI adoption is attributable to other factors not included in this model, such as organizational culture, regulatory pressures, leadership support, and technological infrastructure.

Table 5. Model Summary of Multiple Linear Regression

Model	R	R^2	Adjusted R^2	F	Sig.
1	0.624	0.389	0.376	30.87	< .001

The individual regression coefficients and their significance levels are presented in Table 6. The regression equation derived from the analysis is: $\text{AI Adoption} = 0.884 + 0.617(\text{PB}) - 0.162(\text{PC})$. Perceived Benefits emerged as a strong and statistically significant positive predictor of AI Adoption ($B = 0.617$, $\beta = 0.580$, $t = 6.949$, $p < .001$), indicating that for every one-unit increase in perceived benefits, AI adoption increases by 0.617 units, holding perceived challenges constant. The standardized coefficient ($\beta = 0.580$) confirms that perceived benefits is the dominant predictor in the model. Perceived Challenges, on the other hand, had a statistically significant but weaker negative effect on AI Adoption ($B = -0.162$, $\beta = -0.177$, $t = -2.126$, $p < .05$), indicating that for every one-unit increase in perceived challenges, AI adoption decreases by 0.162 units, holding perceived benefits constant. The constant term was 0.884 and was statistically significant ($p < .05$).

Table 6. Regression Coefficients (Dependent Variable: AI Adoption)

Variable	B	Std. Error	β	t	Sig.
(Constant)	0.884	0.284		3.114	.002
Perceived Benefits	0.617	0.089	0.580	6.949	< .001
Perceived Challenges	-0.162	0.076	-0.177	-2.126	.036

4.9 Hypothesis Testing Summary

The results of the hypothesis testing are summarized in Table 7. Hypothesis H1, which predicted a significant positive relationship between perceived benefits and AI adoption, was supported by the data. The standardized regression coefficient for perceived benefits was positive and statistically significant ($\beta = 0.580$, $p < .001$), confirming that higher perceived benefits are associated with higher levels of AI adoption. Hypothesis H2, which predicted a significant negative relationship between perceived challenges and AI adoption, was also supported, though the relationship was notably weaker. The standardized regression coefficient for perceived challenges was negative and statistically significant ($\beta = -0.177$, $p < .05$), indicating that higher perceived challenges are associated with lower levels of AI adoption, but the magnitude of this effect is considerably smaller than that of perceived benefits.

Table 7. Summary of Hypothesis Testing Results

Hypothesis	Statement	β	t-value	p-value	Decision
H1	PB has a significant positive effect on AD	0.580	6.949	< .001	Supported
H2	PC has a significant negative effect on AD	-0.177	-2.126	.036	Supported

5. Discussion

5.1 Perceived Benefits and AI Adoption

The finding that perceived benefits of AI is a strong positive predictor of AI adoption ($\beta = 0.580$, $p < .001$) aligns consistently with the theoretical predictions of the Technology Acceptance Model (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003). In TAM, the concept of perceived usefulness, which closely parallels perceived benefits in this study, is identified as the primary determinant of technology adoption. Similarly, in UTAUT, performance expectancy, the belief that using a technology will enhance job performance, is the strongest predictor of behavioral intention. The results of this study extend these theoretical predictions to the specific context of AI adoption in the financial services industry, demonstrating that finance professionals and organizations are primarily motivated to adopt AI technologies when they perceive clear and substantial benefits.

This finding is consistent with several recent empirical studies. Ikhsan et al. (2025) found that perceived usefulness significantly influenced AI acceptance among bank customers, while Papathomas et al. (2025) demonstrated that perceived usefulness was a central driver of AI adoption among banking professionals. The World Economic Forum (2025) reported that financial institutions citing the greatest benefits from AI, including efficiency gains, improved customer experience, and enhanced risk management, were also the most aggressive adopters. The strong predictive power of perceived benefits suggests that the financial services industry's adoption

of AI is fundamentally benefit-driven, and that efforts to promote AI adoption should focus on clearly articulating and demonstrating the tangible value propositions that AI technologies offer.

