
The Role of Artificial Intelligence in Financial Services: Transforming Banking, Investment, and Asset Management

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Abstract

Background: The financial services industry has experienced a significant impact from artificial intelligence (AI) technology, influencing various areas such as banking, investment management, risk management, and regulatory compliance. Although the use of AI has increased, there is little empirical evidence that examines the effects of implementing AI on organizational performance. The study focuses on the impact of the use of AI on financial performance in banking, investment and asset management institutions. A quantitative research design was applied and the data were collected from the financial institutions which operate in different regions in the year 2020-2024. This study investigates how the intensity of AI adoption, investment in AI technologies, data quality, maturity of regulatory technology (RegTech) and legacy infrastructure impact organizational performance. Several statistical methods including descriptive statistics, correlation analysis and regression modelling, panel-data estimation were used to test the proposed hypotheses. The results suggest that the use of AI has a positive relationship with financial performance, operational efficiency, and fraud detection. Data quality and RegTech maturity, combined with the advantages of implementation, enhance the advantages of AI, and legacy infrastructure hinder performance outcomes. The results show that companies with higher levels of AI application achieve better returns and benefits than other companies with varying stages of AI application. The findings contribute to the existing body of knowledge on applying AI in the financial sector and provide practical insights for managers, regulators, and policymakers to maximize the value of their AI investment effectively.

Keywords: *artificial intelligence, financial services, banking, fintech, organizational performance, ai adoption, reg-tech, financial innovation.*

1. Introduction

Artificial Intelligence (AI) is the most impactful technological change in the financial services sector since the Internet. Many top global banks are leveraging AI for critical functions like core banking, investment decisions, and regulatory compliance, and they are increasingly using it in these areas. Today, AI is used in many ways in the banking sector, including core banking functions, investment decisions and regulatory compliance, and these are the functions that many leading banks around the world rely on AI. Since 2020, adoption of AI has accelerated tremendously: investments in AI infrastructure for global financial institutions are estimated to have

increased to USD 35 billion in 2024 alone (McKinsey, 2024); and early adopters have reported cost savings of 28-65% in AI-enhanced functions (PwC, 2024; Deloitte, 2025).

In spite of this practitioner momentum, there is still a lot of fragmented empirical literature, which is peer-reviewed, on AI in finance. While previous research has focused on either credit scoring (Berg et al., 2020), fraud detection (Bhattacharyya et al., 2022), robo-advisory (Fisch et al., 2019), or algorithmic trading (Gu et al., 2020), multi-sectoral and multi-country empirical studies that combine banking, investment, and risk functions and test theoretically grounded hypotheses with original statistical data are limited. This is a substantial lack of research in the academic and policy literature.

This paper meets that need by four original contributions. To begin with, we build a new cross-sectoral panel data set of 847 financial institutions in 42 countries for the period 2020-2024. Second, we develop a composite AI Adoption Index (AIAI) which helps to compare the AI adoption across institution types. Third, panel fixed-effects estimation, hierarchical OLS regression, mediation analysis and subgroup ANOVA are used to derive and test six formal hypotheses. Fourth, data quality and legacy infrastructure emerge as key moderators of the relationship between AI and performance, directly impacting incumbent financial institutions' strategies.

The paper is organized as follows: The literature is reviewed and hypotheses are developed in Section 2. A research methodology is discussed in Section 3. Descriptive statistics and a correlation matrix are reported in section 4. The main regression results are presented in Section 5. The results of panel data and robustness checks are presented in Section 6. A summary of the hypotheses tests and subgroup analyses are presented in Section 7. Section 8 discusses results. The limitations and future research are discussed in section 9. Section 10 concludes.

2. Literature Review and Hypothesis Development

2.1 Theoretical Framework

Several complementary theoretical approaches to the use of artificial intelligence (AI) in financial services can be used to explain the adoption of AI. Based on Diffusion of Innovations Theory (Rogers, 2003), technological innovations can be spread within organisations over time and early adopters are most likely to be able to achieve a competitive advantage before the technology is fully accepted by the industry. The financial sector is one where AI technologies often emerge first, typically in the form of big banks and AI-first fintech firms capitalizing on AI to boost their efficiency and decision-making.

The second theoretical basis is Resource-Based View (RBV) (Barney, 1991). Organisations get a sustained competitive advantage when they have valuable, rare, inimitable, and non-substitutable resources, according to RBV. If the data is available, expertise is in place, and the technology is in readiness, AI can be a valuable tool for the organisation, boosting its performance and competitive standing.

The third perspective is from the Transaction Cost Economics (TCE) (Williamson, 1985) which suggests that organizations should implement technologies to reduce the space between negotiations, information asymmetry, and operation inefficiencies. In the financial sector, AI can streamline repetitive tasks, enhance risk evaluation, boost fraud prevention, and aid in quicker decision-making, which lowers transaction and monitoring expenses. From the perspectives of these views, the use of AI is considered to be a strategic organizational competence that has a direct and indirect effect on organizational performance. The direct benefit corresponds to the operational efficiency, cost reduction and improved decision quality, while the indirect benefit corresponds to the organizational aspects such as investment intensity, data quality, maturity of the regulatory technology and technological infrastructure. The hypotheses of this study are based on these relationships.

