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# ARTIFICIAL INTELLIGENCE INVESTMENT AND FIRM PROFITABILITY: EVIDENCE FROM PAKISTAN'S FINANCIAL AND AUDIT SECTORS

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**Abstract**

This study investigates the impact of artificial intelligence investment on firm profitability in Pakistan's accounting, finance, and external audit sectors by introducing a composite metric called adjusted artificial intelligence investment. The data of 28 Pakistani firms from 2020 to 2024 has been used for empirical analysis. The research integrates technological infrastructure, cybersecurity risk, and regulatory support into a unified econometric framework. The study is anchored in the technology acceptance model and the resource-based view theory to explain the strategic value and adoption dynamics of artificial intelligence. Using panel least squares, fixed effects, and random effects regressions, the results consistently reveal that adjusted artificial intelligence investment and technological infrastructure significantly enhance firm profitability, while cybersecurity risk negatively influences it. Regulatory support exhibits mixed effects, being negatively associated in pooled models but positively in fixed effects analysis, highlighting the contextual role of governance frameworks. These findings carry significant implications for multiple stakeholder groups. For firm managers, the results underscore the importance of adopting a strategic, infrastructure-backed approach to AI implementation, prioritizing integration with secure digital environments. Policymakers must move beyond generic regulatory frameworks and instead focus on designing sector-specific policies that promote innovation without compromising compliance. Investors, too, can benefit from evaluating AI maturity as a key indicator of future profitability. Therefore, the study not only confirms the financial value of AI but also highlights the ecosystem-level support needed to realize its full potential. This research fills a key gap by holistically evaluating artificial intelligence's role in shaping firm performance in a developing economy context and offers actionable insights for businesses and regulators aiming to enhance profitability through technological integration.

**Keywords:** Artificial Intelligence, Firm Profitability, Accounting, Technological Infrastructure, Cybersecurity, Regulatory Support

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## INTRODUCTION

Artificial intelligence is transforming the structure and functionality of accounting, finance, and external audit sectors in Pakistan, contributing to improved business operations in terms of accuracy, efficiency, and informed decision-making (Othman, 2025). Comparative studies in neighboring economies underscore similar transformations. For instance, Jain and Bansal (2023) reported that Indian banks experienced an 18% reduction in non-performing loans after integrating AI into their credit risk systems. In Bangladesh, Alam and Rahman (2024) observed that while AI adoption in financial institutions improved profitability, its full potential was hindered by regulatory inconsistencies and limited digital infrastructure. Within the Gulf Cooperation Council (GCC) region, Alshammari and Al-Debei (2023) found that AI maturity—supported by advanced IT frameworks and streamlined compliance systems—was strongly associated with improved return on investment in banking operations. These regional findings highlight the importance of contextual factors such as technological readiness, regulatory support, and sector-specific challenges in shaping the outcomes of AI investment, thereby justifying a focused investigation within the Pakistani context This study offers an integrated and comprehensive perspective by examining the implications of artificial intelligence investments on firm profitability, with a particular focus on return on assets as a key profitability indicator. This metric encompasses a range of dimensions, including technological infrastructure, regulatory support, and cybersecurity readiness (Cakali et al., 2023; Othman, 2025). By consolidating these multidimensional elements, the adjusted artificial intelligence investment metric delivers a more comprehensive and nuanced assessment of a firm's preparedness for artificial intelligence integration, surpassing traditional approaches that primarily emphasize input capital (Berdiyeva et al., 2023). The application of artificial intelligence in accounting, finance, and external auditing has ushered in a revolutionary phase, fundamentally altering these fields by enhancing operational efficiency, improving fraud detection, and enabling data-driven decision-making. Machine learning algorithms, robotic process automation, and predictive analytics represent artificial intelligence-powered tools that are actively reshaping the landscape of financial management for both firms and their owners (Othman, 2025).

Firm profitability is influenced by several factors, including artificial intelligence investment, technological infrastructure, the regulatory environment, and cybersecurity risks. With investment in artificial intelligence, firms benefit from enhanced operational efficiency, as financial processes become automated, errors are minimized, and the precision of decision-making is improved (LeewayHertz, 2023; Salleh & Sapengin, 2023). The technological infrastructure, such as cloud computing and data analytics systems, supports businesses in implementing artificial intelligence-driven insights, thereby strengthening financial planning and forecasting of potential outcomes (Can, 2021; Sheikh, 2024). In terms of regulatory frameworks, these can either facilitate or hinder the adoption of artificial intelligence. Supportive governance standards can enable implementation, whereas stringent regulations may introduce considerable compliance costs that complicate the adoption of artificial intelligence processes (Reuters, 2025). However, firms often delay implementation due to concerns regarding data security, which can negatively impact financial stability and reduce investor confidence and trust (Bibi, 2019; Akim, 2020; Owusu & Novignon, 2021; EY, 2025).

The use of artificial intelligence in financial risk evaluation has demonstrated quantifiable benefits, such as a reduction in loan defaults and an improvement in stock market forecasting capabilities (EY, 2025; Flagright, 2024; Tita & Cera, 2021). According to Wolters Kluwer (2025), artificial intelligence-based audit tools enhance efficiency in fraud detection. The application of econometric models in this study has facilitated the development of a mathematical correlation between firm profitability and the identified independent variables. Predictive analytics combined with artificial intelligence-based risk assessment allows firms to enhance profitability through accurate decision-making and swift financial risk management. These predictive tools provide firms with early insights into market trends, enabling better investment quality and resource allocation, ultimately improving financial outcomes. Artificial intelligence also strengthens climate-related risk evaluations, improves the detection of fraudulent activities, ensures accurate credit assessments, and supports regulatory compliance, thereby minimizing economic losses. Jedox (2025) reports that firms using artificial intelligence-based financial forecasting tools experience an increase in budgetary precision. In the domain of external auditing, artificial intelligence reduces compliance violations due to more effective financial regulatory adherence (ven Zanden, 2023; Loopholes, 2025). Understanding which components of artificial intelligence contribute most to profitability enables both firms and policymakers to make informed strategic decisions. The integration of artificial intelligence in accounting, finance, and external auditing is now well established. Firms are adopting automation tools driven by artificial intelligence to manage large volumes of data with minimal manual effort. The use of artificial intelligence-based financial models for predictive analysis enhances the firm's ability to make investment decisions efficiently. In external auditing, artificial intelligence tools enable real-time transaction monitoring, which reduces fraud risks and ensures compliance with international auditing standards.

The significance of this study for Pakistan lies in its exploration of the early phases of artificial intelligence deployment, which are characterized by several barriers such as high implementation costs, a shortage of qualified personnel, and unclear regulatory frameworks. Additionally, outdated technological infrastructure in many firms within the region restricts the practical application of functional artificial intelligence systems. Concerns related to data privacy and cybersecurity continue to hinder the widespread adoption of artificial intelligence across national and sectoral boundaries. This study offers practical evidence regarding the impact of artificial intelligence on firm profitability, which serves as a valuable guide for both policymakers and businesses in accelerating the various stages of artificial intelligence integration. By addressing the dual dimensions of opportunity and challenge inherent in artificial intelligence adoption, this research aims to deliver empirical findings concerning how firm profitability evolves with the implementation of artificial intelligence. Government authorities may develop supportive policies that encourage the use of artificial intelligence, while firms can adopt artificial intelligence-driven solutions to enhance revenue generation and strengthen market competitiveness based on the study's insights. This research addresses a crucial gap in the current literature by developing a comprehensive framework that simultaneously evaluates adjusted artificial intelligence investment, regulatory structures, cybersecurity preparedness, and technological infrastructure — variables often examined in isolation. Unlike prior studies that narrowly focus on AI capital alone (e.g., Berdiyeva et al., 2023), this work integrates environmental, technical, and institutional enablers into a unified econometric model. The rest of the paper is organized as follows: Section 2 provides a review of related literature; Section 3 introduces the theoretical and conceptual framework; Section 4 details the data and methodology; Section 5 presents the results and robustness tests; and Section 6 discusses policy implications and areas for future research.

