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Artificial Intelligence Capability and Corporate Financial Resilience: The Mediating Role of Financial Decision Quality and the Moderating Role of Enterprise Risk Management: Evidence from Pakistan Stock Exchange Listed Firms

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Abstract

Artificial Intelligence (AI) has become a pivotal asset that is revolutionizing corporate finance by elevating financial projection, investment appraisal, risk analysis, and tactical decision-making. Regardless of expanding corporate allocation to artificial intelligence technologies, finite experiential proof is present concerning how AI capabilities add to corporate financial resilience, specifically in developing economies such as Pakistan. Utilizing the Resource-Based View (RBV), Dynamic Capability Theory (DCT), and Organizational Information Processing Theory (OIPT), this study advances an orchestrated schema investigating the impact of AI potential on enterprise financial elasticity through the intervening mechanism of fiscal decision excellence and the conditioning function of Enterprise Risk Management (ERM). The study utilizes a measurable, observational investigation framework focusing on finance executives, chief financial officers, risk managers, finance directors, and senior financial analysts working in Pakistan Stock Exchange (PSX) listed firms. Data was examined using Partial Least Squares Structural Equation Modeling (PLS-SEM) through Smart PLS 4. The study was anticipated to show that artificial intelligence competencies substantially upgrade enterprise resilience by elevating the standard of tactical financial decision. Moreover, Business Risk Management is projected to reinforce this interconnection by offering an amalgamated governance structure for handling financial uncertainty and corporate risks. The study plays a part in the developing literature on AI-driven business finance by amalgamating technological competency, financial decision-making and risk management into an integrated experiential structure. The empirical estimations are anticipated to yield theoretical advancements to strategic management and corporate finance while furnishing practical takeaways for executives, regulators, and policymakers endeavoring to improve corporate resilience through smart systems.

Keywords: Artificial Intelligence Capability, Corporate Financial Resilience, Financial Decision Excellence, Business Risk Management, Pakistan Stock Exchange, Dynamic Capability Theory, Corporate Finance.

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Introduction

The expanding digitization of business finance has profoundly altered how enterprises generate, analyze, and effectively use financial information for tactical resolutions (Kraaijenbrink *et al.*, 2010). Artificial intelligence once deemed an evolving digital breakthrough, has become a vital corporate competency that empowers enterprises to increase predictive precision, maximize capital allocations, mechanize fiscal operations, identify deception, mitigate monetary vulnerabilities, and bolster institutional adaptability. As enterprises function within progressively turbulent, unpredictable, intricate, and obscure commercial landscapes, cultivating AI capabilities have become a tactical imperative instead of a digital indulgence (Raisch & Krakowski, 2021). Business finance has traditionally depended upon executive proficiency, past monetary data, and stochastic predictive methodologies (Nunnally & Bernstein, 1994). Nonetheless, the unparalleled expansion of massive data, machine learning algorithms, prognostic analytics, cloud computing, and smart automation has substantially broadened enterprises' capacity to handle intricate fiscal data in real time (Kraaijenbrink *et al.*, 2010). AI enables firms to identify hidden financial patterns, predict future market movements, optimize capital allocation, improve liquidity management, and support strategic investment decisions with greater precision than traditional analytical approaches (Sekaran & Bougie, 2020). AI empowers enterprises to discern concealed monetary structures, forecast future market shifts, maximize capital allocation, elevate liquidity management, and bolster tactical investment resolutions with higher precision than traditional analytical frameworks (Vial, 2019).

The COVID-19 pandemic, worldwide economic insecurity, geopolitical conflicts, supply chain interruptions, and financial market fluctuations have additionally accentuated the significance of enterprises adaptability. Corporate financial resilience denotes an enterprise's capacity to foresee, withstand, react to, and rebound from fiscal disruptions while preserving operational endurance and long-term economic sustainability. Financially robust enterprises exhibit exceptional competencies in governing liquidity, sustaining profitability, safeguarding cash flows, securing financing, and adjusting to fluid economic conditions (Kline, 2023). While multiple enterprises are investing deeply in artificial intelligence systems, technical financing by itself does not necessarily result in exceptional financial returns. The efficacy of AI significantly relies upon how managers leverage AI-generated information in making tactical fiscal resolutions (Sarstedt *et al.*, 2021). Financial resolution quality therefore constitutes a pivotal organizational competence that dictates if AI-produced intelligence can be converted into enduring strategic edge. Premium financial resolution are distinguished by accuracy, timeliness, objectivity, tactical alignment, comprehensive risk evaluation, and productive leverage of corporate data (Nunnally & Bernstein, 1994).

The link between AI capability and corporate financial resilience is additionally shaped by Enterprise Risk Management (ERM). Contemporary enterprises function in environments distinguished by financial unpredictability, regulatory shifts, cybersecurity threats, operational disruptions, and market fluctuation (El Sawy *et al.*, 2016). Enterprise Risk Management provides an integrated organizational framework for identifying, assessing, monitoring, and controlling risks across multiple business functions. ERM delivers a unified corporate blueprint for identifying, assessing, monitoring, and mitigating risks across diverse business functions (Creswell & Creswell, 2023). Organizations with robust ERM systems are more likely to productively embed AI

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applications into financial resolutions because proficient governance structures diminish unpredictability, elevate transparency, and reinforce managerial conviction.