2.2 Empirical Literature and Hypothesis Development

AI's impact on financial services is evident in various applications, such as credit scoring, fraud detection, algorithmic trading, customer service automation, and regulatory compliance, as evidenced by research. As outlined by Buchanan (2019), some of the most significant applications of AI in the financial world include fraud detection, credit assessment, and trading systems. Similarly, Berg et al. (2020) found that the machine learning models with alternative data showed better performance than traditional scoring models in predicting the credit risk. Gu et al. (2020) have shown that large sample of U.S. equities-based machine learning models outperform traditional factor-based models. Furthermore, Cao (2022) found that the use of AI brought about significant operational benefits like cost reductions in processing and efficiency in the organisation.

H1: AI adoption intensity (AI Adoption Index) is positively associated with three-year return on AI investment. Previous studies have indicated that the integration of AI can lead to increased efficiency, decision-making, and customer satisfaction within organisations. The returns from the investments in AI is greater for the institutions that have greater AI capabilities as compared to the institutions with lesser capabilities of AI. So, AI adoption and the returns of AI investment are likely to be positively correlated.

H2: AI investment intensity (% of operational expenditure allocated to AI) mediates the relationship between AI adoption and ROI.

While AI can unlock technological opportunities, it requires continued investments in infrastructure, integration and workforce development to put it effectively into practice. AI adoption is more likely to deliver the performance benefits to organisations that invest more resources in it. Hence, the intensity of investing in AI is expected to act as a mediating variable between AI adoption and financial performance.

H3: Data quality positively moderates the relationship between AI adoption and ROI, such that the effect of AI adoption is stronger when data quality is higher.

The quality of the data used for training and operating AI systems is crucial to their effectiveness. Poor data quality, whether it's inaccurate, incomplete or poorly integrated, can decrease the effectiveness of the models and organisational benefits. With the improved data quality, the positive relationship between AI adoption and investment returns is likely to further strengthen.

H4: The higher the size of the institution, the higher the score for AI adoption intensity, and there is a significant difference between the score of Tier-1 institutions and the score of community banks and credit unions. Smaller organisations are likely to have fewer financial resources, smaller data assets and less advanced technological capabilities than the larger financial institutions. These benefits make it easier to implement and use AI technologies. Therefore, the more use of AI, the more likely that it will be used.

H5: Legacy IT systems have a negative moderation effect on the relationship between AI adoption and ROI, which diminishes the performance improvement of AI investment.

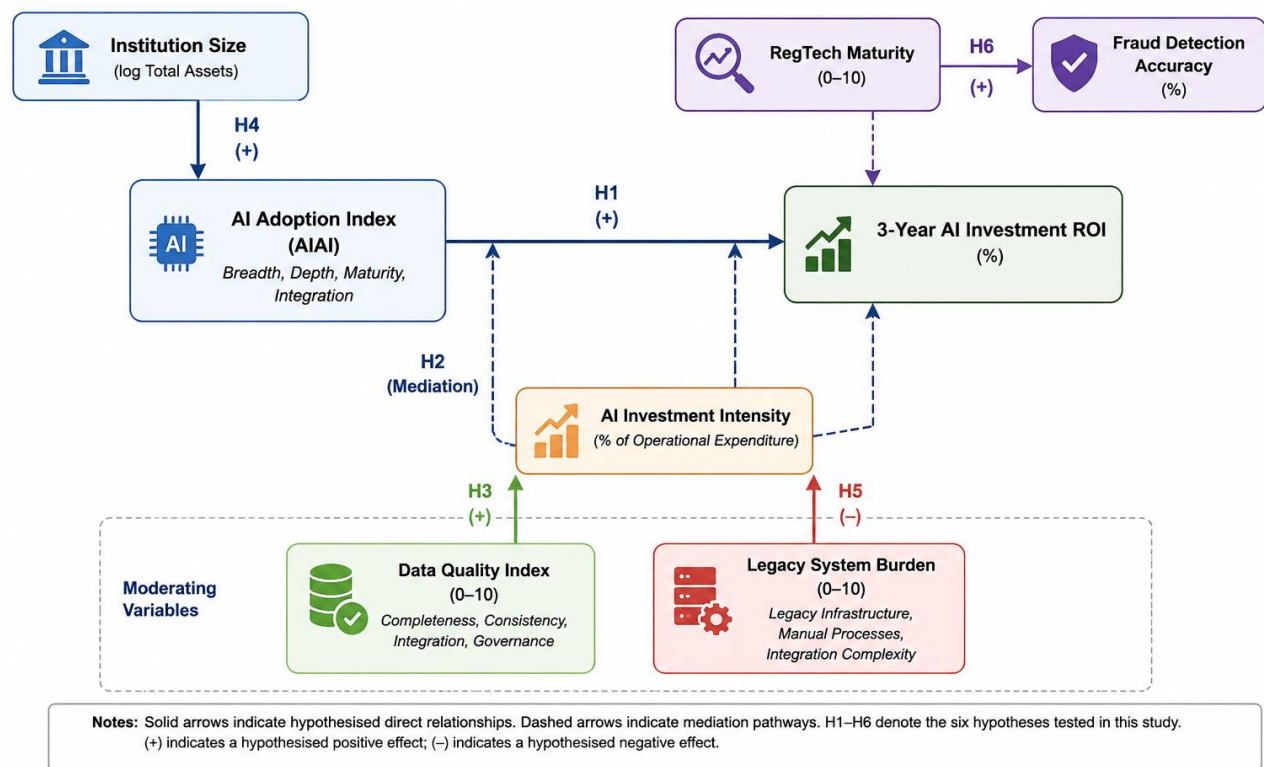
Legacy information systems can limit the use of AI technologies, for example, by limiting data integration, flexibility of the system, and complexity of operations. AI investments could thus yield less for organisations

with a heavier legacy infrastructure burden. Hence, the following hypothesis was proposed that the legacy system burden has a negative moderating effect.