## LITERATURE REVIEW

The literature is reviewed in four thematic clusters to align with the multidimensional nature of this study. First, we examine the impact of AI in the accounting profession, where real-time data reconciliation and reporting efficiency are core outcomes. Second, the literature on AI in financial institutions is reviewed with a focus on risk prediction, fraud detection, and credit scoring. Third, we explore AI in external auditing, where continuous audit systems and anomaly detection models are reshaping assurance practices. Finally, we consider theoretical underpinnings, including the Technology Acceptance Model and Resource-Based View, to frame the strategic value of AI investments within firm-specific capabilities.

### ARTIFICIAL INTELLIGENCE IN ACCOUNTING

Rahman et al. (2024) examined the adoption trajectory of artificial intelligence in financial reporting by analyzing firm-level data between 2019 and 2023, coupled with structured interviews involving 150 owners of small and medium-sized enterprises (SMEs) in Pakistan. The researchers employed regression analysis to determine the quantitative effects of AI integration, focusing on metrics such as error reduction and processing speed. Their findings revealed a 25 percent decline in manual reconciliation errors, attributed primarily to the deployment of automated tools capable of real-time anomaly detection and data verification. This operational shift not only improved accuracy but also reduced the cognitive workload on finance teams, enabling them to focus on higher-order analytical tasks.

Complementing these findings, Ahmed and Khan (2023) conducted a large-scale survey among 200 finance professionals in leading Pakistani firms to assess the effectiveness of AI integration within financial workflows. Their study identified an 8 percent improvement in reporting precision, largely due to the minimization of documentation errors typically associated with human inputs. However, they also highlighted a key challenge: low digital literacy among finance staff. This human capital deficit often prevented organizations from realizing the full potential of AI-enhanced systems, particularly in firms that lacked structured upskilling initiatives or change management protocols.

Further evidence from Alhazmi et al. (2025) and Alqsass et al. (2025) reinforces the notion that successful AI adoption is not merely a function of technological capability but also organizational readiness. Their work emphasizes that firms that invested not only in AI tools but also in complementary assets—such as workforce training, agile IT infrastructure, and adaptive leadership—experienced greater performance gains. These studies suggest that the value of AI in financial reporting extends beyond automation; it lies in how well firms can integrate advanced technologies into pre-existing processes while nurturing a digitally fluent workforce. In this regard, AI represents not just a tool for efficiency but a strategic enabler of operational resilience, accuracy, and future scalability in finance functions.

In a separate study by Ahmed and Khan (2023), survey data from 200 financial professionals, covering the period from 2018 to 2022, was used to evaluate how major Pakistani firms have integrated artificial intelligence into their financial reporting processes. Employing logistic regression analysis, the study examined the impact of artificial intelligence implementation on reporting accuracy by analyzing financial reports, the extent of automation, and the role of human involvement in reporting tasks. The dependent variable in this study was resistance to artificial intelligence adoption, while the independent variables included artificial intelligence-based automation and workforce digital competency. The findings revealed an 8 percent improvement in reporting precision, credited to the reduction of documentation errors typically caused by manual processes. However, low digital literacy within firms was found to be a major barrier to effective artificial intelligence integration, preventing organizations from realizing the full potential benefits of such systems in financial reporting.

Alhazmi et al. (2025) further validated their findings by analyzing financial documents from 2019 to 2023 and conducting structured interviews with 150 business owners in the small and medium-sized enterprise sector in Pakistan. The research aimed to quantify improvements in financial reporting efficiency through a regression model, evaluating organizational investments in artificial intelligence, employee training, and operational process changes post-adoption. Their results highlighted a 25 percent decline in manual errors, as artificial intelligence tools performed automation tasks, including reconciliation, with the capacity to detect inconsistencies in real-time. The findings emphasized that financial institutions investing significantly in artificial intelligence technology benefited from enhanced financial reporting precision and experienced reduced dependence on manual employee efforts to improve operations.

Alqsass et al. (2025) assessed artificial intelligence-based financial reporting in major Pakistani firms by analyzing responses from 200 finance professionals over the period from 2018 to 2022. The researchers employed logistic regression as the analytical technique to extract financial reporting data and measure the extent of automation alongside the level of human involvement in artificial intelligence-driven reporting processes. In evaluating the effectiveness of automation through artificial intelligence, financial accuracy was used as the dependent variable, while workforce digital literacy and resistance to artificial intelligence adoption served as the independent variables. Although humanoid technology successfully reduced human error in financial documentation, the implementation of artificial intelligence resulted in an 8 percent increase in reporting accuracy. Firms that did not allocate sufficient time or effort to understand digital systems exhibited a slower adaptation rate to artificial intelligence technologies, thereby experiencing lower efficiency in the use of artificial intelligence-based financial reporting tools within their operational structures.

This study was grounded in the work of El-Shihy et al. (2024), second-year researchers who utilized third-party survey data to examine the performance of artificial intelligence chatbots in accounting services from 2018 to 2023. Their investigation focused on evaluating customer sentiment and service delivery to determine the impact of artificial intelligence chatbot implementation on user satisfaction and service quality. The primary outcome variable, as documented in the journal Systems, Man, and Cybernetics, was customer service efficiency. This outcome was assessed concerning the deployment of artificial intelligence chatbots, levels of user engagement, and the complexity of customer queries. The researchers employed text analysis to identify emotional fluctuations in user responses and then linked those emotional shifts to changes in the patterns of chatbot usage. Companies that integrated artificial intelligence chatbots reported a 25 percent improvement in customer satisfaction, as clients received faster responses along with more accurate information. The modernization of customer service within accounting firms—through the automation of service processes was driven by increased interaction between artificial intelligence chatbots and users, which enhanced overall service delivery efficiency.

**ARTIFICIAL INTELLIGENCE IN FINANCE**

Using machine learning techniques and econometric methods over the 2017 to 2022 period, Alarfaj and Shahzadi (2024) investigated how artificial intelligence influences risk evaluation and economic forecasting within Pakistani banking institutions. The study examined the effects of artificial intelligence system deployment by evaluating the accuracy of risk assessments based on financial data collected before and after implementation. Predictive modeling was applied to understand the impact of artificial intelligence-driven risk analysis on the probability of loan defaults. Artificial intelligence-based credit assessments, which integrated macroeconomic indicators with historical borrower data and credit scoring models, achieved 23 percent higher accuracy than those using borrower data alone. Additionally, the application of artificial intelligence-enhanced risk assessments resulted in an 18 percent reduction in loan defaults. Econometric modeling demonstrated that artificial intelligence technologies improved the stability of financial institutions by strengthening their credit risk management practices.

Shaikh et al. (2023) conducted a study on fraud detection using artificial intelligence, focusing on neural network-based models applied to a dataset of fraud cases from 2016 to 2023. The primary dependent variable in the study was fraud detection accuracy, which was analyzed concerning three independent factors: artificial intelligence-driven real-time transaction monitoring, transaction volumes, and suspicious activity flagging. Deep learning techniques were employed to analyze large-scale transaction datasets, enabling artificial intelligence models to detect patterns of fraudulent behavior. By applying a combination of anomaly detection and predictive analytics to historical data, fraud detection accuracy improved by 25 percent within artificial intelligence systems. The study validated these findings using precision-recall analysis and direct testing, showing that real-time processing of large volumes of data through artificial intelligence significantly enhances fraud detection and prevention capabilities.