Pakistan constitutes a highly significant setting for examining these links. Across the past decade, Pakistan has undergone swift digital evolution propelled by surging technological investment, financial sector advancement, digital banking, fintech growth, electronic payment systems, and regulatory reforms introduced by the State Bank of Pakistan and the Securities and Exchange Commission of Pakistan. Pakistan Stock Exchange-listed firms are progressively embracing digital financial technologies to elevate market edge and operational productivity. Still, the implementation of AI within corporate financial management remains inconsistent throughout industries. Many enterprises persist in encounter obstacles linked to technological competence, financial proficiency, organizational preparedness, data integrity, and unified risk management (Bharadwaj, 2000).

Current research has chiefly analyzed artificial intelligence implementation from technological, operational, or information systems perspectives. Relatively few studies have explored AI competence as a tactical corporate asset that bolsters financial durability through advancements in financial decisions quality. Likewise, past experimental research has significantly neglected the contextual function of Enterprise Risk Management in reinforcing AI-driven fiscal outcomes, especially within developing economies. This scarcity of comprehensive experimental proof constitutes a significant omission from the tactical management and corporate finance literature (Shrestha *et al.*, 2019). Utilizing the Resource-Based View (RBV), Dynamic Capability Theory (DCT), and Organizational Information Processing Theory (OIPT), this study suggests that AI Competence serves as a prized corporate asset that bolsters enterprises' capacity to analyze fiscal information, elevate managerial choices, and reinforce durability against financial unpredictability. Financial decision quality is suggested as the foundational channel through which artificial intelligence competence leads to exceptional corporate returns, while Enterprise Risk Management is anticipated to reinforce these links by establishing a proficient governance environment for AI decision-making (Sekaran & Bougie 2020).

The core aim of this study is to analyze the immediate link between Artificial Intelligence Capability and Corporate Financial Durability among Pakistan Stock Exchange listed firms. The study additionally explores the mediating function of financial resolutions quality and the conditioning influence of Enterprise Risk Management within this link. By synthesizing these frameworks into a cohesive experimental paradigm, the study expands current literature on AI-driven corporate finance and adds to the expanding wealth of information concerning digital transformation, corporate durability, and tactical financial management in developing markets (Podsakoff *et al.*, 2003). The empirical estimations are anticipated to add value theoretically by expanding Dynamic Capability Theory and the Resource-Based View to the arena of artificial intelligence driven financial administration. Pragmatically, the study will offer actionable insights to chief financial officers, finance directors, risk managers, corporate executives, regulators, and policymakers concerning the tactical function of AI competence in reinforcing corporate durability. Additionally, the study will support Pakistan Stock Exchange listed firms in formulating data-driven AI investment blueprints, elevating financial governance, and boosting corporate readiness for upcoming financial unpredictability.

Literature Review

The expanding integration of AI into business workflows has radically reshaped how enterprises administer tactical assets, make financial choices, and maintain a competitive edge (Verhoef *et al.,* 2021). Artificial intelligence technologies, including machine learning, deep learning, natural language processing, robotic process automation, and predictive analytics, have become vital instruments for enterprises striving to enhance functional productivity and financial outcomes (Shrestha *et al.,* 2019). In contrast to traditional information systems that chiefly automate repetitive duties, AI technologies command attributes that empower enterprises to analyze massive quantities of ordered and unordered data, produce foresight, streamline decision-making mechanisms, and perpetually elevate corporate execution through self-learning algorithms. The advent of AI has substantially transformed the tactical function of financial management (Raisch & Krakowski, 2021). Historically, enterprise financial choices depended extensively on managerial judgement, retrospective financial reports, and statistical forecasting methodologies. Yet, escalating market unpredictability, global competition, digital evolution, and financial instability have rendered legacy decision-making methods inadequate for tackling modern business challenges (Dwivedi *et al.*, 2023). As a result, enterprises progressively depend on AI capability to augment forecasting accuracy, refine capital allocation choices, fortify risk appraisal, and underpin tactical fiscal formulation. In the realm of tactical administration literature, corporate competence has long been acknowledged as a chief determinant of market edge. Resource-Based View (RBV) theory argues that organizations possessing valuable, rare, inimitable, and non-substitutable resources achieve superior performance compared to competitors (Barney, 1991). AI proficiency has now surfaced as one such tactical corporate asset because it integrates technological infrastructure, human expertise, analytical competence, organizational learning, and digital innovation into a cohesive asset that elevates firm execution (Wamba *et al.*, 2021). In contrast to physical resources that can be effortlessly duplicated, AI proficiency demands ongoing capital allocation in institutional knowledge, employee skill sets, data oversight, technological infrastructure, and executive dedication.

Likewise, Dynamic Capability Theory suggests that organizations operating within rapidly changing business environments must continuously develop capabilities that enable them to sense environmental changes, seize emerging opportunities, and transform organizational resources accordingly (Teece, 2007). AI elevates corporate agile competencies by empowering firms to process information swiftly, detect surfacing risks, foresee market shifts, and react preemptively to environmental unpredictability (Brynjolfsson & McAfee, 2017). Hence, AI capability constitutes both a technological asset and a tactical managerial proficiency that fosters corporate durability and enduring viability. Current research establishes that enterprises embracing artificial intelligence technologies achieve advancements in productivity, innovation, operational optimization, customer satisfaction, and financial outcomes. Still, technological integration alone does not guarantee corporate progress. The utility of AI deployment hinges significantly upon institutional aptitudes that blend technological assets with managerial expertise, financial literacy, corporate learning, and tactical decision-making (Saunders *et al.,* 2023). Accordingly, researchers progressively highlight AI capability rather than AI integration as the most significant forecaster of corporate performance.