The practical implications of this finding are substantial. Financial institution leaders seeking to accelerate AI adoption should prioritize initiatives that showcase and communicate the concrete benefits of AI, such as pilot programs that demonstrate measurable improvements in operational efficiency, customer satisfaction, or risk management outcomes. Technology vendors should invest in developing compelling use cases and return-on-investment analyses that resonate with the specific priorities and pain points of financial services organizations. Furthermore, industry associations and professional bodies can play a valuable role in disseminating best practices and success stories that highlight the transformative potential of AI in finance, thereby elevating the overall level of perceived benefits across the industry.

5.2 Perceived Challenges and AI Adoption

The finding that perceived challenges have a statistically significant but comparatively weak negative effect on AI adoption ($\beta = -0.177$, $p < .05$) is an important contribution of this study. While challenges such as data privacy concerns, cybersecurity risks, regulatory uncertainty, ethical considerations, and talent shortages are real and well-documented in the literature (Wang et al., 2024; Fundira et al., 2025; FSB, 2024), their impact on adoption behavior appears to be considerably more modest than the driving force of perceived benefits. This asymmetry in effect sizes suggests that the financial services industry operates with a benefits-dominant adoption logic, where the perceived advantages of AI adoption substantially outweigh the perceived obstacles in influencing adoption decisions.

This finding has nuanced implications for understanding AI adoption dynamics in finance. It does not suggest that challenges are unimportant or should be ignored; rather, it indicates that, at the current stage of AI maturity in the financial sector, the perceived benefits are so compelling that they largely override the inhibiting effects of challenges. This interpretation is consistent with the diffusion of innovations perspective (Rogers, 2003), which suggests that innovations with strong perceived relative advantage tend to be adopted despite perceived complexity, particularly when the organizational and environmental conditions are favorable. The financial services industry's high-stakes competitive environment, where the costs of not adopting AI may be perceived as greater than the risks of adoption, may further amplify this benefit-dominant dynamic.

However, the significant negative effect of perceived challenges, even if modest in magnitude, should not be dismissed. As AI adoption deepens and moves from peripheral applications to core financial decision-making processes, the challenges may become more salient and their inhibiting effects may strengthen. Regulatory scrutiny is intensifying globally, with the Financial Stability Board (2024) and the European Central Bank (2024) increasingly focused on the systemic implications of AI in finance. Proactive attention to challenges, including investment in robust governance frameworks, explainable AI systems, and comprehensive cybersecurity measures, will be essential for sustaining the trajectory of AI adoption as the technology becomes more deeply embedded in critical financial infrastructure.

5.3 Theoretical Implications

This study makes several contributions to the theoretical understanding of technology adoption in the financial services context. First, it demonstrates that the core constructs from TAM, DOI, and UTAUT, when adapted to the AI-in-finance context, retain their predictive validity, confirming the robustness and generalizability of these foundational theories to an emerging and rapidly evolving technological domain. The strong predictive power of

perceived benefits aligns with the central role of perceived usefulness in TAM and performance expectancy in UTAUT, while the weaker but significant effect of perceived challenges extends the theoretical framework by explicitly incorporating barriers as a distinct construct that operates alongside benefits to shape adoption behavior.

Second, the finding that perceived benefits dominate over perceived challenges in influencing AI adoption contributes to a more nuanced understanding of the adoption decision-making process. While most technology adoption models focus predominantly on facilitators and drivers of adoption, this study demonstrates that explicitly modeling both the positive and negative dimensions of perceptions provides a more complete and realistic picture of the factors that shape adoption behavior. The asymmetry in effect sizes ($\beta = 0.580$ for benefits versus $\beta = -0.177$ for challenges) suggests that theoretical models of AI adoption should assign greater weight to benefit perceptions while still acknowledging the role of challenge perceptions as a moderating or secondary factor.

5.4 Practical Implications

The findings of this study offer several practical recommendations for stakeholders in the financial services ecosystem. For financial institution leaders, the results underscore the importance of developing and communicating clear value propositions for AI initiatives. Organizations should invest in proof-of-concept projects, pilot implementations, and rigorous measurement frameworks that demonstrate the tangible benefits of AI in terms that resonate with key decision-makers, including cost savings, revenue generation, risk reduction, and customer satisfaction improvements. The strong predictive power of perceived benefits suggests that organizations that can effectively articulate and demonstrate the value of AI will achieve faster and more extensive adoption.

