

Artificial Intelligence Adoption and Firm Financial Performance: Evidence from Publicly Listed Companies

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Abstract: This study aimed to examine the relationship between artificial intelligence adoption and firm financial performance among companies listed on the Tehran Stock Exchange using accounting- and market-based performance indicators. This quantitative longitudinal study used balanced panel data from 146 nonfinancial companies listed on the Tehran Stock Exchange during 2018–2024, yielding 1,022 firm-year observations. Artificial intelligence adoption was measured using a disclosure-based Artificial Intelligence Adoption Index constructed from annual reports and official corporate disclosures. Firm financial performance was assessed using return on assets (ROA), return on equity (ROE), and Tobin's Q. Firm size, financial leverage, firm age, sales growth, asset tangibility, and liquidity were included as control variables. Panel-data econometric analysis was conducted using random-effects generalized least squares models with firm-clustered robust standard errors, while year and industry effects were controlled. Artificial intelligence adoption was positively and significantly associated with ROA ($\beta = 0.0067$, $SE = 0.0014$, $z = 4.79$, $p < 0.001$), ROE ($\beta = 0.0104$, $SE = 0.0026$, $z = 4.00$, $p < 0.001$), and Tobin's Q ($\beta = 0.0710$, $SE = 0.0140$, $z = 5.07$, $p < 0.001$). Financial leverage was negatively associated with all three performance measures, whereas sales growth and liquidity showed significant positive relationships with ROA, ROE, and Tobin's Q. The overall models were statistically significant, explaining 34.7% of variation in ROA, 30.1% in ROE, and 39.2% in Tobin's Q. Greater artificial intelligence adoption was associated with stronger accounting profitability and higher market valuation among publicly listed companies, suggesting that AI can function as a value-enhancing organizational capability when supported by appropriate financial, technological, and managerial resources.

Keywords: artificial intelligence adoption; financial performance; return on assets; return on equity; Tobin's Q; panel data; Tehran Stock Exchange.

1. Introduction

Artificial intelligence (AI) has emerged as one of the most consequential technological developments shaping contemporary business models, organizational processes, and financial decision-making. The growing availability of computational power, large-scale data, machine learning algorithms, natural language processing, predictive analytics, and intelligent automation has enabled firms to redesign activities that were traditionally dependent on manual judgment, repetitive processing, or retrospective analysis. In the financial domain, AI is increasingly embedded in accounting systems, risk assessment, credit analysis, fraud detection, customer relationship management, investment analysis, forecasting, budgeting, auditing, and strategic planning. This development is not limited to technology-oriented firms; rather, AI adoption is becoming relevant across industries because it affects how firms allocate resources, process information, manage uncertainty, and generate economic

value. Digital finance has therefore moved beyond the simple automation of existing processes toward increasingly intelligent systems capable of pattern recognition, predictive inference, adaptive decision-making, and real-time response to changing business conditions [1]. As these technologies become more deeply integrated into organizational routines, an important empirical question is whether their adoption translates into measurable improvements in firm financial performance.

The economic logic underlying AI adoption is closely related to the capacity of intelligent systems to improve the quality, speed, and scalability of organizational decision-making. Firms operate in environments characterized by information asymmetry, uncertainty, operational complexity, and pressure to reduce costs while simultaneously improving responsiveness and innovation. AI may address these challenges by identifying patterns that would be difficult to detect manually, generating more accurate forecasts, automating routine decisions, and assisting managers in allocating resources more efficiently. Evidence from fintech-oriented organizations suggests that AI can support resource optimization by enabling firms to identify inefficiencies, refine operating processes, and deploy financial and technological resources more strategically [2]. Similar technological value mechanisms have also been discussed in relation to broader digital innovations, where adoption creates value not merely through the presence of the technology itself but through its capacity to transform processes, improve coordination, and generate new organizational capabilities [3]. From this perspective, AI adoption may influence profitability through cost reduction, revenue enhancement, improved asset utilization, more effective risk management, and superior strategic responsiveness.

The financial services sector has been among the earliest and most visible environments for AI deployment because of its dependence on high-volume data processing, risk assessment, compliance, transaction monitoring, and customer analytics. Prior studies have documented the increasing use of AI in banking and financial services for automated advisory systems, credit scoring, fraud detection, algorithmic decision-making, customer segmentation, and operational support [4]. In banking systems specifically, AI adoption has been associated with opportunities to improve digital payment ecosystems, strengthen transaction monitoring, enhance service efficiency, and support more adaptive financial operations, although implementation remains constrained by infrastructure, data quality, cybersecurity, governance, and organizational readiness [5]. These developments demonstrate that AI is not a single-purpose technology; rather, it functions as a general-purpose organizational capability that may affect multiple financial and operational processes simultaneously. This breadth of application makes the relationship between AI adoption and firm-level performance particularly important, because improvements arising in separate functional areas may accumulate and ultimately influence accounting profitability and market valuation.

The potential financial effects of AI adoption can also be understood through information-processing and decision-quality mechanisms. High-quality financial decisions depend on timely, relevant, and reliable information. AI systems can process heterogeneous data at greater speed and scale than conventional manual procedures, allowing managers to integrate financial, operational, customer, and market information more effectively. In financial reporting contexts, AI-based tools may support more accurate classification, anomaly detection, reconciliation, estimation, and disclosure processes. Recent research has therefore examined whether AI adoption can improve financial reporting quality, while also emphasizing that the effectiveness of intelligent accounting systems depends partly on users' trust in their outputs and underlying processes [6]. Similarly, the adoption of AI in integrated financial reporting and auditing has been linked to broader changes in audit quality, reporting processes, and the production of decision-useful corporate information [7]. These findings are important

for firm performance because financial reporting quality and audit quality affect information asymmetry, investor confidence, internal monitoring, financing conditions, and managerial accountability, all of which can indirectly influence corporate value.

At the same time, the adoption of AI is shaped by organizational perceptions and institutional conditions rather than technological availability alone. Perceived usefulness and perceived ease of use have been identified as important determinants of organizational willingness to adopt AI in financial reporting, suggesting that firms are more likely to institutionalize AI when users believe that the technology improves task performance and can be integrated into existing workflows without excessive complexity [8]. Evidence from internal auditing likewise indicates that AI adoption depends on a combination of technological, professional, organizational, and behavioral factors, including perceived benefits, competence, organizational support, and the readiness of users to work with intelligent systems [9]. In public-sector auditing, propensity toward AI adoption has similarly been linked to institutional, organizational, and individual factors, confirming that successful implementation depends on more than the mere acquisition of software or analytical tools [10]. These findings imply that the financial consequences of AI adoption may vary across firms because organizations differ in their capacity to absorb, govern, and exploit new technologies.

