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USE OF ARTIFICIAL INTELLIGENCE IN FINANCE: EVIDENCE FROM FIRMS LISTED ON THE PAKISTAN STOCK EXCHANGE

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Abstract
Artificial Intelligence (AI) is increasingly playing a vital role in contemporary business financial management. The present study propose an empirical framework to study the use of AI in finance by the companies listed on Pakistan Stock Exchange (PSX). The study highlights how the use of AI is correlated with corporate financial performance, financial forecasting capability, investment efficiency and firm value. A longitudinal panel of non-financial firms listed on PSX is envisioned for the years 2018-2025. The theoretical framework includes the elements of the Technology–Organization–Environment framework and Dynamic Capabilities Theory. The study suggests fixed-effects panel regression and nonlinear specifications and endogeneity-robustness procedures. The paper builds upon the current body of literature in two ways: First, it introduces Pakistan-specific evidence from the listed companies and second, it suggests a clear approach to assessing AI adoption based on publicly available corporate disclosures.

INTRODUCTION

AI has grown from a niche computational technology to an all-purpose technology that can impact how businesses gather information, analyze markets, and make managerial decisions. As the amount of big data and cloud computing grows, along with the capabilities of new machine learning algorithms, AI has more applications in business processes. In finance, these applications include financial forecasting, risk assessment, fraud detection, investment analysis, budgeting, financial reporting and automated decision support (Makridakis, 2017; Huang & Chai, 2020). AI's relevance to corporate finance comes from the fact that an increasing amount of structured, as well as unstructured, information is used to make financial decisions. Typical financial analysis of this nature is based on past financial information and on managerial judgment and traditional statistical methods. AI systems can handle substantially more data, detect non-linear

relationships, and continually revise predictions based on new data. Machine-learning techniques have therefore been the focus of significant research within the field of financial forecasting and financial planning (Wasserbacher & Spindler, 2022). Such implications are especially interesting for companies providing their services in the emerging markets. When firms are located in emerging markets, they may have information constraints, financing constraints, and unstable economic conditions, differences in technological infrastructure, etc. While AI can address some of the challenges related to information processing, there are also investments needed in data, technology, human skills, cybersecurity, and organizational change for its implementation. An emerging-market sample of 115 Algerian firms provides recent evidence that controlling for the characteristics of firms is crucial: it brings apparent differences in performance between AI adopters and non-adopters largely to the level of statistical insignificance (Guettoufi, 2026). The case of Pakistan is interesting in this regard. The Pakistan Stock Exchange has a financial-reporting platform which hosts annual and quarterly reports of listed companies, and also maintains information regarding listed companies and corporate-governance compliance (Pakistan Stock Exchange Limited, 2026a, 2026b). Furthermore, listed companies have statutory obligations with regard to annual audited financial statements (Securities and Exchange Commission of Pakistan [SECP] 2026). These public disclosures enable one to create a firm-level, longitudinal data set that integrates variables associated with disclosures of AI into accounting and market data. Research on AI and corporate finance is starting to be conducted within Pakistan. With a sample of 100 firms on the PSX, Zaib et al. (2025) examined the accuracy of financial forecasts and found a positive correlation between the use of AI tools and the accuracy of financial forecasts. However, the overall issues of profitability, investment efficiency and market valuation in the Pakistani context have not been discussed in detail. Therefore, the present study explored an extensive empirical model to study the adoption of AI in finance by the listed companies of the Pakistan Stock Exchange (PSX). This study does not just focus on the technology of AI; it also examines the finance of AI and how it can impact corporate results. Although there has been a significant amount of international research work on the use of AI in corporate finance, there is still a major gap in the Pakistani context. Most of the empirical evidence has come from developed economies and big emerging markets; and the firm-level evidence in Pakistan has been limited. Financial forecasting has been studied in Pakistan, while the studies conducted have focused less on the profitability and efficiency of investments and market values. Furthermore, the use of AI is not a uniform accounting variable, requiring the development of an AI Adoption Index that is transparent and reproducible, based on disclosure. The literature also offers conflicting results on whether AI use is necessarily associated with better corporate performance, so it is crucial to include control variables, firm fixed effects and endogeneity tests. Beyond that, the contribution of organizational capabilities, and the potential for nonlinear effects, are not well studied in emerging-market contexts. These gaps inspire the current research on AI adoption in PSX-listed firms and the research design of this paper considers firm-level characteristics and potential endogeneity while studying the relationship between AI adoption and profitability, forecasting, investment efficiency and firm value.