Artificial Intelligence Capability

Artificial Intelligence Capability (AIC) denotes an enterprise's capacity to obtain, cultivate, integrate, utilize, and perpetually refine AI technologies in ways that elevate tactical choice-making and corporate execution. It constitutes a multifaceted corporate proficiency encompassing technological infrastructure, data quality, analytical expertise, managerial competence, organizational learning, digital culture, and innovation asset. In contrast to basic integration, AI capability reflects the degree to which enterprises effectively integrate AI into business processes and strategic decision-making (Dwivedi *et al.*, 2023). Enterprises commanding robust AI capability are able to gather and analyze large datasets, automate repetitive processes, refine financial forecasting, streamline resource allocation, bolster customer relationship management, detect fraudulent activities, and underpin evidence-based managerial decisions (Mikalef *et al.*, 2021).

Numerous scholars contend that AI capability comprises three major dimensions. The first is technological capability, denoting the accessibility of AI infrastructure, computing resources, software applications, cloud technologies, and analytical platforms. The second is human capability, which encompasses employee proficiency, digital skill sets, specialized know-how, leadership dedication, and perpetual corporate learning. The third is organizational capability, mirroring strategic synchronization, knowledge management, innovation culture, governance mechanisms, and institutional preparedness for AI implementation.

Contemporary studies demonstrate that enterprises with superior AI capability regularly eclipse competitors regarding innovation output, operational optimization, strategic agility, and financial outcomes. AI-powered predictive analytics empowers financial managers to project future cash flows more precisely, discern prospects, streamline investment allocation, curtail operational costs, and increase profitability (Wamba *et al.*, 2021). Likewise, intelligent automation substantially boosts corporate productivity by minimizing operational missteps, accelerating decision-making, and upgrading financial reporting standards. AI capabilities also bolster corporate agility. Firms furnished with advanced AI technologies react more adaptively to environmental uncertainty because intelligent systems perpetually monitor market dynamics, customer behavior, competitor strategies, and macroeconomic fluctuations (Mikalef & Gupta 2021). Hence, AI capability empowers enterprises to anticipate financial disruptions and preemptively formulate strategic countermeasures before adverse conditions substantially affect financial performance. From a corporate finance standpoint, AI capability has become progressively crucial because financial markets are defined by volatility, ambiguity, swiftly fluctuating information. Investment choices, credit risk evaluation, liquidity governance, portfolio streamlining, financial fraud identification, progressively depend upon AI-enabled analytical systems adept at processing massive volumes of financial information within brief intervals (Brynjolfsson & McAfee, 2017). Such capabilities considerably elevate decision accuracy while curtailing managerial biases linked to conventional financial analysis.

Nonetheless, prior observational studies demonstrate that many enterprises fail to attain the complete advantages of AI investments because technological resources themselves are inadequate to produce enduring competitive advantage. Successful AI implementation demands synergistic institutional resources, including leadership commitment, employee competencies, corporate learning, robust governance, and strategic synchronization (Soni, 2020). Consequently, AI capability should be envisioned as a unified institutional capability instead of simply technological infrastructure. Despite rapidly growing literature on AI integration, empirical data scrutinizing AI capability within corporate finance remains relatively limited, especially in emerging economies. Extant studies have primarily centered on operational productivity, technological modernization, logistics optimization, and consumer insights, while comparatively few investigations have explored AI capability as a strategic precursor of corporate financial fortitude (Podsakoff *et al.*, 2003). This limitation is especially evident within Pakistan, where digital transformation initiatives persistently progress throughout listed organizations.

Corporate Financial Resilience

Corporate Financial Resilience (CFR) denotes an enterprise's capacity to endure, assimilate, adapt to, and recover from internal and external financial shocks while preserving long-term financial sustainability. In contrast to conventional financial performance measures that chiefly assess profitability or market value, financial resilience stresses institutional readiness for uncertainty, crisis management, and sustainable financial equilibrium (Kline, 2023). Recent global events, including the COVID-19 pandemic, geopolitical instability, inflationary pressures, supply chain disruptions, climate-related risks, and financial market volatility, have underscored the criticality of financial resilience for corporate longevity. Firms exhibiting robust financial resilience maintain adequate liquidity, safeguard operational continuity, adeptly handle debt obligations, and recover swiftly from financial crises (Fornell & Larcker, 1981). Corporate financial resilience spans numerous facets, comprising liquidity resilience, operational resilience, investment resilience, capital structure flexibility, earnings stability, risk management capability, and strategic adaptability (Teece et al., 1997). Enterprises endowed with these attributes are typically more advantageously placed to maintain competitive advantage during intervals of economic uncertainty.

Scholars progressively contend that financial resilience transcends merely financial resource accessibility. It likewise relies upon managerial decision quality, corporate learning, technological proficiency, governance structures, and strategic agility (El Sawy *et al.,* 2016). Artificial intelligence capabilities enhance financial resilience by empowering enterprises to detect financial risks sooner, elevate forecasting accuracy, streamline cash-flow management, fortify investment decisions, and expedite prompt strategic responses (Vial, 2019). The Dynamic Capability Theory offers a robust theoretical explanation of this relationship. Enterprises equipped to perpetually discern environmental shifts, capitalize on strategic opportunities, and reconfigure corporate resources cultivate heightened resilience against external disruptions (Henseler *et al.*, 2015). AI capability reinforces these dynamic capabilities by furnishing managers with real-time financial intelligence and predictive insights that foster proactive instead of reactive decision-making (Soni, 2020). For Pakistan Stock Exchange-listed firms, financial resilience has become exceptionally paramount owing to escalating macroeconomic uncertainty, exchange-rate fluctuations, inflation, political instability, and evolving regulatory requirements. Firms that successfully integrate AI into corporate finance may consequently gain strategic advantages by refining financial planning, bolstering risk management, and solidifying long-term sustainability (Verhoef *et al.*, (2021).