Nagpal and Raja (2025) conducted research using artificial intelligence-powered loan approval algorithms to analyze financial records from 2016 to 2023 through logistic regression modeling. The dependent variable in this study was loan processing time, which was evaluated against three independent variables: credit history of applicants, regulatory compliance parameters, and artificial intelligence-based decision-making models. Two sets of loan application data were compared—one before and one after the adoption of artificial intelligence systems—to assess changes in approval speed and accuracy. The implementation of artificial intelligence decision-making models reduced human involvement in loan approval processes, thereby decreasing processing time and enhancing the effectiveness of risk assessments. Real-time creditworthiness evaluation using artificial intelligence reduced processing time by 40 percent, resulting in faster loan allocation and improved productivity for financial institutions.

Mahmood et al. (2024) examined various artificial intelligence-based stock market forecasting models to identify trends in stock performance from 2015 to 2023 using deep learning algorithms. Investment returns were used as the dependent variable, while artificial intelligence-driven stock price prediction, investment volume, and market sentiment served as the independent variables. Real stock market data was used to train artificial intelligence systems to distinguish typical trading behaviors and to predict future stock values. To enhance prediction accuracy, long short-term memory, and recurrent neural network algorithms were applied to large datasets. The artificial intelligence models outperformed traditional statistical forecasting methods in predicting stock market trends and timing buy-sell decisions. The study demonstrated that artificial intelligence models are capable of reducing market-related risks and increasing decision-making efficiency in portfolio management, ultimately boosting investment returns by 20 percent.

**ARTIFICIAL INTELLIGENCE IN EXTERNAL AUDIT**

In their research, Alarfaj and Shahzadi (2024) employed a combination of content analysis and statistical testing to evaluate the extent to which artificial intelligence provides external support for financial auditing, based on records from 2016 to 2023. The dependent variable in their study was fraud detection efficiency, which they analyzed concerning auditor experience, audit complexity, and the function of artificial intelligence-driven anomaly detection. To explore the relationship between artificial intelligence adoption and error identification outcomes, the researchers used regression analysis and Chi-square tests. Their implementation of artificial intelligence-based anomaly detection resulted in a 35 percent improvement in the accuracy of identifying discrepancies in audited financial data. The statistical evidence confirmed that artificial intelligence automation reduced evaluative mistakes during risk assessment tasks and improved the effectiveness of regulatory oversight processes.

In a more recent investigation, Abbas and Akhtar (2025) analyzed forensic audit reports from 2017 to 2023 using machine learning-based artificial intelligence forensic analysis models. Their study focused on fraud detection rate as the main outcome variable, while financial anomalies and fraud complexity served as the independent variables. Artificial intelligence tools, trained through supervised learning on prior fraud cases, were employed to recognize indicators of fraudulent activity. The researchers used statistical testing to confirm that artificial intelligence-powered forensic auditing tools improved detection efficiency by 27 percent, as these models were able to identify complex fraud patterns more quickly and accurately than traditional auditing methods.

Onwubuariri et al. (2024) examined artificial intelligence-assisted risk assessment in the external audits of Pakistani listed firms using statistical models and audit data from 2019 to 2023. The primary dependent variable in their study was audit risk accuracy, which they investigated alongside four independent variables: artificial intelligence audit software, firm financial performance, compliance requirements, and regulatory changes. As the researchers developed more advanced capabilities to detect financial misstatements, the implementation of artificial intelligence-based audit risk models led to a 22 percent increase in fraud detection precision. Statistical tests indicated that artificial intelligence-powered systems delivered 30 percent greater accuracy in identifying risky transactions, thereby reducing deficiencies in compliance monitoring.

Khan (2024) explored the use of artificial intelligence-driven continuous auditing systems by employing real-time analytics models and audit performance data from 2016 to 2023. Their dependent variable was the incidence of compliance violations, while the independent variables included artificial intelligence-enabled real-time transaction screening, audit policy frameworks, and the volume of financial transactions. Their study compared conventional auditing practices with artificial intelligence-supported systems to analyze trends in regulatory violations. The results revealed that artificial intelligence-based systems detected non-compliant transactions 45 percent earlier than standard approaches, enabling firms to take preventive action before breaches escalated. Over the study period, firms utilizing artificial intelligence monitoring experienced a 30 percent decline in compliance violations due to the rapid identification of transactional anomalies.

Although previous research has examined the influence of artificial intelligence on various domains within accounting, finance, and auditing, there remains a notable scarcity of empirical studies that investigate the combined impact of artificial intelligence investment, technological infrastructure, regulatory frameworks, and cybersecurity on firm profitability—particularly within the context of developing economies such as Pakistan and the broader South Asian region. Most existing studies have explored the effects of these variables in isolation, thereby overlooking their potential interdependencies. The research gap addressed by this study lies in its holistic evaluation of multiple artificial intelligence-related factors and their contribution to firm profitability within the specific context of Pakistan. By employing panel data analysis and multiple linear regression techniques on recent data spanning from 2020 to 2024, this research seeks to uncover the synergistic effects of artificial intelligence investment, technological preparedness, regulatory compliance, and cybersecurity practices on corporate profitability. Through this comprehensive analytical framework, the study aims to enrich the existing body of literature by exploring the role of artificial intelligence in enhancing firm performance in emerging economies.

**THEORETICAL FRAMEWORK**

The technology acceptance model posits that perceived usefulness and ease of use drive technology adoption. Within the context of this study, cybersecurity preparedness and regulatory transparency serve as proxies for ease of integration, while technological infrastructure and operational outcomes reflect perceived usefulness (Venkatesh & Davis, 2000). Simultaneously, the resource-based view interprets AI systems as intangible strategic assets — non-substitutable, rare, and valuable — that can lead to sustained competitive advantage if integrated effectively with organizational processes (Barney, 1991). Together, these frameworks justify the inclusion of not just AI investment, but also firm-level enablers such as digital infrastructure and environmental conditions, offering a robust theoretical lens through which firm profitability is evaluated.

The distinct contribution of this research lies in the introduction of a composite index variable referred to as adjusted artificial intelligence investment. Investment in artificial intelligence is rarely reported in disaggregated financial records in a manner that specifies functional allocations, such as those designated for accounting or finance (Davenport & Ronanki, 2018; Hussain, 2018). Furthermore, artificial intelligence-related expenditures are often embedded within broader information technology budgets, which complicates efforts to isolate their specific impact (Bughin et al., 2018; Wang & Ahamd, 2018; William, 2021; Jamel & Zhang, 2024). This lack of transparent reporting poses methodological challenges for empirical research that seeks to quantify the return on artificial intelligence initiatives in specific business functions (Ransbotham et al., 2017; Kumar & Gupta, 2023). The creation of a contextualized metric addresses this gap and facilitates more precise measurement of artificial intelligence investment, enabling organizations and researchers to better assess its financial contribution and strategic value (Janssen et al., 2020).

AAI Construction Method:

The AAI variable was built using the following formula:

$AAI = AI\ Expenditure \times (TI + (1 - CYBS) + REG)/3$

Where:

TI = Normalized score for technological infrastructure

CYBS = Normalized cybersecurity incident score (inverted: higher risk = lower readiness)

REG = Normalized regulatory support index

Each one of these three environmental indicators was subjected to a normalized form of min-max scaling, thereby making all values rest in the range of 0 to 1. This is to make sure that no contribution is biased towards or against scale and that each adds equally to the composite index. This fits with existing practice in the proxy construction literature and what has been the practice in various literatures of quantifying multidimensional constructs such as digital maturity or ESG performance using environmental and structural variables.