Background of the Study.

Artificial Intelligence and Corporate Finance

Artificial Intelligence refers to the computational methods that allow for systems to carry out tasks that involve learning, predicting, classification, pattern recognition, language processing, decision making, etc. In finance, AI can include machine learning, deep learning, natural language processing, anomaly detection and automated decision-making processes. A review of the literature in the field of finance and deep learning reveals that deep learning models have been

applied to various tasks, such as financial forecasting and market analysis (Huang & Chai, 2020; Jiang, 2021). In the business realm, AI can aid in financial tasks in a number of ways. First is that predictive models could alleviate revenue, cost and cash-flow forecasting. Secondly, anomaly detection algorithms can help detect fraudulent or unusual transactions. Third, AI could help with risk assessment, analyzing data that goes beyond financial ratios. Fourth, machine-learning models can help in investment and resource allocation decisions. Fifth, natural-language-processing (NLP) systems can be used to gain insights from vast amounts of textual disclosures and market information.

AI and Financial Forecasting

The forecasting process is especially well suited for AI since forecasting is a process of detecting patterns in large data sets. Machine-learning models can handle the interactions and the nonlinear relationships, which may not be easily described by the traditional linear models. Wasserbacher and Spindler (2022) point out that machine learning is well-positioned for highly-automated information extraction for financial forecasting, planning and analysis, but warn that prediction does not necessarily equal causal inference. Deep learning has also been explored in finance for prediction in the financial markets, with a focus on the complexity, noise and non-stationarity of financial data (Jiang, 2021). So, although AI can increase prediction accuracy, it won't always lead to better investment results.

AI and Financial Performance

AI has the potential to impact financial performance in a variety of ways, such as through cost savings in processing, better forecasting, fewer errors, enhanced risk management, and more effective allocation of financial resources. Huang and Lin (2025) examined financial performance, productivity and market value, and found evidence that the implementation of AI may lead to an enhancement of financial performance and market value, but the impact on each firm was not consistent. However, embracing AI adoption can also have a substantial expense. The business needs to purchase software, hardware, data infrastructure, employee training and cybersecurity. A failure to implement and poor data quality can diminish gains. The study by Guettoufi (2026) shows the impact of not controlling for firm characteristics when making simple comparisons between AI adopters and non-adopters.

AI and Corporate Financial Asset Allocation.

The other is the allocation of corporate financial assets. In 2008-2022, Li et al. (2024) examined the financial asset-allocation efficiency of 25,811 firm-year observations of Chinese A-share listed companies and found that AI adoption significantly improves financial asset-allocation efficiency. Their analysis also revealed that organizational dynamic capabilities played a moderating role between the two variables, indicating that the capacity to absorb, integrate and exploit new technologies was an important variable to consider when understanding how social media and new technology influences a firm's performance.

Literature Review

There are several paths in the literature of AI in finance. The first is about prediction in the financial markets and algorithmic decision making. This review paper by Jiang (2021) showed the current applications of deep learning in stock market prediction and how neural-network-based approaches are being increasingly used. There is also a growing merging of AI into financial markets, with Posth et al. (2021) looking at self-play algorithms for trading and financial-market prediction. A second stream is related to financial services and risk management. The Financial Stability Board (2017) recorded an increasing number of instances of the application of AI and machine learning to credit assessment, insurance pricing, trading, regulation, surveillance and fraud detection. The report highlighted AI's roles in introducing efficiency and in posing threats to financial stability. A third stream is related to the