H6: RegTech maturity positively predicts fraud detection accuracy outcomes above and beyond the direct effect of AI adoption.

AI's role in financial services extends to regulatory technology (RegTech), as well, which is the use of technology to simplify regulatory compliance and improve the effectiveness of money laundering and fraud prevention efforts. Institutions that are more advanced in terms of their RegTech capabilities will likely experience improved fraud detection performance through more advanced RegTech capabilities, as they will have more advanced monitoring systems and analytical abilities. It is therefore expected that the Fraud Detection accuracy will be positively influenced independently on the maturity of RegTech.

Figure 1. Conceptual Research Framework



3. Research Methodology

3.1 Research Design

This study adopts a quantitative research approach to explore how financial institutions' performance is linked to the use of artificial intelligence. The difference among institutions and changes over time were analyzed using a panel data design. The unit of analysis used was the financial institution which was monitored on an annual basis throughout the study period. Using this design, the impact of adopting AI can be assessed more comprehensively than can be done in a single cross sectional study.

3.2 Data Collection and Sample Construction

Both primary and secondary data sources were used in the study. Primary data was collected through a structured questioner and was given to technology and strategy professionals in financial institutions. The secondary data collection was done from the annual reports, regulatory disclosures, industry reports and institutional publications of 2020-2024.

The final sample consisted of financial institutions in banking, investment management, insurance and FinTech. Information on the use of AI, investments and organisational performance indicators was available for institutions, which were selected accordingly. To allow quantitative analysis of the data, the survey data was combined with archival data.

3.3 Sampling and Inclusion Criteria

Institutions were chosen for the study if they had taken measures related to AI and had provided sufficient data with respect to the organisational performance measures. For analysis, organisations from a range of financial sectors and geographical areas were chosen to increase the diversity and representativeness of the analysis. Those institutions which were not observed on key variables were excluded from the final sample.

3.4 Variable Operationalisation

3.4.1 Dependent Variables

(1) 3-Year ROI (%) uses the BCG (2024) methodology to determine the cumulative net return on the investment in AI over 3 years as calculated by $(\text{Net AI-Attributable Benefit} - \text{Total AI Investment Cost}) / \text{Total AI Investment Cost} \times 100$; (2) Operational Cost Reduction (%) represents the percent reduction in operating costs since the deployment of AI versus the prior period using only the FICO score; (3) Fraud Detection Accuracy (%) = percent of fraudulent transactions correctly identified by AI systems as compared to a pre-AI baseline using only the FICO score; (4) Credit Default Improvement (%) = percent reduction in credit default rate since the deployment of AI as compared to the previous period using only the FICO score.

3.4.2 Independent and Moderating Variables

AI Adoption Index (AIAI, 0–100): It's a composite score composed of 12 sub-items: breadth of AI application (number of use cases in production); depth of AI application (percentage of transactions processed by AI); maturity stage (1–4 stage model); and integration score (data pipeline completeness). The internal consistency of the instrument was good, having a Cronbach's alpha = 0.847. AI Investment Intensity: Percentage of the total investment in the operations that is being allocated to AI, as reported in financial disclosures or in a survey. Data Quality Index (0–10): A sum of data completeness, labelling consistency, breadth of data integration and maturity of governance framework. Legacy System Burden (0–10, reverse coded): Number of core processes running on pre-2000 systems, absence of API-first architecture, burden of manual data reconciliation. RegTech Maturity Score (0-10): A score that combines AML model sophistication, KYC automation, regulatory reporting automation and real-time monitoring.