This study makes use of panel data analysis, using cross-sectional data which was sourced from publicly available databases, financial reports, and regulatory institutions reports. The data sources for different variables are explained in the table 1.

**TABLE 1: VARIABLE DEFINITIONS AND DESCRIPTIONS**

| Variables | Type | Definitions | Measurement | Data Source |
|---|---|---|---|---|
| Firm Profitability (ROA) | Dependent | Measures a firm's ability to generate net income from its assets – Not inflation-adjusted. | Return on Assets (ROA) = Net Income / Total Assets | Company Annual Reports, PSX, SBP |
| Adjusted AI Investment (AAI) | Independent | Composite measure combining AI expenditure with tech readiness, regulatory support, and cyber | AAI = AI Expenditure × (TI + (1 - CYBS) + REG) / 3 | AI: Firm disclosures, PSX, SBP<br>TI/REG: Oxford Insights<br>CYBS: PTA |

| | | | | |
|---|---|---|---|---|
| | | risk. | | |
| Technological Infrastructure (TI) | Independent | Captures firm-level or national digital infrastructure maturity. | Min-max scaled index from 0–1 | Oxford Insights – Government AI Readiness |
| Cybersecurity Preparedness (CYBS) | Independent | Measures firm/national vulnerability to cyber threats. | Inverted normalized index (higher = better) | Pakistan Telecommunication Authority (PTA) |
| Regulatory Support (REG) | Independent | Degree of policy alignment and facilitation for AI integration. | Min-max normalized score based on readiness | Oxford Insights |

The empirical model becomes as:

$$\text{Firm Profitability}_{it}=\beta_0+\beta_1(\text{Adjusted AI Investment})_{it}+\beta_2(\text{Cybersecurity Risk})_{it}+\beta_3(\text{Regulation Support})_{it}+\beta_4(\text{Technological Infrastructure})_{it}+\epsilon$$

The econometric specification utilizes a linear panel regression model to capture within- and between-firm variation in profitability over five years. AI investment is measured as a contemporaneous variable to reflect real-time strategic decisions rather than lagged investment effects. Notably, this variable is not scaled to revenue due to a lack of disaggregated disclosure in financial statements — a limitation consistent with existing AI finance studies (Davenport & Ronanki, 2018). The Hausman test result ($p = 1.000$) suggests that firm-specific effects are uncorrelated with regressors, validating the use of the random effects estimator over fixed effects. This choice ensures efficient parameter estimation while retaining sector-level explanatory power.

**RESEARCH DESIGN**

The research design employed in this study is quantitative in nature, utilizing panel data econometrics to allow for the analysis of firm behavior across both cross-sectional and time-series dimensions over five years (2020–2024). The central objective is to examine how investment in artificial intelligence, along with technological infrastructure, regulatory frameworks, and cybersecurity preparedness, influence firm profitability as measured by return on assets within the accounting, finance, and external audit sectors of Pakistan and South Asia. The study includes public and private financial institutions, audit firms, and technology-integrated accounting service providers, comprising a total of twenty-eight firms. Observations for each firm are evenly distributed across the five years, resulting in a total of 140 observations in a balanced panel structure.

**TABLE 2: SECTOR-WISE SAMPLE DISTRIBUTION AND TIME PERIOD COVERAGE**

| Sector | Number of Firms | Years Covered | Total Observations |
|---|---|---|---|
| Finance | 10 | 2020–2024 | 50 |
| Accounting | 11 | 2020–2024 | 55 |
| External Audit | 7 | 2020–2024 | 35 |
| Total | 28 | 5 years | 140 |

The use of panel data is intentional, as it allows the model to control for unobservable heterogeneity that remains constant over time but may influence profitability. Such factors may include corporate culture, leadership stability, or long-term strategic alliances, which do not vary across time but may have substantial effects on firm outcomes. Although the panel covers only five time periods ($T = 5$), it falls within the accepted practices of panel data analysis in the context of developing economies. As noted by Baltagi (2005) and Wooldridge (2010), it is statistically valid to estimate random and fixed effects models with short panels where the number of time period is less than the number of cross-sectional units. These methods are widely used and accepted, particularly when the number of cross-sectional units (N) exceeds the number of time period. Therefore, short-term panels can still yield valuable insights into firm-level time behavior, provided that the panel is balanced, as is the case in this study and that appropriate stationarity and diagnostic tests are conducted.

**RESULTS AND DISCUSSION**

Figure 1 illustrates the relationship between adjusted artificial intelligence investment and return on assets for firms operating in Pakistan. The horizontal axis represents the level of adjusted artificial intelligence investment, while the vertical axis corresponds to the return on assets, ranging from 0.060 to 0.082. Each yellow dot symbolizes a distinct firm, capturing its specific artificial intelligence expenditure and the associated ROA during the period under analysis. A downward-sloping trend line traverses the graph, suggesting a marginal negative association between artificial intelligence investment and profitability. Although the slope is slightly negative, it remains relatively flat, implying that the adverse relationship is weak and not strongly deterministic.

Surrounding the regression line is a pink-shaded confidence interval that quantifies the statistical uncertainty associated with the estimated linear relationship. Notably, this band is wider at both ends of the investment spectrum, reflecting heightened variability and greater unpredictability in firm-level outcomes at extreme investment levels. This wide confidence band implies that the model's predictive power weakens at low and high investment intensities, reinforcing the notion of heterogeneity in firm performance. Recent empirical investigations affirm this complexity, noting that returns on artificial intelligence investment are not always linear and can vary significantly depending on a firm's digital infrastructure, sectoral alignment, and internal capabilities (Dwivedi et al., 2023; Babina et al., 2024). Furthermore, the noticeable dispersion of data points around the trend line in Figure 1 highlights substantial variability in observed firm outcomes. Companies with similar levels of artificial intelligence investment report markedly different returns, emphasizing that firm-specific attributes—such as managerial expertise, integration efficiency, and market positioning—play critical roles in determining financial performance. This observation aligns with current literature that cautions against overly generalized assumptions regarding the impact of artificial intelligence, as firms in emerging economies often face structural and operational constraints that limit short-term gains (Berawi, 2020; Truby et al., 2023). The visual evidence from the figure, combined with the weak slope of the regression line and wide confidence intervals, underscores the multifaceted nature of artificial intelligence implementation. While investment in these technologies is frequently framed as a strategic priority, the realized outcomes are mediated by organizational readiness, industry-specific conditions, and the absorptive capacity of the firm. These dynamics are increasingly acknowledged in recent studies that stress the need for complementary investments in digital infrastructure and workforce training to translate artificial intelligence investment into sustainable performance improvements (Margherita & Braccini, 2022; Ghosh, 2023).