The technology-organization-environment perspective provides a useful framework for understanding such heterogeneity. Research on the insurance industry has shown that AI adoption is influenced by technological readiness, organizational resources, managerial support, competitive pressure, and environmental conditions [11]. This perspective suggests that firms possessing stronger digital infrastructure, more skilled employees, better data resources, and greater managerial commitment may be more capable of converting AI investments into operational and financial benefits. Conversely, firms that adopt AI symbolically or without the necessary organizational complementarity may fail to realize comparable performance gains. Therefore, the simple presence of AI-related initiatives may not be sufficient; what matters is the extent to which AI becomes integrated into decision processes, operational routines, and strategic functions. This distinction is particularly relevant when AI adoption is measured across publicly listed companies, where disclosure can range from isolated references to automation to evidence of broader deployment across reporting, forecasting, customer management, production, risk, and investment functions.

Strategic management of AI is consequently becoming an important component of financial services and corporate transformation. A strategic framework for smart financial services emphasizes that AI adoption should be aligned with organizational objectives, data architecture, governance structures, customer needs, and managerial capabilities in order to generate sustainable value [12]. From a performance perspective, this strategic alignment may create several pathways to improved financial outcomes. AI can contribute to operational efficiency by reducing processing time and labor intensity, to revenue growth by supporting personalization and market intelligence, to working-capital management by improving forecasting, and to risk control by identifying anomalies and emerging threats. It can also improve the speed of managerial response to market changes, thereby potentially strengthening competitive positioning. These mechanisms provide a theoretical basis for expecting a positive association between AI adoption and financial performance, although the strength of this association may depend on firm size, leverage, growth opportunities, liquidity, and industry characteristics.

AI adoption is also increasingly connected to fintech ecosystems and user-centered financial innovation. Research examining fintech adoption shows that AI-related financial technologies are shaped by users' financial-services knowledge, innovativeness, and perceived institutional support, while government support may

strengthen the conditions under which technological capabilities are accepted and used [13]. Although such studies often focus on individual or service-level adoption, they have broader implications for firm performance because the effectiveness of AI-enabled financial products depends on both organizational implementation and market acceptance. When firms successfully integrate AI into service delivery, customer analytics, and financial interfaces, they may reduce transaction frictions, improve engagement, and differentiate themselves from competitors. Prior research on AI adoption in financial services has accordingly linked intelligent technologies to marketing-related outcomes, demonstrating that AI can influence customer targeting, service responsiveness, and commercial performance [14]. These commercial effects may eventually be reflected in sales growth, profitability, and market valuation.

However, the anticipated benefits of AI must be considered alongside significant ethical, governance, and control challenges. Financial decision-making often involves sensitive data, distributive consequences, credit access, investment allocation, and judgments that can materially affect individuals and organizations. AI systems may reproduce bias, operate opaquely, expose firms to privacy risks, or generate decisions that are difficult to explain and audit. The ethical consequences of AI adoption in financial decision-making have therefore received increasing scholarly attention, particularly in relation to accountability, transparency, fairness, privacy, and the need for human oversight [15]. A broader analysis of AI ethics in financial decision-making similarly emphasizes that algorithmic efficiency should not be separated from concerns regarding responsibility, bias, explainability, and institutional trust [16]. These concerns are financially relevant because poorly governed AI systems may create compliance costs, reputational damage, legal exposure, model risk, and loss of stakeholder confidence. Thus, AI adoption may generate value only when firms develop adequate governance mechanisms to control its associated risks.

Differences between incumbent financial institutions and newer fintech organizations further illustrate why the financial consequences of AI adoption cannot be assumed to be uniform. Comparative evidence indicates that fintech firms and established financial institutions often experience AI adoption differently because they vary in organizational structure, legacy systems, regulatory exposure, data architecture, and innovation culture [17]. Fintech firms may have greater flexibility and technological agility, whereas incumbent firms may possess stronger financial resources, established customer bases, and richer historical datasets but face greater integration costs. Similar variation may exist among publicly listed firms outside the financial sector. Large companies may have greater capacity to finance AI investments, recruit specialized personnel, and acquire data infrastructure, while smaller listed firms may adopt targeted AI applications that deliver efficiency gains at lower scale. These differences justify the inclusion of firm-specific characteristics when estimating the association between AI adoption and financial performance.

The relationship between AI and financial outcomes is particularly relevant in emerging-market settings, where digital transformation is occurring under conditions of institutional volatility, financing constraints, unequal technological readiness, and heterogeneous corporate governance. Firms operating in such environments may face high incentives to use AI to improve efficiency, forecasting, and resource allocation, but they may simultaneously encounter barriers involving infrastructure, skilled labor, regulatory uncertainty, data governance, and access to advanced technological resources. Because many existing studies have concentrated on banking, insurance, fintech, auditing, or specific organizational functions, the broader firm-level financial consequences of AI adoption remain less clearly established. In particular, research has frequently examined antecedents of adoption, user acceptance,

reporting quality, marketing outcomes, or sector-specific implementation rather than directly linking the extent of AI adoption to multiple dimensions of firm financial performance.

This limitation is important because financial performance is multidimensional. Accounting-based measures such as return on assets and return on equity capture realized profitability and the efficiency with which firms use assets and shareholder capital, whereas market-based indicators such as Tobin's Q incorporate investor expectations concerning growth, intangible assets, technological capabilities, and future cash flows. If AI adoption improves both internal efficiency and external expectations about future competitiveness, its association should potentially be observable across both accounting and market-based outcomes. Conversely, if AI adoption primarily represents costly experimentation or remains insufficiently integrated into organizational processes, its short-term effect on profitability may be weak even when capital markets respond positively to the strategic signal conveyed by technological investment. Examining several financial indicators is therefore necessary to distinguish between operational profitability and market valuation effects.

The Tehran Stock Exchange provides a relevant setting for investigating these relationships because listed companies operate across diverse industries and differ substantially in size, age, leverage, technological capability, and competitive conditions. The increasing attention given to intelligent financial reporting, internal auditing, digital finance, and AI-enabled management in the Iranian context further suggests that artificial intelligence is becoming an important element of corporate modernization [8, 9, 12]. At the same time, variation in the pace and intensity of adoption creates an empirical opportunity to determine whether companies demonstrating broader AI implementation also exhibit superior financial outcomes after differences in firm characteristics are taken into account. Such analysis can contribute to the literature by moving beyond adoption intention and sector-specific use cases toward a firm-level assessment of economic consequences among publicly listed companies.