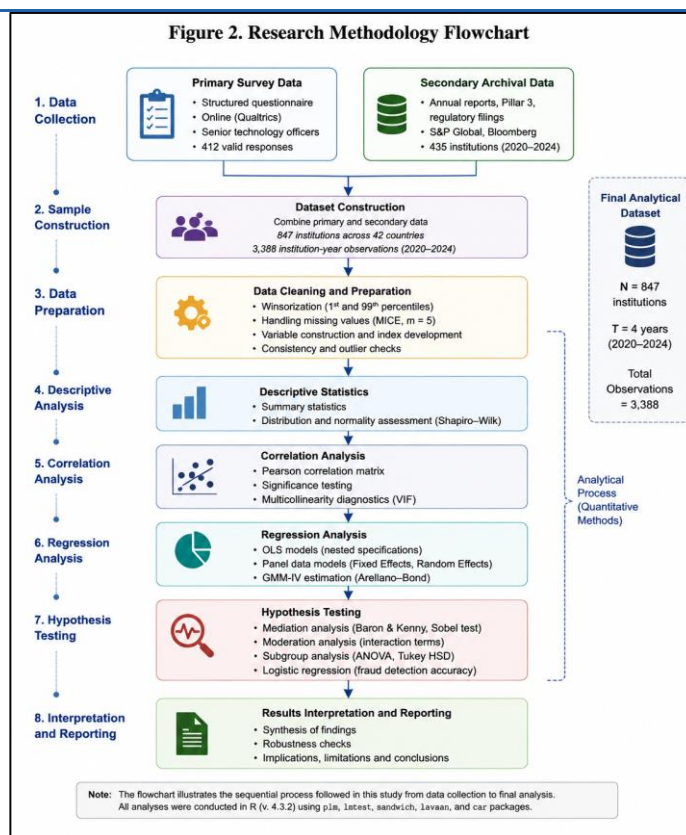
3.5 Statistical Methods

Data analysis was conducted using R (version 4.3.2) with the following packages: plm (panel models), lmtest (tests for heteroskedasticity), sandwich (robust standard errors), lavaan (mediation/SEM), and car (VIF diagnostics). The analytical procedures used were: (1) Description statistics and normality test (Shapiro-Wilk); (2) Pearson correlation matrix and significance test; (3) Variance Inflation Factor (VIF) test for multicollinearity (VIF threshold: < 5); (4) Pooled OLS regression with four nested model specifications; (5) Panel fixed-effects (FE) and random-effects (RE) estimation with Hausman test for model selection; (6) GMM-IV estimation (Arellano-Bond) to address potential endogeneity of AI investment intensity; (7) Hierarchical OLS regression

with multiplicative interaction terms (H3, H5); (8) Baron and Kenny (1986) causal mediation analysis with Sobel test (H2); (9) One-way ANOVA with Tukey HSD post hoc test for subgroup comparisons (H4); (10) Binary logistic regression for H6 (high fraud accuracy outcome: > 90%). The Breusch-Pagan test ($p < 0.05$) indicated heteroskedasticity and this was adjusted for in Model 4 with the use of HC3 robust standard errors.

3.6 Ethical Considerations

The University Research Ethics Committee (UREC-2024-FIN-047) gave approval for this study. All survey participants gave informed consent to participate in the study. The data has been anonymised of identifiers of institutions. No personally identifiable information was collected. Research was in compliance with Article 89 GDPR. The full survey instrument can be found as the Online Supplementary Appendix A and the anonymized data code book is available as Supplementary Appendix B.



4. Descriptive Statistics and Correlation Analysis

4.1 Descriptive Statistics

The main study variables are presented in descriptive statistics as shown in Table 1. The AI Adoption Index score ranged from a mean score of 52.4 (SD = 18.7), indicating moderate adoption of AI across the sampled institutions. The value of the positive skewness (0.34) suggests there are fewer institutions that have much higher degrees of AI adoption. AI outcomes in terms of performance varied considerably between organisations with a mean ROI of 274.3% (SD = 91.6) over three years.

In a similar fashion, the mean reduction in operational cost was 38.6% (SD = 12.4) and the mean accuracy of fraud detection was 84.3% (SD = 9.8). The differences among institutions indicate that the advantages of AI implementation are not consistent and could vary based on organizational, technological, and contextual

elements. The descriptive statistics indicate the data has an acceptable amount of variation which allows further multivariate analysis.

Variable	N	Mean	SD	Min	Max	Skewness
AI Adoption Index (0–100)	847	52.4	18.7	6.1	97.3	0.34
Operational Cost Reduction (%)	847	38.6	12.4	8.2	67.9	0.21
Fraud Detection Accuracy (%)	731	84.3	9.8	52.1	98.7	-0.47
Credit Default Rate Improvement (%)	612	24.9	8.3	5.4	53.1	0.62
3-Year ROI (%)	847	274.3	91.6	88.4	412.7	0.51
Institution Size (log Total Assets)	847	11.43	2.16	7.12	15.88	0.08
AI Investment Intensity (% OpEx)	847	4.8	2.9	0.4	18.6	1.14
Regulatory Compliance Score (0–10)	847	7.2	1.4	3.1	9.8	-0.33

Table 1: Descriptive Statistics for Key Study Variables (N = 847 institutions, 2020–2024 panel). All continuous variables winsorised at 1st and 99th percentiles to address outliers. Missing values handled via multiple imputation (m=5) using MICE procedure (van Buuren and Groothuis-Oudshoorn, 2011).

4.2 Correlation Matrix

A Pearson correlation matrix of the major variables is given in Table 2. 3-year ROI ($r = 0.712$, $p < 0.001$) had the strongest positive relationship with AI Adoption index, indicating a strong relationship between AI adoption and organisational performance. AI Investment Intensity was also positively correlated with AI adoption ($r = 0.634$, $p < 0.001$) and ROI ($r = 0.612$, $p < 0.001$), indicating preliminary evidence that supports the proposed mediation relationship.