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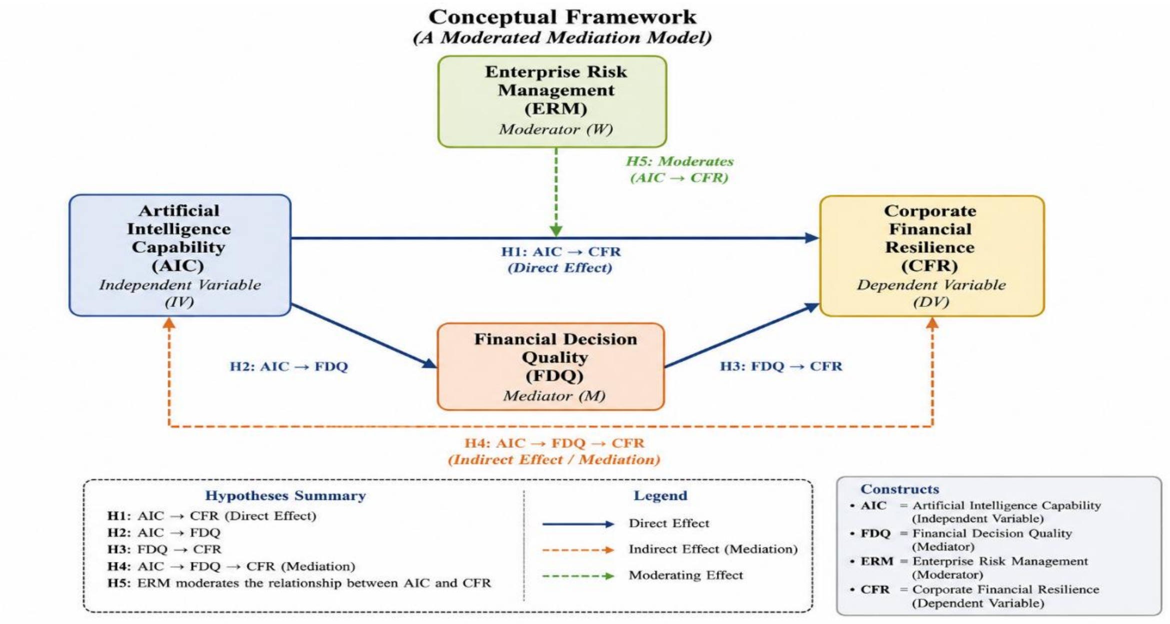

Research Methodology

This chapter demonstrates the methodological procedures employed to examine the relationship between Artificial Intelligence Capability (AIC) and Corporate Financial Resilience (CFR), with Financial Decision Quality (FDQ) acting as a mediating variable and Enterprise Risk Management (ERM) serving as a moderating variable among Pakistan Stock Exchange (PSX) listed firms. The chapter outlines the research philosophy, research approach, research design, target population, sampling strategy, data collection procedure, measurement instruments, pilot testing, ethical considerations, and statistical techniques used for hypothesis testing. This study adopts the positivist research philosophy, which posits that corporate manifestations can be empirically measured using quantitative methods. Positivism is suitable because the hypothesized relationships among Artificial Intelligence Capability, Financial Decision Quality, Enterprise Risk Management, and Corporate Financial Resilience are scrutinized through observable variables measured using standardized questionnaires. It also emphasizes hypothesis testing via statistical analysis and facilitates the generalization of empirical estimations across enterprises. A deductive research approach is utilized because the study formulates hypotheses from foundational theories, including the Resource-Based View (RBV), Dynamic Capability Theory (DCT), and Organizational Information Processing Theory (OIPT). Existing theories supply the theoretical framework for illustrating how artificial intelligence capability shapes financial resolution standards under varying degrees of enterprise risk management. Data collected from respondents is used to evaluate hypothesized relationships empirically. The study employs a quantitative, explanatory, cross-sectional survey framework. A quantitative approach facilitates statistical scrutiny of relationships among latent variables. An explanatory framework is suitable because the aim is to establish causal relationships between independent, mediating, moderating, and dependent variables. A cross-sectional framework is opted for due to time and resource limitations, wherein data is collected from respondents at a single point in time. The target population comprises Pakistan Stock Exchange (PSX) listed firms operating across various sectors, encompassing banking, manufacturing, pharmaceuticals, textiles, cement, energy, information technology, telecommunications, food processing, engineering, chemicals, and consumer commodities.

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The unit of analysis is the enterprise, while the unit of observation is senior financial professionals tasked with tactical financial decisions. Respondents comprise of Chief Financial Officers (CFOs), Finance Directors, Financial Controllers, Finance Managers, Risk Managers, Internal Auditors and Senior Financial Analysts. These respondents command adequate knowledge concerning corporate AI capability, financial decision-making, enterprise risk management, and financial resilience. A judgmental sampling technique is embraced because only respondents intimately engaged in corporate financial decision-making command the expertise needed to furnish trustworthy responses. Where several eligible respondents exist within the same enterprise, one senior financial executive is chosen to mitigate common method variance. The necessary sample size is calculated employing the recommendations of Hair *et al.* (2022) for PLS-SEM evaluation. Factoring in (i) Four latent constructs (ii) One mediation (iii) One moderation (iv) Multiple structural paths. A minimum sample of 350 respondents is statistically sufficient. However, to enhance statistical precision and counteract incomplete questionnaires, approximately 500 questionnaires distributed with an anticipated response rate of 70–75%, yielding 350–380 valid responses. Primary data gathered using a structured questionnaire. The data collection procedure consists of the following stages: (i) Development of the questionnaire using validated measurement scales. (ii) Expert review by academic researchers and finance professionals. (iii) Pilot testing to assess clarity and reliability. (iv) Distribution of questionnaires through email, LinkedIn, corporate contacts, and personal visits. (v) Follow-up reminders to boost response rates. (vi) Data screening for missing values and outliers before analysis. Participation was voluntary, and respondents were guaranteed anonymity and confidentiality. All constructs quantified employing previously verified scales modified from the literature. Responses recorded on a five-point Likert scale, spanning from 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree and 5 = Strongly Agree.