Accordingly, this study aims to examine the relationship between artificial intelligence adoption and firm financial performance among companies listed on the Tehran Stock Exchange, using return on assets, return on equity, and Tobin's Q as complementary accounting- and market-based measures of financial performance.

2. Methods and Materials

This study employed a quantitative, applied, and longitudinal research design to investigate the relationship between artificial intelligence adoption and the financial performance of publicly listed companies. The research was conducted using firm-level panel data, which enabled the simultaneous examination of variations across companies and changes within individual companies over time. The statistical population consisted of companies listed on the Tehran Stock Exchange (TSE), Tehran, Iran. The study period covered seven fiscal years from 2018 to 2024, allowing sufficient temporal variation to capture the gradual diffusion of artificial intelligence technologies within corporate operations and to assess their potential financial consequences over multiple reporting periods. Companies were selected through purposive screening based on predefined inclusion criteria. To be included in the study, a company was required to have been continuously listed on the Tehran Stock Exchange throughout the study period, have a fiscal year ending consistently during the observation period, have complete audited financial statements and annual reports available for all required variables, and have sufficient disclosure to permit the assessment of artificial intelligence adoption. Financial institutions, banks, insurance companies, investment companies, and other financial intermediaries were excluded because of the distinctive structure of their financial statements, regulatory requirements, capital structure, and performance measures, which could reduce comparability with nonfinancial firms. Companies with substantial changes in fiscal year, prolonged trading

suspension, or incomplete financial and disclosure data were also excluded. Following the application of these criteria, the final sample consisted of exactly 146 publicly listed companies located and registered within the Tehran Stock Exchange market environment. With seven annual observations for each company, the balanced panel dataset comprised 1,022 firm-year observations. The firm-year constituted the unit of analysis. The longitudinal nature of the design was particularly appropriate because artificial intelligence adoption is not necessarily an immediate or binary organizational event; rather, it may develop progressively through investments in data analytics, automated decision systems, machine learning, intelligent customer-service technologies, predictive systems, process automation, and related digital capabilities. Accordingly, the panel structure provided an appropriate basis for evaluating whether differences in the degree of AI adoption were systematically associated with differences in firm financial performance after controlling for other firm-specific characteristics.

Data were collected through a structured secondary-data extraction procedure using publicly available corporate and financial information. The principal sources included audited annual financial statements, boards of directors' reports to shareholders, annual activity reports, explanatory notes accompanying financial statements, and other official disclosures made by the sampled companies through the Tehran Stock Exchange and the Comprehensive Database of All Listed Companies, commonly known as the CODAL disclosure system. A researcher-developed data extraction checklist was used to ensure that identical information was collected systematically for every firm and fiscal year. The principal independent variable was artificial intelligence adoption. Because a standardized financial reporting item for AI investment was not consistently available across the sampled companies, AI adoption was operationalized using a disclosure-based Artificial Intelligence Adoption Index developed through systematic content analysis of corporate annual reports and related official disclosures. The index captured whether and to what extent a company reported the implementation or organizational use of technologies and applications directly associated with artificial intelligence, including machine learning, intelligent data analytics, predictive analytics, automated decision-making, natural language processing, intelligent customer-service systems, recommendation systems, robotic process automation incorporating intelligent functions, computer vision, AI-assisted production or quality-control systems, and AI-supported risk, forecasting, or planning applications. Disclosures referring only to general computerization, information technology, conventional software, or digitalization without an identifiable artificial intelligence component were not treated as evidence of AI adoption. Each annual report was examined using a standardized coding protocol, and the identified AI-related indicators were aggregated into a firm-year AI adoption score, with higher scores representing broader and more intensive organizational adoption of artificial intelligence. To improve measurement consistency, terminology was standardized before coding, synonymous AI-related expressions were treated consistently, and the coding procedure was applied uniformly across firms and years.

Firm financial performance was evaluated using complementary accounting-based and market-based measures because no single financial indicator captures all dimensions of corporate performance. Return on assets (ROA) was used as the primary accounting-based performance indicator and was calculated as net income divided by average total assets, reflecting the efficiency with which corporate assets generated earnings. Return on equity (ROE) was calculated as net income divided by average shareholders' equity and represented the profitability generated from owners' invested capital. Tobin's Q was employed as a market-oriented measure of firm performance and valuation and was calculated using the market value of equity and the book value of liabilities relative to the book value of total assets. The use of these three indicators enabled the study to distinguish between operating profitability, shareholder-oriented accounting performance, and capital-market valuation. A series of

firm-level control variables was also collected to reduce omitted-variable bias and isolate the relationship between AI adoption and financial performance. Firm size was measured as the natural logarithm of total assets; financial leverage was calculated as total liabilities divided by total assets; firm age was measured as the number of years since establishment; sales growth was computed as the annual percentage change in net sales; asset tangibility was measured as the ratio of tangible fixed assets to total assets; and liquidity was represented by the current ratio. Industry affiliation and fiscal year were additionally recorded to control for systematic industry-specific and macro-temporal effects. All monetary figures were obtained from audited financial reports and standardized before analysis. The extracted dataset was reviewed for coding errors, duplicate observations, inconsistencies across reporting periods, and missing values. Continuous financial variables were also examined for extreme observations, and values at the tails of the distributions were winsorized where appropriate to reduce the disproportionate influence of exceptional observations while retaining the firms in the panel.

Data analysis was conducted using a panel-data econometric framework suitable for repeated observations of the same firms across multiple years. Prior to hypothesis testing, the dataset was screened for completeness and accuracy, after which descriptive statistics, including the mean, standard deviation, minimum, and maximum, were calculated for all continuous variables to characterize the distribution of AI adoption, financial performance, and firm-specific controls. Correlation analysis was subsequently performed to provide an initial assessment of the direction and magnitude of the relationships among the study variables. Multicollinearity among explanatory variables was assessed using correlation coefficients and variance inflation factors, with variance inflation factor values below commonly accepted critical levels interpreted as evidence that multicollinearity did not materially compromise model estimation. The principal empirical analysis estimated separate panel regression models for ROA, ROE, and Tobin's Q. In each model, financial performance served as the dependent variable, the Artificial Intelligence Adoption Index constituted the principal explanatory variable, and firm size, leverage, firm age, sales growth, asset tangibility, and liquidity were entered as control variables. Year effects were incorporated to account for economy-wide shocks and temporal changes affecting all sampled firms, while industry effects were considered to capture structural differences among sectors.