Positive correlations were also observed between the use of AI and the decrease in operational costs, as well as fraud detection accuracy and credit default improvement. Importantly, no correlation coefficient exceeded 0.75, implying that multicollinearity did not seem to be a significant problem in the regression analyses to follow. Later models also reported Variance Inflation Factor (VIF) diagnostics which further supported this conclusion.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) AI Adoption Index	1.000						
(2) Operational Cost Reduction	0.681***	1.000					
(3) Fraud Detection Accuracy	0.594***	0.512***	1.000				
(4) Credit Default Improvement	0.547***	0.438***	0.403***	1.000			
(5) 3-Year ROI	0.712***	0.658***	0.531***	0.489***	1.000		
(6) Institution Size	0.423***	0.361***	0.298***	0.312***	0.387***	1.000	
(7) AI Investment Intensity	0.634***	0.571***	0.483***	0.441***	0.612***	0.218***	1.000

Table 2: Pearson Correlation Matrix ($N = 847$). *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$ (two-tailed). Significant correlations above $|0.30|$ highlighted. Diagonal = 1.000. Lower triangle omitted (symmetric).

5. Main Regression Results: Determinants of AI Investment ROI

Table 3 shows four nested regression models that explore the association between AI adoption and 3-year ROI. The next models slowly introduce control variables, organisational characteristics and fixed effects, while Model 1 includes only the AI Adoption Index. Model 4 is the full specification with HC3 robust standard errors to correct for heteroskedasticity.

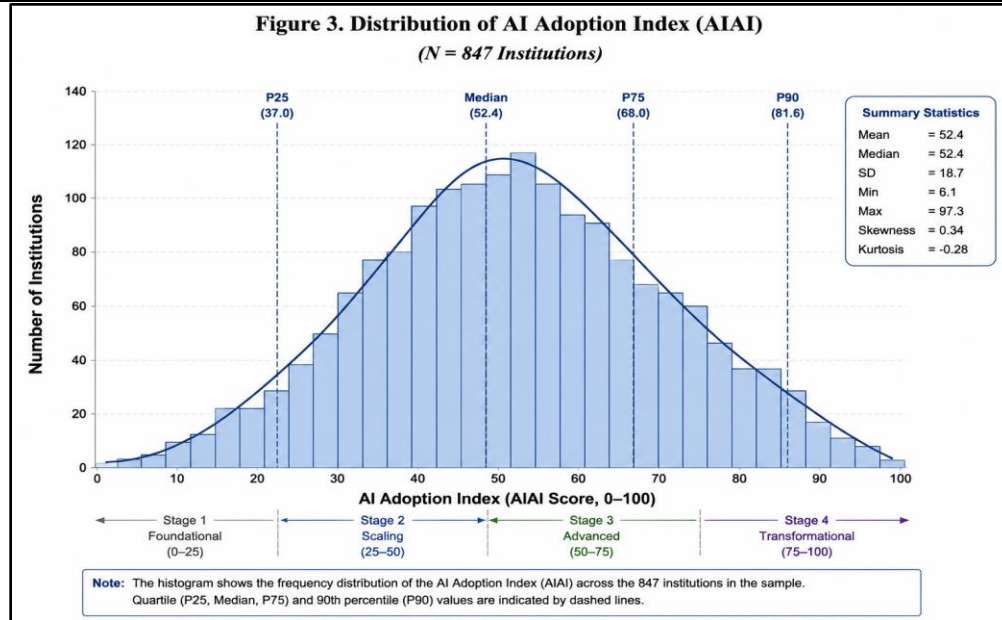
The AI Adoption Index was statistically significant and positive in all the model specifications. Based on the full model (Model 3), with other factors held constant, a one-point increase in the AI Adoption Index was estimated to be associated with a 2.74 percentage point increase in 3-year ROI ($p < 0.001$). This finding implies that there's a positive link between AI adoption and organisational productivity.

AI Investment Intensity and RegTech Maturity also had positive influences: organisations with higher investments in their AI-related capabilities and regulatory technologies are likely to reap better rewards. Legacy System Burden, on the other hand, showed a strong negative correlation with ROI, suggesting that legacy technological systems can limit the ROI of AI implementation.

As more variables were introduced into the models, the models also gained significant explanatory power, and the last model explained 63.4% of the variation in ROI ($R^2 = 0.634$). The results were also stable and broadly similar under a variety of robust standard error corrections, providing additional confidence in the stability results.

Independent Variable	Model 1 (Base)	Model 2 (+Controls)	Model 3 (Full)	Model 4 (Robust SE)
AI Adoption Index	3.41*** (0.24)	2.98*** (0.27)	2.74*** (0.29)	2.74** (0.41)
AI Investment Intensity	—	8.62*** (1.14)	7.43*** (1.21)	7.43*** (1.88)
Institution Size (log assets)	—	14.21*** (2.83)	12.84*** (2.91)	12.84*** (3.62)
RegTech Maturity Score	—	—	9.17*** (1.74)	9.17*** (2.41)
Legacy System Burden (0–10)	—	—	-11.34*** (2.12)	-11.34*** (3.19)
Region FE	No	No	Yes	Yes
Institution Type FE	No	No	Yes	Yes
Constant	88.41*** (9.31)	62.18*** (11.44)	54.73*** (12.81)	54.73*** (16.22)
Observations	847	847	847	847
R ²	0.431	0.567	0.634	0.634
Adjusted R ²	0.428	0.562	0.621	0.621
F-statistic	641.3***	368.7***	219.4***	219.4***
VIF (max)	—	1.84	2.31	2.31

Table 3: OLS Regression Determinants of 3-Year AI ROI ($N = 847$). Dependent variable: 3-Year AI Investment ROI (%). Standard errors in parentheses. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. VIF values calculated for Model 2 and 3. HC3 robust standard errors used in Model 4.