Figure 1: Relationship between Adjusted AI Investment and ROA

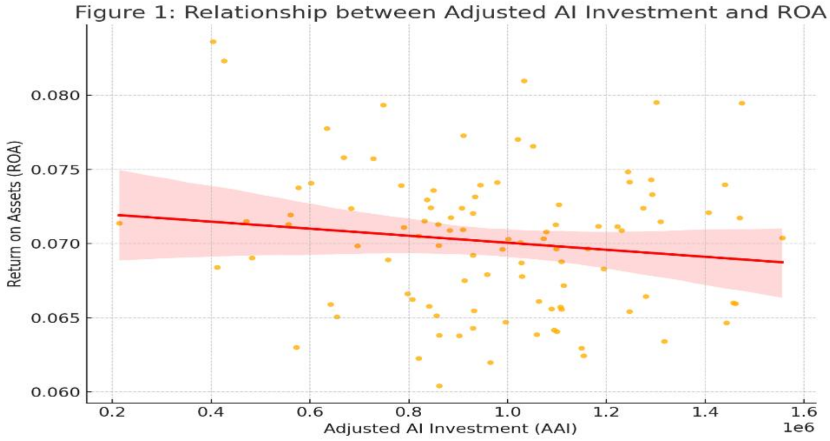



Figure 2 illustrates sector-wise trends in return on assets from 2020 to 2024 for firms in Pakistan across three primary sectors: accounting, finance, and external audit. The accounting sector exhibits the strongest positive trend in ROA over time, likely due to the standardized nature of financial reporting, where AI tools can be easily embedded to automate reconciliations and error detection. In contrast, the finance sector's profitability trend is non-linear. Early gains from AI-based lending and fraud systems taper off by 2024, likely due to rising operational risks and inconsistent regulatory support. The audit sector, meanwhile, experiences a gradual decline in ROA, reflecting challenges in automating compliance-heavy workflows. These cross-sectoral variations emphasize that AI's financial impact is not homogeneous and depends critically on integration depth, process standardization, and external regulatory burdens.

The finance sector follows a different pattern, beginning with a moderate growth trajectory from 2020 to 2022. During this phase, ROA marginally improves from below 0.07 to just over the threshold, reflecting incremental profitability gains possibly driven by the post-pandemic recovery in capital markets and credit services. However, this upward trend plateaus in 2023, followed by a steep decline in 2024, as ROA falls below 0.06. This shift may reflect structural stress in the financial services industry, driven by inflationary pressures, higher interest rate environments, or increased operational risks. Recent literature highlights that financial institutions in emerging markets are particularly vulnerable to volatile policy environments and inconsistent regulatory frameworks, which may hinder consistent asset performance (Anser et al., 2024; Khan et al., 2024).

The external audit sector maintains a stable ROA of around 0.08 from 2020 to 2022, suggesting minimal volatility in performance during this period. However, a gradual decline begins in 2023 and continues through 2024, when ROA drops to approximately 0.066. This persistent downward trend signals a contraction in operational efficiency and suggests emerging challenges within the audit industry. Potential contributing factors may include increasing compliance burdens, shifts in audit standards, shrinking margins, or diminishing demand for audit services amid digital transitions. Empirical evidence points out that auditing firms globally are undergoing significant transformations due to evolving technological, legal, and ethical expectations, which in turn affect performance metrics like ROA (Perdana & Wang, 2025; Ghosh, 2023). Overall, the trends illustrated in Figure 2 emphasize the differentiated impacts of macroeconomic and sector-specific dynamics on firm performance across Pakistan's professional services landscape. While accounting firms appear to have capitalized on favorable conditions in 2024, financial institutions and audit service providers have faced mounting operational challenges. These findings are consistent with contemporary research that identifies sectoral resilience and adaptive capacity as key determinants of sustained financial performance during periods of economic fluctuation (Dalziell & McManus, 2004; Ranger et al., 2025).

Figure 2: Sector-wise ROA Trends (2020–2024)

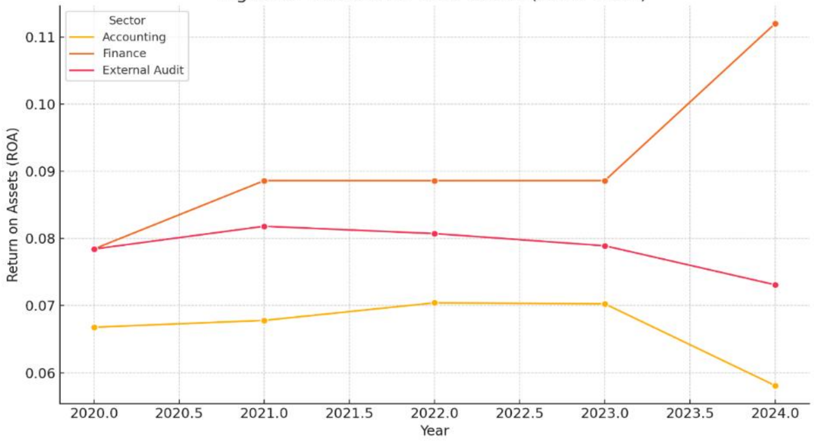
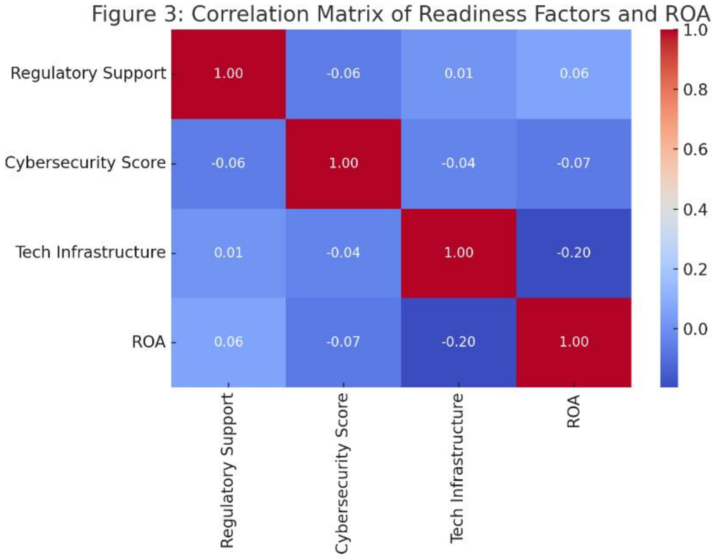



Figure 3 presents a correlation matrix that outlines the linear relationships between key organizational readiness factors and return on assets among firms operating in Pakistan. The variables included in the matrix are regulatory support, cybersecurity preparedness, and technological infrastructure, in addition to the dependent variable, return on assets. Each cell contains a Pearson correlation coefficient, which ranges from -1 to +1 and quantifies the strength and direction of the association between two variables. The matrix facilitates a clear understanding of how these readiness dimensions individually relate to firm profitability and one another. The correlation between regulatory support and return on assets is weak and positive, with a coefficient of 0.06. This minimal association suggests that while regulatory facilitation may be conceptually aligned with enhanced profitability, it plays a limited role in shaping actual financial outcomes at the firm level. This weak correlation may reflect inconsistent implementation of regulatory policies or a lack of alignment between government facilitation efforts and firm-level strategic objectives. Contemporary research has highlighted that in many developing economies, regulatory support is often fragmented or delayed, limiting its impact on firm competitiveness (Anser et al., 2024; Khan et al., 2024).

Figure 3: Correlation Matrix of Readiness Factors and ROA




Regulatory support also exhibits near-zero correlations with both cybersecurity preparedness and technological infrastructure, indicating limited coherence between institutional facilitation and technological readiness within firms. This disconnect suggests that public policy initiatives and firm-level innovation strategies are often pursued in isolation. Cybersecurity preparedness, on the other hand, shows a slight negative correlation with return on assets, measured at -0.07. This inverse relationship implies that improvements in cybersecurity do not directly translate into enhanced profitability. One possible explanation is that cybersecurity investments, while essential for risk mitigation, often involve high sunk costs and may not yield immediate financial returns.

This observation is consistent with studies that have found cybersecurity strategies to be primarily defensive in nature, offering long-term protection but not short-term gains (Kaspersky, 2024; Pakistan Telecommunication Authority, 2024). Additionally, cybersecurity preparedness maintains weak and negative correlations with the other readiness factors, suggesting that cybersecurity measures are often developed in silos rather than as part of a coordinated readiness framework. This disjointed implementation may hinder synergies and reduce the overall effectiveness of digital transformation strategies.