The appropriate panel estimation specification was determined through formal econometric testing. The pooled ordinary least squares model was initially compared with panel alternatives to determine whether unobserved firm-specific heterogeneity was statistically relevant. Fixed-effects and random-effects specifications were subsequently evaluated, and the Hausman specification test was used to determine whether the unobserved firm effects were correlated with the explanatory variables. Where the Hausman test indicated such correlation, the fixed-effects estimator was preferred; otherwise, the random-effects specification was considered appropriate. Diagnostic tests were performed to examine heteroskedasticity, serial correlation, and cross-sectional dependence in the panel residuals. Where violations of conventional regression assumptions were detected, heteroskedasticity- and autocorrelation-consistent or firm-clustered robust standard errors were applied to obtain reliable statistical inference. To address the possibility that the financial benefits of AI adoption might not occur immediately, supplementary models were estimated using lagged AI adoption measures, thereby assessing whether the extent of AI adoption in one fiscal year was associated with financial performance in the subsequent period. Additional robustness analyses compared results across the three performance measures and alternative operationalizations of AI adoption. All statistical tests were two-tailed, and statistical significance was evaluated at the 0.05 level, with more stringent 0.01 and 0.001 levels also reported where applicable. Regression coefficients, robust standard errors, t statistics, probability values, confidence intervals, and model explanatory power were used to interpret the

magnitude, direction, and statistical reliability of the estimated relationships. The analytical procedure was designed to determine whether higher levels of artificial intelligence adoption were systematically associated with superior financial performance among Tehran Stock Exchange-listed companies after accounting for observable firm characteristics, time-specific influences, industry differences, and persistent unobserved firm heterogeneity.

3. Findings and Results

The final analytical sample consisted of 146 nonfinancial companies listed on the Tehran Stock Exchange and observed continuously over the seven-year period from 2018 to 2024, yielding a balanced panel of 1,022 firm-year observations. In terms of the industrial composition of the sample, 26 companies (17.81%) operated in the chemical and petrochemical industries, 24 companies (16.44%) belonged to basic metals and mining-related industries, 18 companies (12.33%) were active in machinery and equipment, 17 companies (11.64%) operated in the food and beverage industry, 15 companies (10.27%) belonged to the pharmaceutical industry, 14 companies (9.59%) operated in cement and construction-material industries, 13 companies (8.90%) were automobile and automotive-parts manufacturers, and the remaining 19 companies (13.01%) represented other eligible manufacturing and service-related industries. The companies had been in operation for between 8 and 68 years, with a mean organizational age of 31.68 years, indicating that the sample included both relatively young listed firms and well-established corporations. Examination of artificial intelligence-related disclosures also revealed a clear expansion of AI adoption during the study period. In 2018, 46 of the 146 companies (31.51%) reported at least one identifiable AI-related organizational application, whereas this number increased to 55 companies (37.67%) in 2019, 67 companies (45.89%) in 2020, 82 companies (56.16%) in 2021, 98 companies (67.12%) in 2022, 116 companies (79.45%) in 2023, and 127 companies (86.99%) in 2024. This pattern demonstrates that AI-related technologies became progressively more prevalent among the sampled publicly listed companies over the observation period, although considerable between-firm variation remained in the breadth and intensity of adoption.

Table 1. Descriptive Statistics of the Study Variables

Variable	N	Mean	SD	Minimum	Maximum
Artificial Intelligence Adoption Index	1,022	3.840	2.180	0.000	9.000
Return on Assets (ROA)	1,022	0.112	0.071	-0.086	0.318
Return on Equity (ROE)	1,022	0.198	0.128	-0.241	0.594
Tobin's Q	1,022	1.832	0.742	0.641	4.286
Firm Size (ln total assets)	1,022	15.914	1.386	12.774	19.462
Financial Leverage	1,022	0.536	0.187	0.112	0.891
Firm Age (years)	1,022	31.680	12.440	8.000	68.000
Sales Growth	1,022	0.173	0.221	-0.412	0.963
Asset Tangibility	1,022	0.427	0.184	0.071	0.836
Liquidity	1,022	1.471	0.681	0.482	4.136

As shown in Table 1, the Artificial Intelligence Adoption Index had a mean of 3.840 and a standard deviation of 2.180, with observed values ranging from 0 to 9. This relatively wide dispersion indicates substantial heterogeneity in the extent to which publicly listed companies incorporated AI-related applications into their operations. While some firm-year observations contained no identifiable evidence of AI implementation, others reflected extensive adoption across several organizational functions. The mean ROA was 0.112, indicating that, on average, the sampled firms generated net income equivalent to approximately 11.2% of their asset base. ROA ranged from -0.086 to 0.318, confirming the presence of both loss-making and highly profitable firm-year observations. The mean

ROE was 0.198, with a standard deviation of 0.128, suggesting that shareholders earned an average accounting return of approximately 19.8%, although the minimum value of -0.241 indicated that some firms experienced substantial negative returns. Tobin's Q averaged 1.832, exceeding unity and therefore indicating that, on average, the market valuation of the sampled companies was greater than the accounting value of their asset base. The standard deviation of 0.742 and range from 0.641 to 4.286 further indicate meaningful cross-sectional and temporal differences in market valuation. Regarding the control variables, average financial leverage was 0.536, meaning that liabilities represented approximately 53.6% of total assets. Mean annual sales growth was 17.3%, although substantial dispersion was evident, as some firm-years experienced sales contractions of more than 40%, while others recorded growth approaching 100%. The mean asset tangibility ratio was 0.427, suggesting that tangible fixed assets represented approximately 42.7% of total assets. The average liquidity ratio was 1.471, indicating that current assets generally exceeded current liabilities. Collectively, the descriptive results demonstrate sufficient variability in AI adoption, financial performance, and firm characteristics to permit meaningful multivariate panel analysis.

Table 2. Correlation Analysis and Multicollinearity Diagnostics

Variable	1	2	3	4	5	6	7	8	9	10	VIF
1. AI Adoption	1.000										1.32
2. ROA	0.290***	1.000									—
3. ROE	0.250***	0.670***	1.000								—
4. Tobin's Q	0.330***	0.420***	0.360***	1.000							—
5. Firm Size	0.310***	0.150***	0.110***	0.200***	1.000						1.41
6. Financial Leverage	-0.120***	-0.340***	-0.210***	-0.170***	0.290***	1.000					1.48
7. Firm Age	0.180***	0.080*	0.050	-0.060	0.250***	0.030	1.000				1.18
8. Sales Growth	0.210***	0.260***	0.220***	0.310***	-0.040	-0.160***	-0.070*	1.000			1.16
9. Asset Tangibility	0.090**	0.050	0.020	-0.100**	0.220***	0.180***	0.110***	-0.080*	1.000		1.14
10. Liquidity	0.160***	0.280***	0.230***	0.180***	-0.150***	-0.390***	0.040	0.140***	-0.120***	1.000	1.29