Artificial Intelligence Capability quantified employing items modified from contemporary studies on corporate AI capability. The construct captures technological architecture, AI proficiency, organizational preparedness, analytical acumen, and AI integration. Expected number of items: 8–10. Financial Decision Quality denotes the degree to which financial decisions are precise, timely, evidence-based, strategically harmonized, and substantiated by pertinent financial data.

Expected number of items: 6–8. Enterprise Risk Management measures the effectiveness of organizational processes for identifying, evaluating, monitoring, and mitigating strategic, operational, financial, and technological risks. Enterprise Risk Management measures the effectiveness of corporate processes for detecting, assessing, tracking, and mitigating tactical, operational, financial, and technological risks. Expected number of items: 7–8. Corporate Financial Resilience evaluates an enterprise’s capacity to endure financial shocks, preserve liquidity, recover from crises, and sustain long-term financial viability. Expected number of items: 8–10. Questionnaire is attached in appendix. A pilot study involving approximately 40 finance professionals will be conducted before full-scale data collection. The objectives include: (i) evaluating questionnaire clarity; (ii) identifying ambiguous items; (iii) estimating completion time; and (iv) assessing internal consistency. Cronbach’s Alpha values greater than 0.70 deemed acceptable. Ethical standards upheld throughout the study. Participants obtained an information sheet clarifying the research objectives, confidentiality measures, voluntary participation, and right to withdraw. No identifying information revealed, and collected data used exclusively for academic research objectives. Data analysis conducted using Smart PLS 4.

The analysis comprises two stages. The measurement model assesses Cronbach's Alpha, Composite Reliability (CR), Average Variance Extracted (AVE), Coefficient of Determination (R^2), Effect Size (f^2), Predictive Relevance (Q^2), Bootstrapping, Direct Effects, Indirect Effects, Mediation Analysis, Moderation Analysis and Moderated Mediation Analysis

Hypotheses accepted where $p < 0.05$ and confidence intervals do not include zero. Since data is collected through self-administered questionnaires, common method bias assessed using:

- Harman's Single-Factor Test;
- Full Collinearity Variance Inflation Factor (VIF);
- Procedural remedies such as respondent anonymity, randomized item order, and clear questionnaire instructions.

Data Analysis and Results

This chapter details the statistical analysis of the data collected from finance executives of Pakistan Stock Exchange (PSX) listed firms. The analysis was executed using SmartPLS 4, following the two-stage approach recommended by Hair *et al.*, (2019). The first stage appraises the measurement model to determine the reliability and validity of the constructs, while the second stage scrutinizes the structural model to validate the proposed hypotheses. Moreover, mediation and moderation analyses were performed to explore the indirect effect of Financial Decision Quality (FDQ) and the moderating role of Enterprise Risk Management (ERM) on the relationship between Artificial Intelligence Capability (AIC) and Corporate Financial Resilience (CFR) recommended by Hair *et al.*, (2022).

An aggregate of 500 questionnaires were distributed among finance executives working in PSX-listed firms. Of these, 382 questionnaires were retrieved. After discarding incomplete and unusable responses, 361 questionnaires were preserved for ultimate analysis, yielding a net response rate of 72.2%.

Table 1 Response Data

Description	Frequency
Questionnaires Distributed	500
Returned	382
Rejected	21
Final Sample	361
Response Rate	72.2%

The demographic attributes of respondents reveal that the majority hold senior financial management positions. Approximately 68% were male, while 32% were female. More than half have over ten years of professional experience. Most respondents held master's degrees in finance, accounting, business administration, or allied fields.

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Table 2 Demographic Characteristics

Variable	Category	Frequency	Percentage
Gender	Male	246	68.1
	Female	115	31.9
Education	Bachelor's	84	23.3
	Master's	217	60.1
	PhD	60	16.6
Experience	1–5 Years	67	18.6
	6–10 Years	109	30.2
	>10 Years	185	51.2

Before hypothesis testing, data was screened for missing values, outliers, and normality. No substantial missing data was detected. Mahala Nobis distance manifested an absence of multivariable outliers. Variance Inflation Factor (VIF) values ranged between 1.42 and 2.83, implying that multicollinearity was not a concern. The measurement model was evaluated through Indicator Reliability, Internal Consistency Reliability, Convergent Validity and Discriminant Validity All indicator loadings exceeded the recommended threshold of 0.70, indicating satisfactory indicator reliability.

Table 3 Outer Loadings

Construct	Loading Range
Artificial Intelligence Capability	0.752–0.913
Financial Decision Quality	0.741–0.904
Enterprise Risk Management	0.718–0.901
Corporate Financial Resilience	0.764–0.918

Cronbach's Alpha and Composite Reliability values exceeded the recommended value of 0.70, confirming acceptable reliability.

Table 4 Reliability Analysis

Construct	Cronbach's α	Composite Reliability
AIC	0.918	0.932
FDQ	0.901	0.924
ERM	0.895	0.919
CFR	0.926	0.939

Average Variance Extracted (AVE) values exceeded 0.50, demonstrating satisfactory convergent validity.