performance of firms. The research by Huang and Lin (2025) offers recent evidence for a relationship between implementation of AI and financial performance, productivity and market value. Their results validate the importance of looking at AI not just as an operational technology but also as a strategic asset of the company. The fourth stream is on corporate financial decisions. This research by Li et al. (2024) proves that AI can influence financial asset allocation for the company and that the impact of AI depends on organizational capabilities. This is particularly important for the current research as it indicates that AI is not autonomous of the organizational context. Last but not least, there is limited evidence from emerging markets. Dimitri Guettoufi (2026) analyzed Algerian firms and found that it is not all the advantages that emerge from the use of AI that remain when taking firm-specific characteristics into account. This study highlights the need for a strong research design in emerging markets. Zaib et al. (2025) studied 100 firms listed in the Pakistan Stock Exchange (PSX) and found evidence suggesting that AI-powered tools help in enhancing the accuracy of financial forecasting in Pakistan. The current study builds upon this growing body of literature, which focuses on Pakistan, and also adds several corporate-finance outcomes to the literature namely profitability, firm value and efficiency of investment.

Theoretical Framework

Technology–Organization–Environment Framework

The technology–organization–environment (TOE) framework was used to describe how technology was adopted in the organization in this context, in which technology, organizational and environmental contexts were used to describe the adoption of technology (Tornatzky & Fleischer, 1990). The technological context encompasses technologies relevant to the firm and attributes like relative advantage and complexity. Resources, managerial characteristics, human capabilities and organizational structure are examples of the organizational context. Environmental context is related to competition, regulation, conditions of industry, external pressures. The TOE is suitable for companies with varying technological readiness and organizational resources to both accommodate the diversity of industry types and to address the fact that companies vary greatly in terms of their organizational characteristics. There could be more opportunities to invest in AI at larger firms, and more motivation to use more advanced analytical technologies at more competitive firms.

Dynamic Capabilities Theory

Dynamic Capabilities Theory focuses on the capability of firms to be dynamic – to build, integrate and reconfigure internal and external competencies in fast changing environments (Teece et al., 1997). This is where AI fits in; its benefits go beyond just buying technology, they also come with a set of accompanying organizational skills. This view is confirmed directly by the empirical evidence of Li et al. (2024), who demonstrate that absorptive, innovative and adaptive capabilities mediate between the adoption of AI and financial asset allocation. Skewed by this, companies with greater capability could gain a larger financial return from the same amount of investment in AI.

Research Objectives

- To determine the extent of AI adoption among PSX-listed non-financial firms.
- To examine the relationship between AI adoption and corporate financial performance.
- To examine whether AI adoption improves financial forecasting capability.
- To investigate whether AI adoption is associated with investment efficiency.
- To examine the relationship between AI adoption and firm value.
- To investigate whether firm characteristics and organizational capabilities moderate the relationship between AI adoption and financial outcomes.

Research Questions

RQ1: To what extent are PSX-listed firms using Artificial Intelligence in financial activities?
RQ2: Does AI adoption have a significant relationship with the financial performance of PSX-listed firms?
RQ3: Does AI adoption improve financial forecasting?
RQ4: Does AI adoption improve investment efficiency?
RQ5: Is AI adoption associated with firm value?
RQ6: Do firm characteristics and organizational capabilities moderate the relationship between AI adoption and financial performance?
RQ7: Is the relationship between AI adoption and financial performance nonlinear?

Research Methodology

Research Design

The study adopted a quantitative approach, with a longitudinal study design of panel data. The unit of analysis will be at the firm-year level. The study period is recommended to be from 2018 to 2025, to ensure the availability of sufficient time for the diffusion of the various AI related technologies as well as a contemporary focus.

Population and Sample

Companies listed on the Pakistan Stock Exchange comprise the population. The principal sample are non-financial listed companies since banks, insurance companies, and other financial institutions have accounting and reporting frameworks that differ from those of non-financial listed companies. PSX publishes financial reports and listed-company information on a company by company basis. It has a financial-reporting platform that includes annual and quarterly reports, the exchange has listed-company information and governance resources (Pakistan Stock Exchange Limited, 2026a, 2026b). Further, SECP confirms that listed companies are required to file their financial statements annually after audit (SECP, 2026).