Table 2 presents the bivariate correlations among the study variables together with variance inflation factors for the explanatory variables. Artificial intelligence adoption was positively and significantly correlated with all three indicators of firm financial performance. Specifically, AI adoption was positively related to ROA ($r = 0.290$, $p < 0.001$), ROE ($r = 0.250$, $p < 0.001$), and Tobin's Q ($r = 0.330$, $p < 0.001$). The strongest bivariate relationship between AI adoption and the performance indicators was therefore observed for Tobin's Q, suggesting that companies with greater AI adoption tended to exhibit particularly favorable market valuations in addition to higher accounting profitability. AI adoption was also positively correlated with firm size ($r = 0.310$, $p < 0.001$), firm age ($r = 0.180$, $p < 0.001$), sales growth ($r = 0.210$, $p < 0.001$), asset tangibility ($r = 0.090$, $p < 0.01$), and liquidity ($r = 0.160$, $p < 0.001$), while its association with leverage was negative ($r = -0.120$, $p < 0.001$). These patterns indicate that larger and growing firms generally displayed higher levels of AI implementation, whereas highly leveraged firms tended to demonstrate somewhat lower AI adoption. As expected, the three financial-performance measures were mutually positively related, although their correlations remained sufficiently below levels indicative of redundancy. Financial leverage was negatively correlated with ROA ($r = -0.340$, $p < 0.001$), ROE ($r = -0.210$, $p < 0.001$), and Tobin's Q ($r = -0.170$, $p < 0.001$), whereas sales growth and liquidity were positively associated with the performance measures. Importantly, none of the correlations among the explanatory variables approached a level that would suggest serious multicollinearity. This conclusion was reinforced by variance inflation factors ranging from 1.14 to 1.48, substantially below conventional thresholds of 5 or 10. Therefore, the predictors could be entered jointly into

the panel regression models without evidence that excessive linear dependence materially distorted coefficient estimates or standard errors.

Table 3. Panel Model Selection and Diagnostic Test Results

Diagnostic Test	ROA Model	ROE Model	Tobin's Q Model
Breusch–Pagan LM test, χ^2	186.42***	164.73***	218.56***
Hausman specification test, χ^2	9.01	7.69	10.92
Hausman test p-value	0.173	0.262	0.091
Modified Wald/Breusch–Pagan heteroskedasticity test, χ^2	412.36***	389.17***	501.42***
Wooldridge serial-correlation test, F	13.72***	11.89***	16.33***
Pesaran cross-sectional dependence test, CD	3.11**	2.74**	4.02***
Selected estimator	Random-effects GLS	Random-effects GLS	Random-effects GLS
Robust inference	Firm-clustered robust SE	Firm-clustered robust SE	Firm-clustered robust SE

The panel specification and diagnostic results presented in Table 3 confirmed that panel-data estimation was preferable to conventional pooled regression. The Breusch–Pagan Lagrange multiplier tests were statistically significant for the ROA model ($\chi^2 = 186.42$, $p < 0.001$), the ROE model ($\chi^2 = 164.73$, $p < 0.001$), and the Tobin's Q model ($\chi^2 = 218.56$, $p < 0.001$), demonstrating significant firm-level heterogeneity and rejecting the adequacy of pooled ordinary least squares estimation. The Hausman specification tests, however, were not statistically significant for ROA ($\chi^2 = 9.01$, $p = 0.173$), ROE ($\chi^2 = 7.69$, $p = 0.262$), or Tobin's Q ($\chi^2 = 10.92$, $p = 0.091$). These findings indicated that the differences between the fixed-effects and random-effects estimators were not systematic at the 0.05 significance level and therefore supported the use of random-effects generalized least squares models. Diagnostic assessment of the regression residuals nevertheless revealed departures from conventional error assumptions. Significant heteroskedasticity was identified in all three equations, while the Wooldridge tests indicated first-order serial correlation for ROA ($F = 13.72$, $p < 0.001$), ROE ($F = 11.89$, $p < 0.001$), and Tobin's Q ($F = 16.33$, $p < 0.001$). The Pesaran tests additionally indicated statistically significant cross-sectional dependence, suggesting that firm-specific disturbances were partly affected by common market or macroeconomic factors. Consequently, the final random-effects models were estimated with firm-clustered robust standard errors, thereby providing statistical inference resistant to heteroskedasticity and within-firm serial dependence. Year and industry effects were also incorporated into the final specifications to account for temporal shocks and systematic sectoral differences. The diagnostic evidence therefore supported the use of robust random-effects panel models for evaluating the independent association between AI adoption and the financial performance indicators.

Table 4. Random-Effects Panel Regression of Artificial Intelligence Adoption on Firm Financial Performance

Predictor	ROA β (Robust SE)	z	p	ROE β (Robust SE)	z	p	Tobin's Q β (Robust SE)	z	p
AI Adoption	0.0067 (0.0014)	4.79	<0.001	0.0104 (0.0026)	4.00	<0.001	0.0710 (0.0140)	5.07	<0.001
Firm Size	0.0059 (0.0027)	2.19	0.029	0.0095 (0.0049)	1.94	0.052	0.0830 (0.0280)	2.96	0.003
Financial Leverage	-0.1030 (0.0170)	-6.06	<0.001	-0.1610 (0.0310)	-5.19	<0.001	-0.4620 (0.1080)	-4.28	<0.001
Firm Age	0.0003 (0.0002)	1.57	0.118	0.0005 (0.0004)	1.29	0.198	-0.0040 (0.0020)	-1.99	0.047
Sales Growth	0.0410 (0.0090)	4.56	<0.001	0.0670 (0.0170)	3.94	<0.001	0.2910 (0.0660)	4.41	<0.001
Asset Tangibility	-0.0140 (0.0100)	-1.40	0.161	-0.0210 (0.0180)	-1.17	0.244	-0.1350 (0.0730)	-1.85	0.065

Liquidity	0.0120 (0.0040)	3.00	0.003	0.0180 (0.0070)	2.57	0.010	0.0860 (0.0280)	3.07	0.002
Year effects	Yes			Yes			Yes		
Industry effects	Yes			Yes			Yes		
Firm-year observations	1,022			1,022			1,022		
Number of firms	146			146			146		
Wald χ^2	176.84***			149.62***			203.41***		
Overall R ²	0.347			0.301			0.392		