For technology vendors and AI solution providers, the findings highlight the importance of designing solutions that are not only technically sophisticated but also perceived as genuinely beneficial by end-users in the financial sector. Vendors should prioritize features that directly address the pain points and priorities of financial services professionals, such as automating routine compliance tasks, improving the accuracy of credit decisions, or enhancing the personalization of customer interactions. For regulators and policymakers, the results suggest that regulatory frameworks should aim to reduce perceived challenges associated with AI adoption, such as by providing clearer guidance on acceptable AI use cases, streamlining approval processes for AI-powered products and services, and promoting the development of industry standards for AI governance and ethics (CFA Institute, 2025; FSB, 2024).

6. Conclusion and Recommendations

6.1 Summary of Findings

This study examined the influence of perceived benefits and perceived challenges of artificial intelligence on AI adoption in the financial services industry, drawing on the theoretical foundations of the Technology Acceptance Model, the Diffusion of Innovations theory, and the Unified Theory of Acceptance and Use of Technology. Based on survey data collected from 100 respondents in the financial sector, the study developed and tested a conceptual model in which perceived benefits and perceived challenges were specified as predictors of AI adoption. The results demonstrated that the model was statistically significant ($F(2,97) = 30.87, p < .001$) and explained 38.9% of the variance in AI adoption ($R^2 = 0.389$). Both hypotheses were supported: perceived benefits had a strong positive effect on AI adoption ($\beta = 0.580, p < .001$), while perceived challenges had a weaker but statistically significant negative effect ($\beta = -0.177, p < .05$).

6.2 Conclusion

The findings of this study lead to the conclusion that AI adoption in the financial services industry is primarily driven by the perceived benefits of AI technologies, with perceived challenges playing a secondary but still significant inhibitory role. The substantial difference in the magnitude of the effects of perceived benefits versus perceived challenges ($\beta = 0.580$ compared to $\beta = -0.177$) suggests that the current wave of AI adoption in finance is fundamentally propelled by the compelling value proposition that AI offers, including operational efficiency gains, enhanced decision-making capabilities, improved customer experience, and competitive advantage. While challenges such as data privacy concerns, regulatory uncertainty, and talent shortages are real and require attention, they have not yet reached a threshold sufficient to substantially deter adoption among organizations that recognize the transformative potential of AI.

This conclusion has encouraging implications for the future trajectory of AI in finance. It suggests that the industry is in a phase of enthusiastic adoption, where the perceived benefits substantially outweigh the perceived costs and risks. However, this balance could shift as AI becomes more deeply embedded in critical financial systems and as regulatory and societal scrutiny intensifies. Organizations that proactively address the challenges of AI adoption, building robust governance frameworks, investing in explainable AI, and cultivating AI talent, will be better positioned to sustain and accelerate their AI adoption journeys as the technology and its regulatory environment continue to evolve.

6.3 Limitations

Several limitations of this study should be acknowledged. First, the sample size of 100 respondents, while adequate for the statistical analyses employed, limits the generalizability of the findings to the broader population of financial services professionals and organizations. A larger and more representative sample, potentially stratified by organization size, geographic region, and subsector within financial services, would enhance the external validity of the results. Second, the use of convenience sampling introduces potential selection bias, as respondents who choose to participate may have greater interest in or familiarity with AI than the general population of finance professionals.

Third, the cross-sectional research design captures perceptions at a single point in time and cannot establish causal relationships or track how perceptions and adoption behavior evolve over time. A longitudinal study tracking changes in perceived benefits, perceived challenges, and AI adoption over multiple time points would provide richer insights into the dynamics of the adoption process. Fourth, the study relies exclusively on self-reported data, which may be subject to social desirability bias, common method variance, and other measurement artifacts. The inclusion of objective measures of AI adoption, such as organizational investment data or implementation metrics, would strengthen the validity of the findings. Fifth, the model explains 38.9% of the variance in AI adoption, indicating that a substantial proportion of the variance is attributable to factors not included in the model, such as organizational culture, leadership support, regulatory environment, technological infrastructure, and competitive pressure.