Sample criterion	Treatment
PSX-listed companies	Potentially included
Non-financial companies	Included in main sample
Banks and insurance companies	Excluded from main sample or separately analyzed
Insufficient annual reports	Excluded
Missing financial data	Excluded or addressed using appropriate missing-data procedures
Extreme observations	Winsorization at 1% and 99% where justified

Measurement of AI Adoption

One of the chief research hurdles is quantifying the adoption of AI. Adoption of AI is not an accounting variable, as is profitability or leverage/total assets. The study thus suggests an Annual Report Disclosure Artificial Intelligence Adoption Index (AII). The annual reports will be reviewed for keywords including: artificial intelligence, machine learning, deep learning, predictive analytics, generative AI, robotic process automation, intelligent automation, AI-based forecasting, AI-based risk management, AI-based fraud detection, natural language processing and AI-enabled decision making. The method aligns with recent studies that assess AI adoption using textual information in annual reports of listed firms (Li et al., 2024) and adds other indicators to measure AI use, such as AI patents. One of the simplest binary measures is to define AI as 1 if a firm has substantive evidence of AI adoption and AI as 0 if such evidence is lacking. A more descriptive continuous measure can assign points to various applications and have an AI intensity index. Coding of disclosure should only be done when the annual report contains substantive evidence of the use of AI, not when it is a passing reference to the fact that AI is a trend.

Dependent Variables

The financial performance was evaluated by the following ratios: return on assets (ROA), return on equity (ROE) and net profit margin (NPM). Multiple measures minimize reliance on one measure as an accounting indicator. ROA (Net profit/Total assets) – The net profit divided by the total assets. ROE = Net Profit / Shareholders' Equity NPM = Net Profit/Sales The measure of the firm value was based on the Tobin's Q, which is the ratio of the market value of equity plus the book value of debt to the book value of assets. The inefficiency of investments was estimated based on the deviations of expected and actual investments.

Control Variables

- Firm size: natural logarithm of total assets.
- Leverage: total debt divided by total assets.
- Sales growth: annual percentage change in sales.
- Firm age: years since incorporation or listing.
- Capital intensity: fixed assets divided by total assets.
- Board characteristics: board size, independence, financial expertise and other governance indicators where data are available.

Industry and year effects: sector and time controls to account for industry-specific and macroeconomic conditions.

Econometric Models

The baseline panel model is given as follows:

$$FP_{it} = \beta 0 + \beta 1\ AI_{it} + \beta 2\ SIZE_{it} + \beta 3\ LEV_{it} + \beta 4\ GROWTH_{it} + \beta 5\ AGE_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

where FP is financial performance, AI is AI adoption, SIZE is firm size, LEV is leverage, GROWTH is sales growth, AGE is firm age, μ_i represents firm fixed effects, λ_t represents year fixed effects and ε_{it} represents the error term. The principal coefficient of interest is the coefficient $\beta 1$. The sign, magnitude and statistical significance was assessed, without a priori assumption of a specific outcome.

Illustrative Statistical Results

The descriptive statistics showed that there was a great deal of variation in financial performance and degree of AI adoption across the firms in the illustrative sample. The average value of the AI Adoption Index (AI Adoption Index = 0.214) was calculated to be around 21.4% of the AI disclosures in the index, with the highest value being 0.850 in some cases, reflecting larger usage of AI-related technologies within the companies. The relatively high standard deviations of ROA, ROE and NPM showed that there were significant variations in profitability between firms. The average of Tobin's Q for the illustrative sample was 1.36, indicating, on average, the value of the stock market exceeded the book value of the firms' assets. This difference in investment inefficiency also suggested that companies had very different efficiencies in utilizing available resources to invest.

Table 1. Illustrative Descriptive Statistics

Variable	N	Mean	SD	Min	Max	Median
AI Adoption Index	800	0.214	0.183	0.000	0.850	0.200
ROA (%)	800	5.84	8.21	-24.60	31.70	5.20
ROE (%)	800	11.72	17.45	-61.30	68.40	10.10
NPM (%)	800	7.18	10.94	-42.80	44.60	6.30
Tobin's Q	800	1.36	0.91	0.32	6.25	1.12
Investment Inefficiency	800	0.084	0.071	0.002	0.410	0.061
Firm Size (ln assets)	800	17.21	1.64	13.82	21.74	17.08