The multivariate results presented in Table 4 provide consistent evidence of a positive relationship between artificial intelligence adoption and all three measures of firm financial performance after adjustment for firm characteristics, industry differences, and year-specific effects. In the ROA model, AI adoption had a positive and statistically significant coefficient of $\beta = 0.0067$ (robust SE = 0.0014, $z = 4.79$, $p < 0.001$). Because ROA was expressed as a proportion, this coefficient indicates that a one-unit increase in the AI Adoption Index was associated with an approximately 0.67 percentage-point increase in return on assets, holding the other model variables constant. Consequently, a firm with an AI adoption score four units higher than an otherwise comparable company would, on average, be expected to exhibit an ROA approximately 2.68 percentage points higher, illustrating that the estimated relationship was not only statistically significant but also economically meaningful. AI adoption was similarly associated with ROE ($\beta = 0.0104$, robust SE = 0.0026, $z = 4.00$, $p < 0.001$), corresponding to approximately a 1.04 percentage-point increase in return on equity for every one-unit increase in the adoption index. The strongest relative association emerged in the market-based model, where AI adoption was positively associated with Tobin's Q ($\beta = 0.0710$, robust SE = 0.0140, $z = 5.07$, $p < 0.001$). Thus, greater AI adoption was associated not only with higher realized accounting profitability but also with higher capital-market valuation. Several control variables also displayed systematic relationships with performance. Financial leverage had a significant negative association with ROA ($\beta = -0.1030$, $p < 0.001$), ROE ($\beta = -0.1610$, $p < 0.001$), and Tobin's Q ($\beta = -0.4620$, $p < 0.001$), demonstrating that highly leveraged firms generally exhibited weaker performance after other characteristics were controlled. Sales growth was positively associated with each outcome, with coefficients of 0.0410 for ROA, 0.0670 for ROE, and 0.2910 for Tobin's Q, all at $p < 0.001$. Liquidity was also positively related to all three performance measures. Firm size positively predicted ROA ($\beta = 0.0059$, $p = 0.029$) and Tobin's Q ($\beta = 0.0830$, $p = 0.003$), although its relationship with ROE fell slightly short of conventional statistical significance ($\beta = 0.0095$, $p = 0.052$). Firm age was unrelated to ROA and ROE but demonstrated a small negative association with Tobin's Q ($\beta = -0.0040$, $p = 0.047$), while asset tangibility did not reach the 0.05 significance level in any of the models. The Wald tests showed that all three regression specifications were jointly statistically significant ($p < 0.001$), and the overall R² values indicated that the explanatory variables accounted for approximately 34.7% of the variation in ROA, 30.1% of the variation in ROE, and 39.2% of the variation in Tobin's Q. Taken together, the regression findings demonstrate that the positive association between AI adoption and firm financial performance was robust across accounting-based and market-based measures and persisted after adjustment for a broad set of firm-specific determinants.

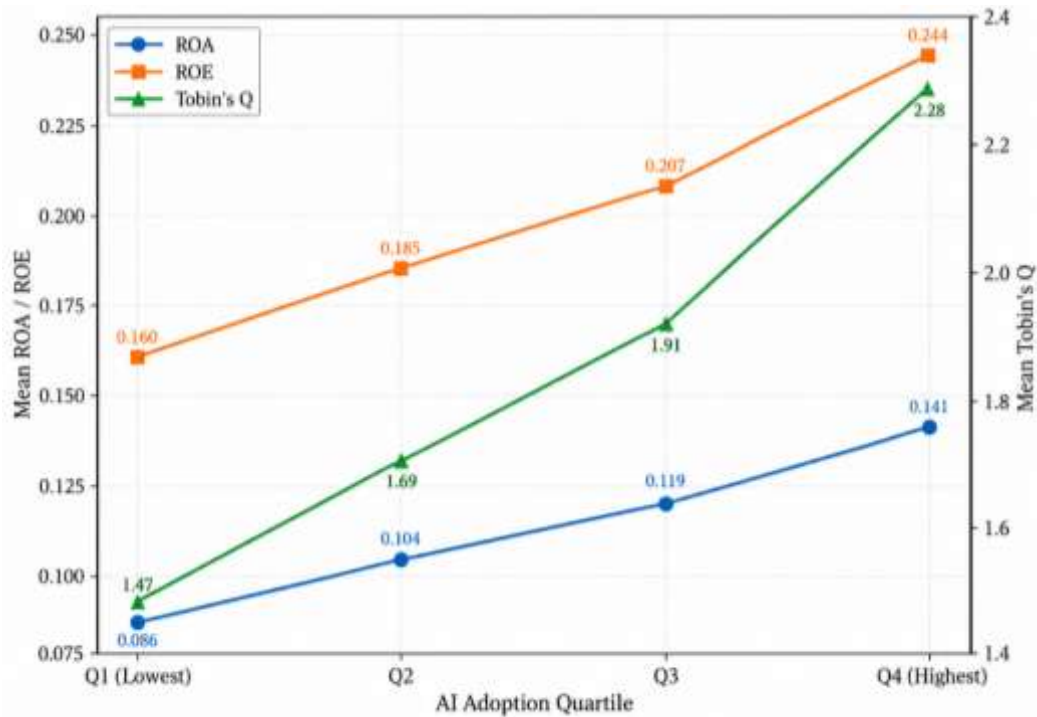


Figure 1. Mean Financial Performance across Quartiles of Artificial Intelligence Adoption

Figure 1 further illustrates the relationship between the extent of artificial intelligence adoption and firm financial performance by comparing the mean performance indicators across increasing AI-adoption quartiles. Firms in the lowest AI-adoption quartile recorded a mean ROA of 0.086, compared with 0.104 in the second quartile, 0.119 in the third quartile, and 0.141 in the highest-adoption quartile. A similarly monotonic pattern was observed for ROE, which increased from 0.160 in the lowest quartile to 0.185, 0.207, and 0.244 across the second, third, and fourth quartiles, respectively. The market-based measure demonstrated an even clearer gradient: mean Tobin's Q increased from 1.47 among firms with the lowest AI adoption to 1.69 in the second quartile, 1.91 in the third quartile, and 2.28 among firms in the highest AI-adoption quartile. Thus, companies characterized by more extensive AI implementation displayed progressively stronger financial outcomes across all three indicators. The graphical pattern was consistent with both the bivariate correlations and the multivariate panel regression estimates and showed no indication that the observed positive relationship was driven exclusively by a small subset of firms. Instead, the progression across adoption categories suggests that higher levels of AI integration were systematically accompanied by higher accounting profitability and market valuation. Although the figure represents an unadjusted descriptive comparison and should therefore not be interpreted as an independent causal test, its pattern complements the regression findings and provides a clear visual representation of the positive association between artificial intelligence adoption and financial performance in the sampled publicly listed companies.