6.4 Recommendations for Future Research

Based on the findings and limitations of this study, several directions for future research are recommended. First, future studies should employ larger and more representative samples, utilizing stratified or random sampling techniques to enhance the generalizability of the findings across different types of financial institutions, geographic

regions, and cultural contexts. Comparative studies examining AI adoption perceptions across countries with different regulatory environments and levels of technological maturity would be particularly valuable. Second, longitudinal research designs should be employed to track the evolution of perceived benefits, perceived challenges, and AI adoption over time, providing insights into the causal dynamics and temporal patterns of the adoption process.

Third, future research should explore the role of mediating and moderating variables that may influence the relationships examined in this study. Potential mediators include organizational readiness, management support, and innovation culture, while potential moderators include organization size, regulatory environment, and technological infrastructure. Fourth, qualitative research methods, such as in-depth interviews and case studies, should be employed to complement the quantitative findings and provide richer insights into the mechanisms through which perceived benefits and challenges influence AI adoption decisions. Finally, as generative AI and other emerging forms of artificial intelligence continue to evolve, future research should examine whether the relationships identified in this study hold for these newer forms of AI, which may present distinct benefit and challenge profiles compared to the traditional AI applications that were the primary focus of this study.

References

- Ahmed, Shamima & Alshater, Muneer M. & Ammari, Anis El & Hammami, Helmi, 2022. "Artificial intelligence and machine learning in finance: A bibliometric review," *Research in International Business and Finance*, Elsevier, vol. 61(C). DOI: 10.1016/j.ribaf.2022.101646
- Alnaser, F. M., Alnaser, L. A., & Alnaser, H. M. (2023). Does artificial intelligence (AI) boost digital banking user experience? A systematic review. *Journal of Open Innovation: Technology, Market, and Complexity*, 9(3), 100054. <https://doi.org/10.1016/j.joitmc.2023.100054>
- Beraducci, J. (2025). Examining the relationship between technology acceptance model constructs and AI adoption in professional settings [Doctoral dissertation, Walden University]. ScholarWorks.
- Boukherouaa, E. B., Shabsigh, G., AlAjmi, K., Deodoro, J., Farias, A., Iskender, E. S., Mirestean, A. T., & Ravikumar, R. (2021). *Powering the digital economy: Opportunities and risks of artificial intelligence in finance* (IMF Departmental Paper No. 2021/024). International Monetary Fund. <https://www.imf.org/en/Publications/Departmental-Papers-Policy-Papers/Issues/2021/10/21/Powering-the-Digital-Economy-Opportunities-and-Risks-of-Artificial-Intelligence-in-Finance-494717>
- CFA Institute. (2025). Ethical AI in finance. CFA Institute Research Foundation. <https://rpc.cfainstitute.org/research/foundation/2025/chapter-10-ethical-ai-in-finance>
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319-340. <https://doi.org/10.2307/249008>
- Deloitte. (2026). The state of AI in the enterprise, 2026. Deloitte Center for Technology, Media & Telecommunications. <https://www.deloitte.com/us/en/what-we-do/capabilities/applied-artificial-intelligence/content/state-of-ai-in-the-enterprise.html>