This positive relationship indicated by the correlation matrix existed between the use of AI and the important business performance metrics. In addition, profitability metrics such as ROA (0.18), ROE (0.16) and Tobin's Q (0.21) were linked positively to AI adoption, indicating that companies with higher levels of AI adoption were more profitable and valued by their shareholders. However, investment inefficiency (-0.14) was negatively associated with AI adoption, suggesting that the higher the level of AI adoption, the lower the investment inefficiency. These correlations, though, did not prove causal relationships and so were not evidence of a link between the adoption of AI and better financial results. The correlation among the variables were moderate in general. Firm size and AI adoption were correlated at 0.39, indicating that larger firms had more reports of AI adoption. The correlations were not high enough that one was a serious problem with multicollinearity.

Table 2. Illustrative Pearson Correlation Matrix

Variable	AI	ROA	ROE	Tobin's Q	Ineff.	Size
AI Adoption	1.00	0.18	0.16	0.21	-0.14	0.39
ROA	0.18	1.00	0.72	0.29	-0.26	0.12
ROE	0.16	0.72	1.00	0.24	-0.21	0.08
Tobin's Q	0.21	0.29	0.24	1.00	-0.18	0.31
Investment Ineff.	-0.14	-0.26	-0.21	-0.18	1.00	-0.10
Firm Size	0.39	0.12	0.08	0.31	-0.10	1.00
Leverage	0.05	-0.19	-0.24	-0.12	0.17	0.28

The fixed-effects regression results were a more stringent test, as the model also adjusted for year-specific and unobserved, firm-specific effects. For ROA, ROE and Tobin's Q, the coefficient of AI adoption was positive (0.021, 0.038 and 0.074 respectively) while the coefficient on investment inefficiency was negative (-0.019). However, the results showed that for the other firms, after adjusting for the other firm characteristics and the year effect, increased use of AI was linked to higher profitability, market valuation, and lower investment inefficiency. The coefficient of 0.021 for ROA, for instance, meant that for every one unit increase in the AI Adoption Index, the illustrative ROA increased by 0.021 unit, while the effect of other variables and fixed effects were constant. Likewise, the positive coefficient of 0.074 for Tobin's Q indicates that there was a positive relationship between the adoption of AI and firm valuation. The negative coefficient for investment inefficiency suggested that investing in inefficient ways was negatively linked with AI adoption. The size of the firm was positively associated with all the different measures of profitability in the illustrative specification. Leverage tended to be negatively related to profitability, and thus, there may be a negative relationship between the financial leverage ratio and the profitability of companies. The positive coefficients of the sales growth category suggested that companies that had higher revenue growth also tended to report more positive financial results.

Table 3. Illustrative Fixed-Effects Regression Results

Variables	ROA	ROE	Tobin's Q	Inefficiency	NPM
AI Adoption Index	0.021**	0.038**	0.074**	-0.019**	0.031*

Firm Size	0.412***	0.865***	0.091***	-0.006	0.173***
Leverage	-0.071**	-0.184***	-0.055*	0.082**	-0.063**
Sales Growth	0.146***	0.121**	0.118***	-0.049*	0.102**
Firm & Year FE	Yes	Yes	Yes	Yes	Yes

These are only illustrative values and should not be quoted as results obtained by PSX-firm until the annual reports and financial data have been gathered, coded and the models estimated.

Table 4. Illustrative Diagnostic and Robustness Tests

Test	Illustrative statistic	p-value	Interpretation
Hausman test	42.18	<0.001	FE preferred to RE
Mean VIF	2.74	—	No severe multicollinearity
Lagged AI coefficient (ROA)	0.018*	0.084	Weaker association
AI^2 coefficient (ROA)	-0.011**	0.031	Illustrative nonlinear pattern

Overall, the illustrative findings indicated that the use of AI was positively correlated with corporate profitability, market valuation and negatively correlated with investment inefficiency. The findings also suggested that the relationship might be nonlinear and the strength of the association decreased if using AI was lagged. These results supported the thesis that AI was not just a technological investment, but rather the financial benefits seemed to be linked to the extent of integration with AI for decision making and forecasting, as well as for risk management and resource allocation functions within the organization.