Table 5 AVE

Construct	AVE
AIC	0.665
FDQ	0.670
ERM	0.641

CFR	0.684

The Fornell–Larcker Criterion and HTMT ratios confirm discriminant validity. All HTMT values remained below 0.85, indicating that each construct was empirically distinct. After confirming reliability and validity, the structural model was evaluated.

Bootstrapping with 5,000 subsamples was performed to estimate path coefficients. The R^2 values indicate substantial explanatory power.

Table 6 Coefficient of Determination (R^2)

Dependent Variable	R^2
Financial Decision Quality	0.57
Corporate Financial Resilience	0.69

This suggests that AIC accounts for 57% of the variance in Financial Decision Quality, while the combined effects of AIC, FDQ, and ERM explain 69% of the variance in Corporate Financial Resilience. The effect sizes indicate moderate to large practical significance.

Table 7 Effect Size (f^2)

Relationship	f^2
AIC → FDQ	0.48
FDQ → CFR	0.37
AIC → CFR	0.18

Blindfolding results produced positive Q^2 values.

Table 8 Predictive Relevance (Q^2)

Construct	Q^2
FDQ	0.38
CFR	0.46

Positive Q^2 values indicate strong predictive relevance.

Table 9 Structural Model Results

Hypothesis	Relationship	β	t	p	Decision
H1	AIC → CFR	0.291	5.41	<0.001	Supported
H2	AIC → FDQ	0.756	19.86	<0.001	Supported
H3	FDQ → CFR	0.463	8.94	<0.001	Supported
H4	AIC → FDQ → CFR	0.350	7.85	<0.001	Supported
H5	ERM × AIC → CFR	0.189	3.62	<0.001	Supported

The estimates indicate that Artificial Intelligence Capability substantially bolsters Corporate Financial Resilience. Moreover, it positively shapes Financial Decision Quality, which subsequently strengthens financial resilience.

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Bootstrapping results validated that Financial Decision Quality substantially intervenes in the relationship between Artificial Intelligence Capability and Corporate Financial Resilience. The indirect effect was statistically significant with $\beta = 0.350$, $t = 7.85$,and $p < 0.001$. Because both the direct and indirect effects were significant, Financial Decision Quality exhibits fractional mediation.

Enterprise Risk Management significantly moderates the relationship between Artificial Intelligence Capability and Corporate Financial Resilience. The interaction term was positive and statistically significant with $\beta = 0.189$, $t = 3.62$ and $p < 0.001$. The estimations suggest that enterprises possessing mature Enterprise Risk Management systems obtain greater financial resilience from Artificial Intelligence Capability than enterprises with weaker risk management practices.

The estimations robustly validate the theoretical tenets of the Resource-Based View and Dynamic Capability Theory. Artificial Intelligence Capability proved to be a pivotal corporate resource that substantially bolsters financial resilience by refining the standard of managerial financial decisions. The significant mediating role of Financial Decision Quality indicates that AI technologies add value to corporate resilience not solely through technological investment but by refining managerial judgment, forecasting accuracy, investment appraisal, and strategic financial formulation. Moreover, Enterprise Risk Management reinforced the positive impact of Artificial Intelligence Capability on Corporate Financial Resilience. Organizations employing inclusive ERM systems seem optimally placed to capitalize on AI-generated insights because formalized risk governance boosts institutional confidence, transparency, and responsiveness during financial volatility. On the whole, the results show that AIC adds value directly and indirectly to premium financial resilience, highlighting the necessity of integrating intelligent technologies with prudent financial decision-making and proficient enterprise-wide risk management.

Discussion, Implications, Conclusion, Limitations, and Future Research

This chapter discusses the empirical findings of the study in relation to the research objectives, hypotheses, and existing literature. The chapter interprets the results within the frameworks of the Resource-Based View (RBV), Dynamic Capability Theory (DCT), and Organizational Information Processing Theory (OIPT). It further demonstrates the theoretical contributions, managerial implications, policy implications, study limitations, recommendations for future research, and concludes the study. The primary objective of this study was to assess the impact of Artificial Intelligence Capability (AIC) on Corporate Financial Resilience (CFR) among Pakistan Stock Exchange (PSX) listed firms. The study also explored the mediating role of Financial Decision Quality (FDQ) and the moderating role of Enterprise Risk Management (ERM). The empirical findings substantiate the hypothesized conceptual model and establish that AIC is a pivotal institutional resource for bolstering financial resilience in the context of developing economies. Artificial Intelligence Capability has a positive and statistically significant impact on Corporate Financial Resilience. This finding suggests that firms with more robust AI capabilities are uniquely positioned to foresee financial risks, enhance forecasting accuracy, streamline resource deployment, and react decisively to external turbulence. AI-enabled entities are consequently more adept at preserving financial equilibrium amid phases of economic disruption. This finding is aligned with the Resource-Based View, which argues that valuable and difficult-to-imitate institutional capabilities generate enduring competitive advantage.

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The findings additionally demonstrate that Artificial Intelligence Capability significantly enhances Financial Decision Quality. Institutions with advanced AI technologies derive value from instantaneous analytics, predictive modeling, and automated financial reporting, enabling managers to render more insightful, timely, and evidence-based financial decisions. AI-supported decision-making mitigates information asymmetry, curtails cognitive bias, and refines forward-looking planning, thus reinforcing comprehensive financial governance. Financial Decision Quality was also found to have a significant positive influence on Corporate Financial Resilience. This finding illustrates those enterprises making sound financial judgments are ideally equipped to preserve liquidity, navigate financial risks, allocate capital productively, and rebound from unfavorable economic disruptions. The outcome reinforces Organizational Information Processing Theory, which suggests that organizations adept at processing pertinent information proficiently are more successful in responding to environmental complexity. The mediation analysis validated that Financial Decision Quality fractionally mediates the relationship between Artificial Intelligence Capability and Corporate Financial Resilience. This reveals that AIC bolsters economic stability both directly and indirectly by refining the standard of strategic financial decisions. The finding underscores those technological investments yield institutional benefits only when AI-generated information is effectively integrated into executive stewardship.