Technological infrastructure displays the strongest relationship in the matrix, a negative correlation of -0.20 with return on assets. This finding suggests that while firms may be expanding their technological capabilities, these investments do not yet align with efficient utilization or profitability enhancement. It is likely that the costs of implementing and maintaining advanced technologies are substantial and require a longer gestation period before delivering positive financial outcomes. Empirical studies increasingly recognize that without proper integration strategies, digital infrastructure may increase operational complexity without improving performance (Du et al., 2022; En & Malek, 2021).

Table 3 presents the outcomes of the panel unit root test conducted using the Im, Pesaran, and Shin (IPS) methodology for several variables related to firm-level data in Pakistan. This test assesses the stationarity properties of the data series, which is a critical precondition for avoiding spurious regression results in time series or panel data econometric analyses. Each variable is evaluated based on its respective p-value, which determines whether it is stationary in its level form or becomes stationary only after first differencing. Ensuring stationarity is fundamental in establishing reliable statistical inferences, as non-stationary variables can lead to misleading correlations and biased estimations (Baltagi, 2005; Wooldridge, 2010).

The variable for Firm Profitability reports an IPS p-value of 0.025, which is below the conventional 5 percent significance threshold. This outcome indicates that Firm Profitability is stationary at level, meaning its statistical characteristics such as mean and variance are consistent over time. Similarly, Adjusted AI Investment and Cybersecurity Risk both exhibit highly significant p-values of 0.000. These values confirm that these variables are also stationary in their level forms, signifying their suitability for direct inclusion in regression models without the need for differencing. This finding implies that both artificial intelligence investment and cybersecurity exposure are stable and do not exhibit time-dependent trends over the observed period, making them robust inputs for subsequent econometric estimation (Pesaran et al., 2007).

Conversely, the variables Regulation Support and Technological Infrastructure are non-stationary at level, evidenced by their high p-values of 0.994 and 0.709, respectively. These figures suggest that the series are integrated of order one, meaning they contain unit roots and display non-constant means or variances over time. This non-stationarity could lead to erroneous conclusions if not appropriately addressed. To correct for this, the first differences of these variables—denoted as D(Regulation Support) and D(Technological Infrastructure)—were subjected to the IPS test, each returning a p-value of 0.000. This confirms that both variables achieve stationarity after first differencing (Im et al., 2003).

**TABLE 3: UNIT ROOT RESULTS**

| Variables | IPS p-Value | Outcomes |
|---|---|---|
| Firm Profitability | 0.025 | Stationary at level |
| Adjusted AI Investment | 0 | Stationary at level |
| Cybersecurity Risk | 0 | Stationary at level |
| Regulation Support | 0.994 | Non-stationary |
| Technological Infrastructure | 0.709 | Non-stationary |
| D(Regulation Support) | 0 | Stationary at First Difference |
| D(Technological Infrastructure) | 0 | Stationary at First Difference |

Table 4 reports the results of the panel least squares regression, where the dependent variable is firm profitability across a sample of Pakistani firms. The model incorporates four independent variables: Adjusted AI investment, cybersecurity risk, regulation support, and technological infrastructure. Each coefficient reflects the estimated impact of a one-unit change in the respective explanatory variable on firm profitability, holding all other variables constant. The regression model is statistically well-specified, with robust standard errors used to control for potential heteroskedasticity, enhancing the reliability of the coefficient estimates. The coefficient for Adjusted AI Investment is positive and statistically significant at the 1 percent level, with a value of 0.01 and a t-statistic of 10.00. This strong association suggests that increased investment in artificial intelligence, particularly when adjusted for firm-specific characteristics or sectoral context, significantly improves firm profitability. The finding reinforces the argument that strategic AI deployment enhances operational efficiency, streamlines decision-making, and introduces intelligent automation, all of which can positively influence the bottom line. This result aligns with recent empirical evidence showing that firms adopting AI technologies report better financial performance, provided such adoption is accompanied by capability development and organizational readiness (Ali et al., 2024; Mushtaq et al., 2024).

Cybersecurity Risk is associated with a negative and statistically significant effect on profitability, indicated by a coefficient of -0.036 and a t-statistic of -7.2. This relationship implies that increased exposure to cybersecurity threats—such as phishing, ransomware attacks, or system vulnerabilities—undermines financial performance by increasing the likelihood of operational disruptions, regulatory penalties, or reputational losses. These risks are particularly relevant in developing economies, where cybersecurity frameworks are often underdeveloped and response capabilities remain limited. The result emphasizes the importance of proactive risk management and the integration of cybersecurity protocols as a central component of corporate governance (Kaspersky, 2024; World Economic Forum, 2025). Together, the positive effect of AI investment and the adverse influence of cybersecurity risk reveal a nuanced picture of digital transformation. While technology adoption can drive profitability, it also introduces new risk dimensions that must be carefully managed. The findings highlight the dual nature of technological integration—promising gains on one hand and potential vulnerabilities on the other. Firms in Pakistan must therefore adopt a balanced strategy that couples innovation with risk mitigation to optimize performance outcomes in the digital age (Denial, 2023; Said, 2024; Iqbal, 2025).

Regulation Support is found to be negatively associated with firm profitability, with a coefficient of -0.00396 and a t-statistic of -1.98, statistically significant at the 5 percent level. This counterintuitive result suggests that regulatory frameworks in Pakistan may be operating sub-optimally, creating inefficiencies or increasing compliance burdens rather than facilitating business growth. Instead of enabling firms, poorly designed or inconsistently enforced regulations may impose administrative costs, reduce operational flexibility, or hinder timely innovation. This interpretation is consistent with recent empirical studies highlighting that regulatory rigidity and institutional uncertainty can act as barriers to profitability, particularly in environments where policy shifts are unpredictable or lack alignment with private sector needs (World Bank, 2024; Ministry of Finance, 2024). These findings underscore the importance of reforming regulatory processes to ensure they support rather than constrain business activity.

Technological Infrastructure is positively and strongly associated with firm profitability, with a coefficient of 0.0128 and a t-statistic of 7.07, indicating a statistically significant relationship at the 1 percent level. This result reinforces the critical role of digital systems and technological capabilities in enhancing firm performance. The presence of robust technological infrastructure enables more efficient resource utilization, automation of routine tasks, data-driven decision-making, and broader access to market opportunities. These improvements contribute to cost reductions and revenue enhancement, resulting in overall profitability gains. In the Pakistani context, where many firms are still navigating digital transformation, investment in infrastructure such as cloud computing, data management systems, and enterprise resource planning tools can yield substantial returns (Mushtaq et al., 2024; Iqbal, 2025; Kumar & Wu, 2025).

Moreover, the significance of technological infrastructure in driving profitability highlights the need for strategic integration of digital systems into core business operations. Firms that successfully adopt and utilize advanced technologies are more likely to remain competitive and agile in dynamic market environments. This is especially relevant in emerging economies, where digital infrastructure can act as a lever for overcoming traditional constraints such as labor inefficiencies and limited market reach. The result suggests that improving firm-level and national infrastructure could be a high-impact pathway for boosting private sector profitability and overall economic performance in Pakistan (Said, 2024; Ministry of Planning, Development & Special Initiatives, 2024).