Overall Interpretation of the Results

The Hausman statistic was illustrative at 42.18 and the p-value had to be less than 0.001, thus the fixed-effects specification was preferred over the random-effects specification. This was in keeping with the application of firm fixed effects as unobserved firm-specific attributes were believed to be related to the explanatory variables. The mean VIF value was 2.74 which was in the acceptable range as per the standard for serious multicollinearity, thus it was unlikely that the estimated coefficients were seriously distorted by the presence of multicollinearity. The coefficient for ROA was slightly lower and statistically less significant with the lagged-AI specification (0.018), though the illustrative p-value was still 0.084 (illustrative p-values are presented for illustrative purposes only and do not imply statistical significance). This specification helped alleviate the concern that the current financial performance and current AI adoption were measured at the same time. Finally, the negative coefficient on the squared AI Adoption Index (-0.011) suggested a possible nonlinear relationship. In substance, that might mean that the benefits of AI utilization didn't get continually bigger: some benefits might be smaller at higher levels of utilization. This understanding aligned with the concept that AI needed to be paired with organizational skills, the organizational infrastructure, and knowledgeable workers to continue to provide economic returns.

Discussion

The main idea behind the study is that AI should not be viewed as an information-technology spend, but as a financial decision-support

capability. If AI is not being used to support budgeting, forecasting, risk management, and investment decision making, a company may report its use of AI without there being any measurable financial benefit. An organization might, for instance, automatically route customer service calls to appropriate departments and teams with AI, but still do its financial forecasting the old-fashioned way. In this instance, the direct impact of the adoption of general AI on a company's financial results could be minimal. A firm which brings machine learning into demand forecasting, cash-flow forecasting, procurement, risk management, and capital allocation, however, can get bigger financial impacts. The difference between the two matters for building the AI Adoption Index. The index should thus differentiate between a superficial reference to AI and any substantive evidence of implementation. The study can also identify if the use of AI is general or just for finance. The literature also indicates that the organizational skills play an important role. Li et al. (2024) discovered that the link between AI adoption and financial asset allocation in the corporate context can be shaped by absorptive, innovative and adaptive capabilities. This means that technology is not enough by itself, as the Dynamic Capabilities Theory suggests, but must be paired with the right human and organizational resources to create value. Meanwhile, the conclusions of Guettoufi (2026) are that the use of AI does not automatically lead to better financial results. Partly, the gap in AI adoption between AI adopters and non-adopters could be explained by firm size, managerial ability, technological readiness or other pre-existing firm attributes. Thus, the proposed fixed-effects and endogeneity-robust design is an important aspect of the study.

Conclusion

The applications of Artificial Intelligence in corporate finance are becoming more and more relevant, as they can handle vast amounts of information, detect intricate patterns and assist in financial decision-making. The applications are financial forecasting, risk management, fraud detection, investment analysis, financial reporting and resource allocation. However, based on the international evidence, AI may positively influence corporate financial decision-making or even financial performance and market value, in certain contexts, but not in all firms (Huang & Lin, 2025; Li et al., 2024; Guettoufi, 2026). The Pakistan Stock Exchange is an appropriate empirical context as listed companies disclose their financial and corporate information in public. PSX prepares financial reports for the company and also provides listed-company information, and the requirements of SECP facilitate listed companies to have annual audited financial statements available (Pakistan Stock Exchange Limited, 2026a, 2026b; SECP, 2026). The study makes a contribution by creating a Pakistan-specific empirical framework which captures the adoption of AI using disclosures reported in the annual reports, and analyses the impact of AI on firm value, investment efficiency, forecasting and profitability. It also includes organizational abilities, characteristics of the company, nonlinear effects and endogeneity issues. Importantly, the paper doesn't contemplate that AI will always have a positive impact on financial performance. It suggests an empirical test that can detect positive insignificant or negative relationships, rather. This is acceptable as recent emerging market research indicates that simple comparisons of adopters versus non-adopters can be misleading (Guettoufi, 2026). The empirical analysis then gathers annual reports and financial data of the chosen PSX listed companies, builds the proposed AI Adoption Index, estimates the estimated panel models and reports the actual statistical results. This would make the current research design into a complete empirical research article for submission to a finance, accounting, technology-management, or emerging-markets journal.

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