4. Discussion and Conclusion

The findings of the present study demonstrated a consistent positive association between artificial intelligence adoption and firm financial performance among companies listed on the Tehran Stock Exchange. Specifically, higher levels of AI adoption were significantly associated with higher return on assets, higher return on equity, and higher Tobin's Q after controlling for firm size, financial leverage, firm age, sales growth, asset tangibility, liquidity, year effects, and industry effects. The results therefore indicate that AI adoption was related not only to stronger

accounting profitability but also to higher market valuation. The descriptive findings further showed that the extent of AI adoption increased substantially over the study period, suggesting that intelligent technologies gradually became embedded in a wider range of corporate activities. In addition, firms in higher AI-adoption quartiles exhibited progressively stronger performance across all three financial indicators. Taken together, these findings suggest that AI adoption may function as an organizational capability through which firms improve operational efficiency, information processing, forecasting, financial control, and strategic responsiveness, thereby strengthening both realized profitability and investors' perceptions of future value.

The positive association between AI adoption and return on assets indicates that firms with greater use of AI were generally more efficient in converting their asset base into earnings. This result is consistent with the view that AI can improve resource allocation, reduce process inefficiencies, support predictive planning, and facilitate more effective utilization of organizational resources. Research on fintech start-ups has similarly emphasized that AI can contribute to resource optimization by improving the allocation and use of financial and operational inputs [2]. From this perspective, the positive coefficient for ROA may reflect the capacity of AI-enabled systems to reduce unnecessary costs, automate repetitive processes, identify inefficiencies, improve forecasting accuracy, and support more timely managerial intervention. In firms where physical, financial, and informational resources are substantial, even relatively modest improvements in allocation efficiency can produce measurable changes in profitability. The result also corresponds with the broader proposition that technological adoption generates value when it is integrated into organizational processes rather than treated merely as a symbolic or isolated investment [3]. Thus, the present findings suggest that AI adoption can become financially meaningful when it is linked to the practical management of assets and operational activities.

The positive relationship between AI adoption and return on equity provides additional evidence that AI-related capabilities may enhance the economic returns generated for shareholders. Higher ROE among firms with greater AI adoption may arise from improvements in revenue generation, cost management, pricing, customer retention, risk assessment, working-capital efficiency, and strategic investment decisions. Prior research on AI in banking and financial services has shown that intelligent technologies are increasingly used to enhance decision-making, automate financial processes, detect anomalies, and improve customer-facing operations [4]. Similar mechanisms have been identified in digital payment and banking ecosystems, where AI can support transaction efficiency, fraud detection, service quality, and operational control [5]. Although the present study covered a broader range of listed companies rather than only financial institutions, the underlying mechanisms remain relevant. Firms that process large volumes of financial, operational, and market data may use AI to generate more precise and timely decisions, thereby improving the productivity of shareholders' invested capital.

The strongest relationship in the present study was observed between AI adoption and Tobin's Q. This finding suggests that the market may place a premium on firms that demonstrate greater engagement with AI-related technologies. Unlike ROA and ROE, which primarily reflect realized accounting outcomes, Tobin's Q incorporates market expectations regarding future earnings, growth potential, intangible capabilities, and strategic competitiveness. The positive association between AI adoption and Tobin's Q may therefore indicate that investors perceive AI capabilities as signals of innovation, adaptability, technological preparedness, and future growth potential. Such an interpretation is consistent with the literature showing that AI adoption can transform customer analytics, service delivery, and marketing performance, thereby increasing the perceived capacity of firms to compete in data-intensive markets [14]. It is also compatible with evidence that AI adoption differs across firms according to their strategic orientation, innovation capacity, technological infrastructure, and organizational

readiness [17]. Consequently, capital markets may respond not only to the current profitability generated by AI but also to expectations that AI-enabled firms will be better positioned to exploit future opportunities.

The results can also be interpreted through the information-quality mechanism. AI adoption may improve financial performance because intelligent systems enhance the collection, processing, verification, interpretation, and dissemination of financial information. Better-quality information can reduce managerial uncertainty, improve planning, strengthen monitoring, and facilitate more accurate resource allocation. Recent research has linked AI adoption to improved financial reporting quality, while emphasizing the importance of users' trust in accounting systems as a mechanism through which technological benefits are realized [6]. Similarly, AI adoption has been investigated in relation to audit quality and integrated financial reporting, indicating that intelligent systems may contribute to more reliable and timely reporting processes [7]. For publicly listed firms, improved reporting quality can have both internal and external consequences. Internally, managers may make more informed decisions; externally, investors and creditors may face lower information asymmetry and greater confidence in reported financial information. These effects may help explain why AI adoption was associated with both accounting performance and market valuation in the present study.

The progressive increase in AI adoption observed during the study period is also consistent with the growing strategic importance of intelligent technologies in finance and corporate management. The diffusion of AI appears to be occurring not simply because such technologies are available, but because organizations increasingly perceive them as useful, accessible, and strategically necessary. Research in financial reporting has shown that perceived usefulness and perceived ease of use are central to explaining organizational willingness to adopt AI [8]. Similarly, studies of internal auditors have shown that AI adoption is affected by professional readiness, organizational support, technological capacity, and perceived benefits [9]. These findings help explain the considerable heterogeneity identified in the AI Adoption Index. Some firms may possess the financial resources, data infrastructure, managerial commitment, and human capital required to implement AI across multiple functions, whereas others may remain at an early or experimental stage of adoption.

This interpretation is reinforced by evidence from the technology-organization-environment perspective. AI adoption in the insurance industry has been shown to depend on technological readiness, organizational characteristics, and environmental pressures [11]. The present results similarly suggest that AI adoption should not be viewed as an isolated technological decision. Instead, its performance effects are likely to depend on complementary resources, including digital infrastructure, skilled personnel, organizational routines, managerial support, and data governance. The positive relationship between firm size and both ROA and Tobin's Q observed in the present study is compatible with this logic, because larger firms may be better positioned to absorb the fixed costs associated with AI implementation and to exploit AI across a broader range of activities. At the same time, the positive association between AI adoption and performance after controlling for size indicates that the observed benefits cannot be attributed solely to the greater resource base of larger firms.

The strategic management literature on intelligent financial services also supports the present findings. Effective AI adoption requires alignment between technological capabilities and organizational strategy, governance, data architecture, and service objectives [12]. In this context, the positive financial effects identified in the present study may reflect the extent to which firms use AI not as a stand-alone technology but as an integrated element of corporate decision-making. When AI is connected to budgeting, forecasting, customer analysis, production planning, risk monitoring, or investment evaluation, its impact can extend across multiple value-creating processes.