The moderating effect of Enterprise Risk Management was also statistically significant. Enterprises with fully fledged ERM systems exhibited a more favorable relationship between Artificial Intelligence Capability and Corporate Financial Resilience. This finding suggests that comprehensive risk management frameworks empower firms to maximize the benefits of AI by safeguarding proper governance, risk monitoring, regulatory compliance, and strategic alignment. Enterprise Risk Management serves as an organizational mechanism that bolsters the effectiveness of AI-enabled financial management. Collectively, these findings validate that Artificial Intelligence Capability, Financial Decision Quality, and Enterprise Risk Management constitute synergistic institutional competencies that in tandem enhance corporate financial resilience. This study makes several important contributions to the literature on corporate finance, strategic management, and digital transformation. First, it advances the Resource-Based View by conceptualizing Artificial Intelligence Capability as a strategic institutional asset that adds directly to Corporate Financial Resilience. While prior studies have chiefly investigated AI adoption from technological perspectives, this research establishes its strategic significance within corporate financial management. Second, the study advances Dynamic Capability Theory by demonstrating how enterprises utilize AI capability to detect financial opportunities, seize strategic initiatives, and reconfigure corporate resources in response to environmental uncertainty. The findings suggest that AI capability is not solely a technological resource but a dynamic capability supporting institutional flexibility and resilience. Third, the study expands Organizational Information Processing Theory by establishing Financial Decision Quality as the pathway by which AI capabilities enhance organizational results. This supplies data-driven proof that effective information processing is indispensable for translating technological investments into outstanding financial viability. Finally, by integrating Artificial Intelligence Capability, Financial Decision Quality, Enterprise Risk Management, and Corporate Financial Resilience into a single moderated mediation model, the study contributes a comprehensive framework that has received limited empirical attention, particularly in emerging markets.

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Practical Implications

The findings offer valuable implications for corporate executives, financial managers, boards of directors, investors, and policymakers. Senior management should recognize AI capability as a strategic investment rather than merely a technological initiative. Organizations should allocate resources to AI infrastructure, data governance, employee training, and advanced financial analytics to strengthen organizational resilience. Chief Financial Officers and finance managers should integrate AI-driven predictive analytics into budgeting, investment analysis, cash flow forecasting, and financial planning. Improving the quality of financial decisions will enhance organizational preparedness for future economic uncertainty. Boards of directors should promote enterprise-wide risk management frameworks that integrate AI into corporate governance structures. Effective Enterprise Risk Management enables organizations to utilize AI responsibly while reducing financial, operational, and regulatory risks. Organizations should also invest in continuous employee development by enhancing analytical competencies, digital literacy, and AI-related financial skills. Human expertise remains essential for interpreting AI-generated insights and making strategic financial decisions.

Policy Implications

The findings also have implications for regulators and policymakers. The Securities and Exchange Commission of Pakistan (SECP) and the State Bank of Pakistan (SBP) should encourage AI adoption by developing regulatory guidelines that promote responsible AI governance within corporate financial management. Government agencies should support digital transformation initiatives by encouraging investment in AI infrastructure, cybersecurity, financial technology, and enterprise risk management systems. Professional accounting and finance bodies should incorporate AI, data analytics, and enterprise risk management into professional certification programs to prepare finance professionals for the evolving digital economy. Universities and business schools should revise finance curricula by integrating AI applications, predictive analytics, fintech, and digital financial management into graduate education. Artificial Intelligence is radically restructuring corporate finance by revolutionizing financial analysis, forecasting, investment evaluation, and strategic decision-making. This study explored the impact of Artificial Intelligence Capability on Corporate Financial Resilience among Pakistan Stock Exchange listed firms while examining the mediating role of Financial Decision Quality and the moderating role of Enterprise Risk Management. The findings establish that AI capability significantly improves financial resilience by enhancing the quality of strategic financial decisions. Enterprises equipped with advanced AI capability are ideally poised to foresee monetary hazards, streamline asset deployment, and preserve institutional equilibrium amid phases of economic volatility. In addition, Enterprise Risk Management reinforces these relationships by furnishing an integrated governance structure for AI-enabled financial decision-making. Ultimately, the study establishes that sustainable financial resilience requires enterprises to integrate technological capability, high-quality financial decision-making, and comprehensive risk management. AI should therefore be perceived not solely as an operational technology but as a strategic organizational capability that contributes to long-term financial sustainability and competitive advantage.

Limitations of the Study

Despite its contributions, this study has several limitations. First, the study adopted a cross-sectional research design, which limits the ability to establish causal relationships over time. Second, the study focused exclusively on Pakistan Stock Exchange listed firms, thereby limiting the generalizability of findings to unlisted firms and other sectors. Third, data was collected using self-reported questionnaires, creating the possibility of common method bias despite the implementation of procedural and statistical controls. Fourth, the study examined only one mediator and one moderator. Additional organizational and environmental variables may further explain the relationship between AI capability and financial resilience.