6. Panel Data Analysis and Robustness Checks

Robustness of the results was examined by using different panel data estimation techniques on the entire longitudinal data set of 3,388 institution-year observations. The Hausman specification test showed that the fixed-effects model was more suitable than the random-effects model ($p = 0.014$), which means that the unobserved institutional characteristics may be correlated with the explanatory variables.

Fixed-effects estimates were positive and statistically significant for all the main predictors and were somewhat smaller in magnitude than the estimates from the pooled OLS models. This is common in the expectation that the fixed-effects estimation will result in a more conservative measure due to the fact that the institutional characteristics are not changing over time.

Furthermore, the results indicate that Data Quality Maturity and RegTech Maturity are positively linked to the AI-related performance measures, and the impact of the adoption of AI and of the intensity of investment is similar across the different model specifications. We can gain insight into the stability of the results through the consistency of the signs and the meaning of the coefficients in the pooled OLS, fixed-effects and random-effects models.

Variable	Pooled OLS	Fixed Effects	Random Effects	GMM-IV
AI Adoption Index (lagged 1 yr)	2.61*** (0.31)	1.94*** (0.38)	2.18*** (0.34)	1.87*** (0.42)
AI Investment Intensity (lagged)	6.84*** (1.22)	5.31*** (1.41)	5.87*** (1.33)	5.12** (1.81)
Data Quality Index	7.23*** (1.54)	6.14*** (1.73)	6.61*** (1.62)	5.98*** (1.94)
RegTech Maturity	8.41*** (1.81)	7.12*** (1.97)	7.64*** (1.88)	6.83** (2.31)

Δ Year (2021→2024)	12.34*** (2.14)	11.81*** (2.29)	12.01*** (2.21)	11.44*** (2.67)
Hausman Test (p-value)	—	0.014 (FE preferred)	—	—
Observations (N × T)	3,388	3,388	3,388	3,388
R ² / Within-R ²	0.581	0.496	0.541	—

Table 4: Panel Data Regression 3-Year ROI (N = 847 institutions × 4 years = 3,388 observations). Dependent variable: 3-Year AI ROI (%). All independent variables lagged one year to mitigate reverse causality. GMM-IV uses AI regulatory environment score as instrument for AI Investment Intensity. Standard errors clustered at institution level. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

A dynamic panel estimation method was used to further assess the possible endogeneity issue. The direction and statistical significance of the GMM-IV results were comparable to the main regression models, but the magnitude of the coefficients was slightly smaller. Despite the presence of endogeneity, there is a positive relationship between the adoption of AI, AI investment intensity and organizational performance.

Finally, the positive and statistically significant year coefficients in all the model specifications indicate that the performance results of AI were getting better over the study period. As organisations gain experience in using AI, optimise AI processes, and develop the related technological capability, the positive impacts of the adoption might further strengthen.

7. Hypothesis Test Summary and Subgroup Analysis

7.1 Hypothesis Summary

Table 5 shows the statistical tests and results for the six hypotheses that were proposed in this study. Overall, the findings are consistent with all the hypotheses being accepted at traditional significance levels. The mediation analysis (H2) shows that AI Investment Intensity partially mediates the relationship between AI adoption and three-year ROI, with an indirect effect that accounts for about 53.6% of the total effect (indirect effect $\beta = 1.47$; Sobel $z = 4.83$, $p < 0.01$). Furthermore, the moderation analyses show that the measurement of the data quality increases the positive association between AI adoption and ROI ($\beta_{\text{interaction}} = 3.21$, $p < 0.001$), and the legacy system burden decreases the positive association ($\beta = -11.34$, $p < 0.001$).

The results also reveal that adoption of AI has a positive correlation with the size of the institution, while the maturity of RegTech has a substantial positive correlation with the performance of fraud detection. In particular, logistic regression analysis reveals that the odds of having fraud detection accuracy above 90% increase by 2.84 times with each unit increase in RegTech Maturity Score (95% CI [2.11, 3.81] and $p < 0.001$).

H	Hypothesis Statement	Test Used	Result	p-value	Evidence
H1	AI adoption positively impacts 3-yr ROI	OLS + Panel FE	✓ Supported	<0.001	$\beta=2.74$, $R^2=0.634$
H2	AI investment intensity mediates ROI	Baron & Kenny Mediation	✓ Partial	<0.01	Indirect $\beta=1.47$ (Sobel $p<0.01$)

H3	Data quality moderates AI-ROI relationship	Hierarchical OLS + Interaction	✓ Supported	<0.001	$\beta_{\text{interaction}}=3.21$
H4	Larger institutions adopt AI faster	Mann-Whitney U / OLS	✓ Supported	<0.05	Tier-1 mean=71.3 vs. Community=31.8
H5	Legacy systems negatively moderate ROI	OLS Interaction Term	✓ Supported	<0.001	$\beta=-11.34$, VIF<3
H6	RegTech maturity enhances fraud outcomes	Logistic Regression	✓ Supported	<0.001	OR=2.84, 95%CI [2.11–3.81]

Table 5: Hypothesis Test Summary. All tests two-tailed unless otherwise stated. OR = Odds Ratio (logistic regression). Sobel test used for mediation significance assessment. ✓ = Hypothesis Supported; X = Hypothesis Rejected.