This multidimensional influence may explain why the relationship remained significant across all three performance indicators rather than being confined to a single measure of profitability.

The findings also align with studies emphasizing the role of institutional and organizational support in technology adoption. Research on fintech adoption has shown that government support, user innovativeness, and financial-services knowledge can shape the adoption and use of AI-enabled financial technologies [13]. Similarly, studies of public-sector auditors indicate that the propensity to adopt AI depends on technological, organizational, and individual factors rather than on technological availability alone [10]. These findings are relevant to publicly listed companies because AI investments often require organizational restructuring, new competencies, and changes in decision rights. Firms that are able to develop such complementary capabilities may be more likely to translate adoption into measurable financial gains. Therefore, the positive relationship found in this study should be understood as the result of AI embedded within a broader organizational system rather than as an automatic consequence of acquiring advanced software.

The negative relationship between financial leverage and all three performance measures is also noteworthy. Highly leveraged firms may face greater financing costs, restrictive debt covenants, and reduced strategic flexibility, which can limit their capacity to invest in long-term technological capabilities. In contrast, firms with stronger liquidity and higher sales growth exhibited better financial performance, which is consistent with the view that financial flexibility and expanding operations create favorable conditions for both technology investment and performance improvement. These control-variable findings reinforce the importance of evaluating AI adoption within the broader financial condition of the firm. AI-related investments may create value more effectively when firms have sufficient liquidity and growth opportunities to support implementation, experimentation, organizational learning, and system integration.

The positive relationship between AI adoption and performance must nevertheless be considered alongside the risks associated with algorithmic decision-making. AI can improve efficiency and analytical capability, but poorly governed systems may create problems involving bias, opacity, privacy, accountability, and excessive dependence on automated recommendations. Prior research has emphasized the ethical consequences of AI in financial decision-making, particularly the risks associated with explainability, fairness, responsibility, and stakeholder trust [15]. Similar concerns have been highlighted in broader analyses of AI-based financial decisions, where ethical and governance considerations are treated as essential components of responsible implementation [16]. The positive financial associations observed in the current study therefore should not be interpreted as evidence that greater technological intensity is invariably beneficial. Rather, the findings suggest that AI adoption can be associated with stronger performance when it is embedded in effective governance, oversight, and decision structures.

The present findings further contribute to the distinction between technological adoption and technological value realization. The literature has repeatedly shown that firms can differ substantially in how they experience and exploit advanced digital technologies. Fintech firms and established financial institutions, for example, differ in their technological legacy, innovation culture, regulatory exposure, and ability to integrate new systems [17]. Such differences are likely to exist across listed firms as well. A company may report AI use but obtain limited value if systems remain fragmented, data quality is weak, or employees lack the skills required to interpret AI outputs. Conversely, firms that successfully embed AI within strategic and operational processes may generate gains that appear in profitability, shareholder returns, and market valuation. This interpretation also helps explain why the extent of adoption, rather than a simple dichotomous indicator, is useful for assessing financial consequences.

Overall, the results support a view of AI as a potentially value-generating organizational capability rather than merely a technological trend. The findings are consistent with evidence that AI contributes to digital finance, resource optimization, financial-service innovation, reporting quality, audit processes, marketing performance, and strategic management [1, 2, 7, 14]. At the same time, the results reinforce the importance of organizational readiness, user acceptance, governance, and institutional support in determining whether technological adoption produces economic benefits [8-11]. The evidence from Tehran Stock Exchange-listed companies therefore extends prior research by showing that AI adoption is associated simultaneously with asset-based profitability, shareholder-oriented profitability, and market valuation.

Several limitations should be considered when interpreting the findings. First, AI adoption was measured using publicly available corporate disclosures, and therefore the index captured reported evidence of adoption rather than the complete technical depth, quality, or effectiveness of AI implementation inside each company. Firms may differ in disclosure practices, and some companies may underreport or overemphasize technological initiatives. Second, the study employed observational panel data, which strengthens the analysis of changes across firms and over time but does not establish definitive causality. Although firm characteristics, industry effects, and year effects were controlled, unobserved factors such as managerial quality, corporate culture, data capability, innovation strategy, or governance quality may simultaneously influence AI adoption and financial performance. Third, the study was limited to nonfinancial companies listed on the Tehran Stock Exchange, and the findings may not be fully generalizable to privately held firms, small and medium-sized enterprises, financial institutions, or companies operating in different institutional settings. Fourth, the performance measures focused on financial outcomes and did not directly evaluate operational efficiency, innovation output, employee productivity, customer satisfaction, or risk reduction. Finally, the study period captured an important stage of AI diffusion, but the financial consequences of some AI investments may require longer periods to materialize.

Future studies should extend the analysis by constructing more detailed measures of AI intensity that distinguish among different technologies, organizational functions, and levels of implementation maturity. Researchers could separately examine AI used in financial reporting, production, marketing, human resource management, supply-chain management, customer service, risk management, and strategic forecasting to determine whether particular applications generate stronger performance effects. Future research could also use alternative identification strategies, including difference-in-differences designs, instrumental-variable estimation, propensity-score methods, or dynamic panel models, to strengthen causal inference. Longitudinal studies covering longer periods would be useful for distinguishing short-term implementation costs from longer-term benefits. Comparative research across industries, stock exchanges, and countries could further clarify how regulatory quality, digital infrastructure, capital-market development, and institutional conditions moderate the relationship between AI and firm performance. Additional studies should also investigate mediating mechanisms such as productivity, cost efficiency, decision quality, innovation capability, financial reporting quality, and operational resilience, as well as moderating factors such as corporate governance, managerial digital competence, data quality, organizational culture, and cybersecurity capability.

Managers of publicly listed companies should approach AI adoption as a strategic organizational investment rather than as a stand-alone technological acquisition. Firms should identify specific business processes in which AI can create measurable value, establish clear performance indicators before implementation, and integrate AI systems with existing financial, operational, and decision-support structures. Investment in employee skills, data quality, cybersecurity, model governance, and cross-functional coordination should accompany expenditure on AI

technologies. Managers should also evaluate AI projects in terms of both financial returns and broader organizational outcomes, including decision speed, forecast accuracy, risk reduction, service quality, and process efficiency. Boards of directors and senior executives should establish governance mechanisms that define responsibility for algorithmic decisions, require regular validation of AI models, and preserve meaningful human oversight. Companies should also communicate material AI initiatives transparently to investors while avoiding exaggerated or purely symbolic claims about technological capability. In practice, firms are likely to obtain the greatest financial benefits when AI adoption is gradual, strategically targeted, measurable, and supported by appropriate organizational capabilities and governance structures.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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