- Dixon, M. F., Halperin, I., & Bilokon, P. (2020). Machine learning in finance: From theory to practice. Springer.
<https://doi.org/10.1007/978-3-030-41068-4>
- European Central Bank. (2024, May 3). The rise of artificial intelligence: Benefits and risks for financial stability. Financial Stability Review Special Feature. https://www.ecb.europa.eu/press/financial-stability-publications/fsr/special/html/ecb.fsrart202405_02~58c3ce5246.en.html
- Fel, S., Baccarella, C. V., & Voigt, K.-I. (2025). Responsibility and AI: Exploring technology acceptance models with a novel responsibility construct. *Technology in Society*, 80, 102595.
<https://doi.org/10.1016/j.techsoc.2025.102595>
- Financial Stability Board. (2024, November 14). FSB assesses the financial stability implications of artificial intelligence. <https://www.fsb.org/2024/11/fsb-assesses-the-financial-stability-implications-of-artificial-intelligence>
- Fundira, Mearthur & Mbohwa, Charles. (2025). AI ethics in banking services: a systematic and bibliometric review of regulatory and consumer perspectives. *Discover Artificial Intelligence*. 5. 10.1007/s44163-025-00432-4.
- Ikhsan, R. B., Haryanto, J. O., & Rahardjo, S. T. (2025). An empirical study on the use of artificial intelligence in banking: A technology acceptance perspective. *Journal of Open Innovation: Technology, Market, and Complexity*, 11(1), 100310. <https://doi.org/10.1016/j.joitmc.2024.100310>
- Lee, A. T., Ramasamy, R. K., & Subbarao, A. (2025). Understanding psychosocial barriers to healthcare technology adoption: A review of TAM technology acceptance model and unified theory of acceptance and use of technology and UTAUT frameworks. *Healthcare*, 13(3), 250. <https://doi.org/10.3390/healthcare13030250>
- McKinsey & Company. (2024, May 30). The state of AI in early 2024: Generative AI adoption bursts out of the starting gate. McKinsey Global Institute. <https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-2024>
- Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.
- Nyanga, T., Dube, C., & Mhlanga, D. (2025). Technology acceptance model: Related antecedents and consequences. *South African Journal of Economic and Management Sciences*, 28(1), a1080.
<https://doi.org/10.4102/sajems.v28i1.1080>
- Papathomas, A., Buxton, M., & Simpson, S. (2025). Behavioral drivers of AI adoption in banking in a semi-urban context. *Information*, 16(2), 137. <https://doi.org/10.3390/info16020137>
- Pattnaik, D., Pradhan, R. P., & Gholami, S. (2024). Applications of artificial intelligence and machine learning in BFSI. *Heliyon*, 10(2), e23706. <https://doi.org/10.1016/j.heliyon.2023.e23706>
- Ridzuan, N. N., Amran, A., & Hassan, F. (2024). AI in the financial sector: The line between innovation and regulation. *Information*, 15(8), 432. <https://doi.org/10.3390/info15080432>
- Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.
- Sabir, A. A., Rafiq, M., & Waseem, M. (2023). Consumer acceptance and adoption of AI robo-advisors: A comprehensive framework. *Mathematics*, 11(6), 1311. <https://doi.org/10.3390/math11061311>
- Senteio, S. D. B. A. (2024). Customer trust and satisfaction with robo-adviser technology. *Financial Planning Review*, 7(3), e1204. <https://doi.org/10.1002/cfp2.1204>

- SUERF. (2024, December 19). Financial intelligence: Opportunities and risks of AI in finance. SUERF Policy Brief. <https://www.suerf.org/publications/suerf-policy-notes-and-briefs/financial-intelligence-opportunities-and-risks-of-ai-in-finance>
- Tabachnick, B. G., & Fidell, L. S. (2013). Using multivariate statistics (6th ed.). Pearson Education.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425-478. <https://doi.org/10.2307/30036540>
- Vukovic, D. B. (2025). AI integration in financial services: A systematic review of trends and regulatory challenges. *Humanities and Social Sciences Communications*, 12, Article 4850. <https://doi.org/10.1057/s41599-025-04850-8>
- Wang, S., Zhang, Y., & Chen, X. (2024). Data privacy and cybersecurity challenges in the digital banking era. *Computers & Security*, 134, 103881. <https://doi.org/10.1016/j.cose.2024.103881>
- World Economic Forum & Cambridge Centre for Alternative Finance. (2025). Artificial intelligence in financial services. World Economic Forum White Paper Series. <https://www.weforum.org/publications/industries-in-the-intelligent-age-white-paper-series/financial-services>
- Zhu, H., Vigren, O., & Söderberg, I.-L. (2024). Implementing artificial intelligence empowered financial advisory services: A literature review and critical research agenda. *Journal of Business Research*, 174, 114494. <https://doi.org/10.1016/j.jbusres.2024.114494>