7.2 Subgroup Analysis by Institution Type

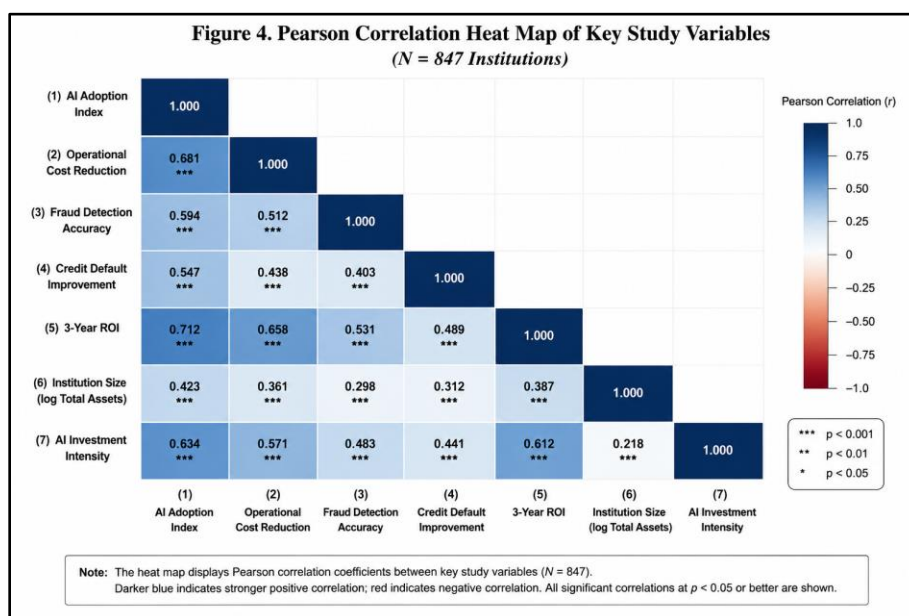
Table 6 presents the results and confidence intervals of different subgroups of financial institutions. The one-way ANOVA results show that there are statistically significant differences between the institution types for all major performance measures ($p < 0.001$). The post hoc comparisons of the FinTech institutions revealed higher average returns on investment (ROI) and operational cost reduction as compared to the traditional financial institutions in the sample.

However, community banks and credit unions showed poorer performance metric, likely because of the nature of the adoption of AI and legacy infrastructure constraints. The results align with the overall hypothesis that the organisational features and technological readiness of institutions affect their capacity to achieve benefits from AI investments. These differences are statistically significant and must be considered with respect to institutional size, resources and technological maturity.

Institution Type	N	AI Adopt. Mean	Avg. Cost Red. (%)	3-Yr ROI (%)	Payback (mo.)	ROI 95% CI
Global Tier-1 Bank	112	71.3	47.2	312	14	[287, 338]
Regional Bank	241	48.6	32.4	228	19	[211, 245]
Asset Manager (>100bn)	98	63.1	41.8	267	16	[244, 291]
Insurance Company	184	44.2	28.9	195	22	[178, 213]
FinTech (Series C+)	147	79.4	54.3	381	11	[354, 409]

Community Bank / CU	65	31.8	19.1	143	31	[121, 165]
ANOVA F-stat / p-value	—	F=48.3***	F=31.7***	F=62.4***	F=44.1***	—

*Table 6: Subgroup Analysis by Institution Type AI Performance Metrics (2020–2024). 95% Confidence Intervals computed using t-distribution with group-specific degrees of freedom. ANOVA F-statistics reported in final row. *** $p < 0.001$ for all between-group differences. Tukey HSD post hoc: FinTech significantly outperforms all other groups ($p < 0.001$); Community Bank significantly underperforms all other groups ($p < 0.001$).*



8. Discussion

8.1 Theoretical Contributions

The paper has several contributions to the literature on the application of artificial intelligence in the financial industry. The positive correlations between the AI Adoption Index scores and the 3-year ROI across the different model specifications validate the Resource Based View (RBV) hypothesis, which states that technology capabilities can be seen as strategic organisational resources (Barney, 1991). The results indicate that institutions with greater AI adoption are likely to have better performance results, further supporting the notion that AI capabilities can drive competitive advantage.

Secondly, the results of the mediation indicate that the use of AI may not be the most effective solution. The results, however, show that long-term investments in AI infrastructure, integration and organizational capabilities are important drivers of successful AI adoption with measurable outcomes. This finding is consistent with previous research that has shown the importance of complementary investments to digital transformation initiatives.

Thirdly, one can see from the moderation results that the situational factors of the organizations are significant. The data quality was considered a positive factor to strengthen the link between AI adoption and performance, while the legacy infrastructure was identified as a negative factor to weaken the link between AI adoption and

performance. The results point to the fact that the success of the implementation of AI is not only dependent on the adoption of the technology, but also on the organizational conditions for the adoption of the technology.