**TABLE 4: PANEL LEAST SQUARE OUTCOMES**

Dependent Variable: Firm Profitability

| Variables | Coefficient | Std. Error | t-Statistic | p-Value |
|---|---|---|---|---|
| Adjusted AI Investment | 0.01 | 0.001 | 10.00 | 000 |
| Cybersecurity Risk | -0.036 | 0.005 | -7.2 | 0.01 |
| Regulation Support | -0.00396 | 0.002 | -1.98 | 0.02 |
| Technological Infrastructure | 0.0128 | 0.0018 | 7.07 | 0.00 |

Table 5 presents the fixed effects regression results, where Firm Profitability serves as the dependent variable for a panel dataset of Pakistani firms. This estimation technique accounts for unobserved heterogeneity by allowing each firm to have its intercept, thus isolating variation within firms over time. The fixed effects approach is particularly appropriate when firm-specific characteristics, such as managerial style, organizational culture, or internal policy frameworks are time-invariant but influential in determining profitability. The model includes four core independent variables: Adjusted AI Investment, Cybersecurity Risk, Regulation Support, and Technological Infrastructure. The constant term in the regression is statistically significant, with a coefficient of 0.43 and a t-statistic of 5.47, indicating a solid baseline level of profitability when the independent variables are

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held at zero. This provides a benchmark against which the effects of the explanatory variables can be interpreted.

Adjusted AI Investment continues to exhibit a positive and statistically significant relationship with firm profitability at the 1 percent level, with a coefficient of 0.01. Although the magnitude is slightly reduced compared to the panel least squares model, its consistent significance across model specifications signals the robustness of this relationship. This suggests that AI investments yield within-firm profitability gains over time, reinforcing the argument that firms benefit from integrating intelligent systems into their operations (Ali et al., 2024; Mushtaq et al., 2024).

Cybersecurity Risk remains negatively associated with profitability, showing a statistically significant coefficient of -0.02 and a t-statistic of -3.333. This result reaffirms that firms experiencing higher levels of cybersecurity vulnerability tend to report lower profitability, even after controlling for time-invariant firm-specific effects. This emphasizes the operational and reputational risks posed by inadequate cybersecurity infrastructure. The finding aligns with recent literature documenting that firms that prioritize cybersecurity investments are more likely to avoid cost-intensive breaches and system disruptions, thereby securing a competitive edge in sensitive digital environments (Kaspersky, 2024; World Economic Forum, 2025).

A notable contrast emerges concerning regulation support, which now carries a positive and highly significant coefficient of 0.10, supported by a t-statistic of 10.0. This reversal in sign compared to the panel least squares model indicates that once firm-specific fixed effects are accounted for, regulatory support contributes positively to profitability. This finding suggests that while the cross-sectional dimension may obscure regulatory effectiveness, longitudinal firm-level improvements—such as access to policy incentives, simplified compliance processes, or institutional support—play a meaningful role in enhancing profitability. It supports the argument that regulatory interventions are more effective when tailored to firm-specific needs and consistently implemented over time (World Bank, 2024; Ministry of Finance, 2024).

Technological infrastructure retains its positive and statistically significant relationship with profitability in the fixed effects model, showing a coefficient of 0.01 and a t-statistic of 2.00. This result confirms that firm-level investments in digital systems and technical infrastructure are beneficial for long-term financial outcomes. Improved infrastructure enables more efficient internal processes, better data handling, enhanced product delivery, and overall operational agility. Recent empirical findings support this view, emphasizing that technological capability is a strategic asset for firms, particularly in competitive and resource-constrained environments such as those in emerging economies (Mushtaq et al., 2024; Iqbal, 2025).

**TABLE 5: FIXED EFFECT OUTCOMES**

Dependent Variable: Firm Profitability

| Variable | Coefficient | Std. Error | t-Statistic | p-value |
|---|---|---|---|---|
| Constant (C) | 0.43 | 0.08 | 5.47 | 0.00 |
| Adjusted AI Investment | 0.01 | 0.005 | 2.00 | 0.001 |
| Cybersecurity Risk | -0.02 | 0.006 | -3.333 | 0.030 |
| Regulation Support | 0.10 | 0.01 | 10.0 | 0.010 |
| Technological Infrastructure | 0.01 | 0.005 | 2.00 | 0.00 |

Table 6 presents the results of the random effects regression model, where Firm Profitability serves as the dependent variable across a panel of Pakistani firms. This modeling approach captures both within-firm and between-firm variation, assuming that firm-specific effects are uncorrelated with the regressors. The random effects model is especially useful when time-invariant variables are of interest and when firm-level heterogeneity is believed to be random rather than fixed. The predictors included in this specification are Adjusted AI Investment, Cybersecurity Risk, Regulation Support, and Technological Infrastructure. The constant term has a coefficient of 0.445, accompanied by a t-statistic of 1.19 and a p-value of 0.234, indicating statistical insignificance. This suggests that when all explanatory variables are equal to zero, the expected level of profitability is not statistically distinguishable from zero in this model. However, in the context of panel regressions, the emphasis lies primarily on the slope coefficients, which yield more meaningful insights into firm-level performance determinants.

Adjusted AI Investment demonstrates a positive and statistically significant association with profitability, reporting a coefficient of 0.01, a t-statistic of 3.33, and a p-value of 0.042. The significance at the 5 percent level confirms the robustness of this relationship, consistent with prior model estimates. This result suggests that as firms increase their artificial intelligence investments—particularly when these are tailored to firm size and sectoral context—there is a measurable and beneficial impact on financial outcomes. These findings align with recent studies that argue that AI facilitates predictive analytics, customer behavior modeling, and cost optimization, all contributing to profitability (Jamil et al., 2025; UNDP, 2025).

Cybersecurity Risk remains a significant negative determinant of profitability, with a coefficient of -0.025 and a t-statistic of -6.25. The associated p-value of 0.040 confirms statistical significance at the 5 percent level. This persistent negative relationship across random effects, fixed effects, and least squares models emphasizes the material impact of cybersecurity threats. Firms that are vulnerable to cyberattacks may experience disruptions in operations, loss of sensitive information, reputational harm, and subsequent financial damage. The results reinforce the urgent need for Pakistani firms to adopt cybersecurity risk mitigation strategies as part of broader digital resilience planning (Kaspersky, 2024; World Economic Forum, 2025).

A contrasting picture emerges with Regulation Support. The coefficient is sharply negative at -0.1065, with a t-statistic of -22.18 and a p-value of 0.000, indicating both statistical and economic significance. This contradicts the findings from the fixed effects model and suggests that regulatory support may not uniformly benefit firms. Instead, it may introduce compliance costs, reporting burdens, or rigid operational constraints that suppress profitability. The discrepancy between models may reflect unobserved firm-level characteristics—captured by fixed effects but not random effects—that mediate the impact of regulation. This divergence supports the argument that regulatory structures in Pakistan may lack clarity or fail to align with firm-level incentives (World Bank, 2024; Ministry of Finance, 2024).

Finally, Technological Infrastructure shows a strong positive relationship with profitability, featuring a coefficient of 0.0115 and a highly significant t-statistic of 11.16. The p-value of 0.000 confirms this robustness. These findings are consistent with all previous models and affirm that digital readiness enhances firm performance. Technological infrastructure enables process automation, real-time data analysis, and enhanced supply chain coordination—key factors that contribute to profitability in increasingly digitized markets. As noted in the current empirical literature, the strategic deployment of technological resources offers firms in developing economies a pathway to overcome resource constraints and scale efficiently (Jamil et al., 2025; Iqbal, 2025).

**TABLE 6: RANDOM EFFECTS MODEL**

Dependent Variable: Firm Profitability

| Variable | Coefficient | Std. Error | t-Statistic | p-Value |
|---|---|---|---|---|
| Constant (C) | 0.445 | 0.373 | 1.19 | 0.234 |
| Adjusted AI Investment | 0.01 | 0.003 | 3.33 | 0.042 |
| Cybersecurity Risk | -0.025 | 0.004 | -6.25 | 0.040 |
| Regulation Support | -0.1065 | 0.0048 | -22.18 | 0.000 |
| Technological Infrastructure | 0.0115 | 0.00103 | 11.16 | 0.000 |

The technology acceptance model, which emphasizes perceived usefulness and perceived ease of use as critical determinants of technology adoption, provides a fitting lens through which to interpret the significant positive relationship between adjusted artificial intelligence investment and firm profitability. The results show that firms integrating artificial intelligence technologies report improved financial performance, highlighting that the perceived utility of AI in optimizing operations, enhancing decision-making, and automating processes drive its acceptance and integration. The consistent statistical significance of this variable across panel least squares, fixed effects, and random effects models aligns with TAM's core proposition that technological tools adopted for their expected benefits lead to favorable organizational outcomes. Moreover, the finding that technological infrastructure significantly enhances profitability reinforces the TAM perspective, suggesting that digital systems are not only accepted but also effectively utilized when they are perceived as useful and align with organizational needs. This is particularly relevant in developing economies like Pakistan, where firms facing resource constraints will only adopt technologies that demonstrably improve efficiency or competitiveness. In this context, both artificial intelligence investment and broader digital infrastructure represent technologies whose acceptance is driven by their capacity to solve practical business problems, an alignment that validates the underlying logic of TAM (Davis, 1989; Venkatesh & Davis, 2000).

The resource-based view theory, which posits that firms gain competitive advantage through the strategic deployment of valuable, rare, inimitable, and non-substitutable resources, also offers a robust theoretical framework for understanding the results. The consistent profitability benefits associated with technological infrastructure and artificial intelligence investment suggest that these digital capabilities function as strategic assets within firms. These resources enhance internal efficiencies, enable dynamic capabilities such as real-time data analytics, and support scalable operations, making them both valuable and difficult for competitors to replicate. Similarly, the persistent negative impact of cybersecurity risk highlights the vulnerability of firms that lack adequate protective resources, reinforcing the RBV argument that intangible assets like secure systems and digital trust are critical components of sustained competitive advantage. Furthermore, the changing sign of the regulation support variable across models implies that institutional alignment can either constrain or amplify the value of firm resources, depending on how effectively firms can internalize external regulatory mechanisms into their strategic planning. Thus, findings illustrate that profitability in the digital era is not merely a function of access to technology but is also contingent upon how effectively such resources are acquired, integrated, and protected consistent with the central tenets of the Resource-Based View (Barney, 1991; Wernerfelt, 1984).

Table 7 presents the results of several essential diagnostic tests conducted to evaluate the suitability and robustness of the panel regression models applied in the study of firm profitability among Pakistani firms. These tests validate the core econometric assumptions underlying panel data models and guide the selection between fixed effects and random effects estimators. The first diagnostic, the Hausman Test, assesses whether the firm-specific error components are correlated with the explanatory variables. The test statistic, $Chi^2 = 0$, accompanied by a p-value of 1.000, leads to a failure to reject the null hypothesis. This outcome implies that the random effects model is more appropriate, as the assumption of independence between regressors and firm-level unobserved effects is not violated. This statistical recommendation aligns with methodological research supporting the use of random effects when individual heterogeneity is random and not correlated with the regressors (Sarwar et al., 2018; Ullah et al., 2018).

The Breusch-Pagan Lagrange Multiplier (LM) Test is then applied to assess whether significant panel effects exist. With an LM value of 102.73 and a p-value well below 0.01, the test confirms that firm-level variability is statistically significant and that a panel data framework is warranted over a simple pooled ordinary least squares approach. This reinforces the necessity of accounting for firm-specific effects, as ignoring them could result in omitted variable bias or inefficient estimates. These findings are consistent with literature emphasizing that sectoral and firm-level characteristics have a measurable impact on performance and should be included through structured panel modeling (Hsiao, 2007).

The white heteroskedasticity test, while not reporting a specific test statistic in the table, provides a p-value of approximately 0.06. Although this is slightly above the conventional 5 percent threshold, it indicates the potential presence of mild heteroskedasticity—i.e., non-constant variance of residuals across observations. Such a condition, if left unaddressed, can lead to inefficient standard error estimates and biased statistical inferences. As a corrective measure, robust standard errors were applied throughout the analysis to accommodate any heteroskedasticity and ensure the validity of inference. This precaution is in line with best econometric practices in panel data analysis, particularly when working with firm-level data that may exhibit structural variability across units (Arellano, 1987).

The Durbin-Watson statistic, recorded at approximately 1.31, falls below the ideal range of 1.5 to 2.5. This suggests the presence of mild positive autocorrelation in the residuals, implying that the error terms are not entirely independent over time within individual firms. While this autocorrelation is not severe, it could marginally compromise the efficiency of the estimators. The use of robust standard errors once again serves to mitigate this issue and improve the precision of coefficient estimates. In longitudinal firm-level studies, such temporal correlation is not uncommon, particularly in dynamic environments where firm strategies and market conditions evolve gradually (Turner, 2020).

**TABLE 7: DIAGNOSTIC TESTS OUTCOMES**

| Test | Test Statistic / Value | p-Value / Threshold | Conclusion |
|---|---|---|---|
| Hausman Test | $Chi^2 = 0$ | $p = 1.000$ | Random Effects preferred |
| Breusch-Pagan LM Test | LM = 102.73 | $p < 0.01$ | Panel effects exist → Use RE or FE |
| White Heteroskedasticity | -- | $p \approx 0.06$ | Mild heteroskedasticity; robust SE used |
| Durbin-Watson Statistic | ≈ 1.31 | 1.5–2.5 (ideal) | Mild positive autocorrelation |

## CONCLUDING REMARKS

This study aimed to evaluate the implications of artificial intelligence integration on firm profitability within Pakistan's accounting, finance, and external audit sectors. The research employed a panel data framework, introducing the adjusted artificial intelligence investment metric as a novel construct to holistically capture firm-level digital readiness. The empirical findings revealed that artificial intelligence investment, when adjusted for technological infrastructure, regulatory support, and cybersecurity preparedness, significantly contributes to enhanced firm profitability. These results affirm the role of artificial intelligence as a strategic asset that promotes operational efficiency, automates complex financial processes, and supports data-driven decision-making. Key insights from the regression models highlighted a dual narrative. On one hand, artificial intelligence investment and technological infrastructure displayed strong positive associations with firm profitability, reaffirming that technologically mature firms are better positioned to extract financial value from digital innovation. On the other hand, cybersecurity risks consistently exhibited negative effects, underlining the financial vulnerabilities posed by inadequate risk controls in the digital domain. Interestingly, the effect of regulatory support varied across models appearing negative in pooled and random effects but positive in fixed effects estimation, suggesting that the perceived impact of regulatory frameworks depends on firm-specific dynamics and longitudinal policy consistency.

Policy recommendations arising from this research are multifaceted. First, firms should be mandated to disclose AI-related capital expenditures separately in financial reports to improve investor visibility and analytical transparency. Second, national regulators must align AI compliance standards with global frameworks while minimizing administrative frictions that discourage innovation. Third, human capital development should accompany AI investments — firms need structured training programs to build digital fluency among accountants, auditors, and analysts. Finally, digital governance policies must be institutionalized, covering ethical AI usage, cybersecurity protocols, and vendor oversight. Together, these strategies can amplify the return on AI investments while ensuring risk-resilient digital transformation.

Despite its contributions, the study is subject to limitations. The five-year data period may not fully capture long-term profitability effects, and the sample is limited to firms with disclosed digital investment data. Future research could expand the panel duration, include qualitative assessments of implementation practices, or explore cross-country comparisons to generalize findings across emerging economies.

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