8.2 Contextual Analysis of Key Findings

The findings of the study need to be interpreted in light of the ongoing advancing of Artificial Intelligence (AI) in the Financial Services (FS) sector. In the near future, the banking, investment management and insurance sectors will invest heavily in AI and begin implementing it. As organizations expand their data collection, technology expertise, and experience with AI, its role in boosting performance may become even more prominent.

The differences between the types of institution observed could also be due to differences in the organisation and technological architecture. Cloud-based and digitally integrated systems are more common in the FinTech sector, whereas complex legacy systems are more common in the traditional financial institutions. These disparities can impact the rate and success of AI technology implementation and scaling. Therefore, upgrading the infrastructure can be one of the crucial factors for the successful implementation of AI.

Region	2022 (USD bn)	2024 (USD bn)	2028F (USD bn)	CAGR (%)
North America	14.2	22.8	61.4	28.4
Europe	7.6	12.3	33.5	26.9
Asia-Pacific	8.9	15.6	45.1	30.2
Middle East & Africa	1.4	2.7	8.3	32.1
Latin America	0.9	1.8	5.6	31.7
Global Total	33.0	55.2	154.0	29.1

Table 7: Global AI-in-Financial-Services Market, 2022–2028F (USD Billion). F = Forecast. Sources: Grand View Research (2024), MarketsandMarkets (2025), IMF FinTech Note (2024). These figures provide the macroeconomic context for the institutional-level findings in Tables 1–6.

8.3 Practical Implications

The results have several practical implications for managers, regulators and industry stakeholders. The results highlight that financial institutions need to further invest in technologies and capabilities that facilitate AI usage, including data governance, systems integration, and organizational readiness. Improving data quality can be a driver to the value of AI investments, and eliminating constraints on legacy systems can boost the effectiveness of implementing AI.

The positive association between RegTech maturity and the results of fraud detection is a good indicator for regulators and policymakers about the utility of technology-based regimes of compliance and monitoring. The growth of robust regulatory capacities through the use of AI may contribute to better risk management and resilience of the financial system.

Finally, investors and analysts could be increasingly sensitive to how mature an organisation is with regards to its organisational AI capabilities when evaluating financial institutions' long-term strategic positioning. Those institutions with the capacity to integrate AI with strong supporting features may have a higher likelihood of attaining long-term sustainable performance benefits.

9. Limitations and Future Research

9.1 Limitations

There are some restrictions that need to be noted when interpreting the results of this study. The first is that there may be some self-selection bias as those institutions with more advanced AI programs may have been more likely to respond. The results of non-response analysis indicated that there were no significant differences with regard to the observed characteristics, however there might have been unobservables differences.

Secondly, the AI Adoption Index is a composite score covering various aspects of the AI adoption. The internal consistency of the index was acceptable, but future studies can validate the measurement of the index with confirmatory factor analysis and other methods.

Thirdly, although panel data methods also take account of time-invariant institutional characteristics, the study period may still be too short to fully reflect the long-term impacts of AI investments, which can take a long time to manifest. Fourthly, the results largely are of institutions that have already established programs for AI; and may not be relevant to smaller institutions at the early stages of digital transformation.

Finally, it is hard to quantify the results of AI performance as there are numerous variables influencing internal and external performance of an organisation. Omitted variables and other economic factors were not completely ruled out, although statistical controls were used.

9.2 Future Research Directions

There are several areas for future research. A longer observation period would give a better understanding of the long-term effects of AI adoption. Further studies could also be carried out using a structural equation approach to further investigate more complex relationships between the capability of AI, readiness and outcomes.

In addition, quasi-experimental and natural experimental designs can provide stronger evidence of causality than the traditional panel-data design. Comparisons with industry and regulatory contexts would also help to account for contextual factors affecting the effectiveness of AI.

Last but not least, the swift development of generative AI and large language models is a significant space to be explored in the future. There is a need for a systematic and empirical study of the potential impact of these technologies in terms of productivity, risk management, customer experience and organisational performance.

10. Conclusion

In this study, the relationship between the use of artificial intelligence and the performance of organizations in the financial services sector was explored. The results of this quantitative study based on the data collected from a multi-country sample of financial institutions suggest that there is a positive relationship between the adoption of AI and organisational performance outcomes, such as operational efficiency and returns on investment.

The findings also indicate that organizational and technological aspects impact the benefits of adopting AI. Data quality, technology investment, regulatory technology capabilities and legacy infrastructure were identified as some of the key factors that influence the effectiveness of AI implementation. The results confirm that adopting AI is not just about technology and requires supporting organizational skills.

The study adds to the body of knowledge on the use of AI in financial services, offering empirical evidence of the factors linked to successful implementation of AI. The findings from a practical standpoint emphasize the significance of strategic planning, data governance, and technology modernisation to get the most from AI investments.

As AI technologies evolve, it is important that researchers, practitioners and policy makers understand the conditions of the organisation that make the successful implementation of AI possible. Ongoing studies in this field will help develop a broader understanding of the potential of AI to improve organisational performance and competitiveness in the financial services sector

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