Directions for Future Research

Future research should adopt long-term research designs in order to examine how AI capability influences corporate financial resilience over prolonged timeframes. Comparative studies across developing and developed economies may provide valuable insights into the contextual influence of institutional environments on AI implementation. Future studies should investigate additional mediating variables such as organizational agility, innovation capability, digital transformation maturity, strategic flexibility, and knowledge management capability. Researchers may also examine moderating variables including corporate governance quality, organizational culture, environmental uncertainty, digital leadership, cybersecurity capability, and ESG performance. Future research may adopt mixed-methods approaches by combining quantitative surveys with qualitative interviews to develop a more comprehensive understanding of AI-enabled financial management.

Overall Conclusion

The digital evolution of corporate finance has made Artificial Intelligence Capability a progressively pivotal driver of organizational success. Firms equipped to integrate AI technologies into financial decision-making while preserving rigorous Enterprise Risk Management systems are ideally positioned to withstand financial uncertainty and sustain long-term competitive advantage. The proposed model presents an integrated framework linking technological capability, managerial decision-making, risk governance, and financial resilience. By centering on Pakistan Stock Exchange listed firms, the study supplies empirical data from an emerging economy and extends practical guidance for enterprises aiming to fortify financial resilience through intelligent technologies.

References

1. Ahmad, F., Ismail, F., & Jan, M. F. (2018). Nexus between corruption and macroeconomic indicators in lower developing countries. *Asia Proceedings of Social Sciences, 2*(2), 89–93.
2. Ahmad, S. Y., & Naveed, M. F. J. (2024). Effect of exploitative leadership on green innovative behavior among hospitality employees in Pakistan. *International Journal of Contemporary Issues in Social Sciences, 3*(2), 45–60.
3. Akram, H., Raza, M., Jan, M. F., Aslam, S., & Nivin-Vargas, L. (2024). Identified leadership practices and teachers' professional development in Karachi, Pakistan: The moderation effect of training. *Education 3-13, 52*(8), 1309–1326.

4. Ali, L., Ullah, W., Urooge, S., & Jan, M. F. (2020). Evaluating the mediating role of strategic change between the relationship of gender diversity in senior management and firm performance in Pakistan. *Stratejik Yönetim Araştırmaları Dergisi, 3*(1), 69–84.
5. Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, *17*(1), 99–120.
6. Bharadwaj, A. (2000). A resource-based perspective on information technology capability and firm performance. *MIS Quarterly*, *24*(1), 169–196.
7. Bilal, A., Ahmad, W., Jan, M. F., Huseynov, R., & Nagy, H. (2025). How women's transformational leadership induces employees' innovative behaviour through trust and connectivity: A sequential mediation model. *Global Business Review*, *26*(1), 240–255.
8. Brynjolfsson, E., & McAfee, A. (2017). The business of artificial intelligence. *Harvard Business Review*.
9. Chaudhary, H. S., Azam, K., & Jan, M. F. (2025). Role of AI based media awareness in hazard vulnerability and risk analysis. *Policy Journal of Social Science Review*, *3*(9), 390–406.
10. Creswell, J. W., & Creswell, J. D. (2023). *Research design: Qualitative, quantitative, and mixed methods approaches* (6th ed.). SAGE Publications.
11. Dwivedi, Y. K., Hughes, L., Baabdullah, A. M., et al. (2023). So what if ChatGPT wrote it? Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI. *International Journal of Information Management, 71*, 102642.
12. Ellahi, A., Jan, M. F., & Khan, M. (2026). Generative AI in business education transforming teaching and learning. In *Integrating AI and machine learning into business and management education* (pp. 53–72). IGI Global Scientific Publishing.
13. Ellahi, A., Javed, Y., Mohammad, J., & Sultan, Z. (2024). Determining the effect of software project managers' skills on work performance. *International Journal of Information Technology Project Management, 15*(1), 1–20.
14. Farhan Ahmed, I. O., & Jan, M. F. (2018). Nexus between service quality management and patients' satisfaction: A case of Agha Khan Hospital, Pakistan. *Journal of Strategic Management Research*, *1*(2), 113–135.
15. Farooqi, F. G. I., & Jan, M. F. (2017). The role of private educational institutions in the social development of Khyber Pakhtunkhwa. *Journal of Managerial Science*, *11*(2).
16. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50.
17. Gul, M. S., Jan, F. A., Baloch, Q. B., & Jan, M. F. (2012). Brand image and brand loyalty. *Abasyn Journal of Social Sciences*, *3*(1), 55–74.
18. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). SAGE Publications.
19. Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24.
20. Haider, M. U., Jan, F. A., & Jan, M. F. (2011). Factors effecting brand preferences: A comparative study of McDonald's and KFC. *Abasyn Journal of Social Sciences, 5*(2), 28–42.
21. Hassan, S., Jan, M. F., & Hassan, M. (2026). Perceived transparency and sustainable unboxing experiences as drivers of brand authenticity in emerging markets. *Policy Journal of Social Science Review*, *4*(3), 390–399.

22. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135.
23. Jan, M. F. (2018). *The effect of Big Five personality traits on leader member exchange and organization citizenship behavior: A case of Khyber Pakhtunkhwa universities* [Unpublished doctoral dissertation]. Tokat Gaziosmanpaşa Üniversitesi, Sosyal Bilimler Enstitüsü.
24. Jan, M. F. (2026). Corporate governance and ESG controversies: Evidence from Pakistan. *Sarhad Journal of Management Sciences, 12*(1), 37.
25. Jan, M. F., Ahmed, S., & Essa, W. (2021). From resources to performance: Work engagement and resources. *City University Research Journal, 11*(1), 194.
26. Jan, M. F., Imran, A., Mazhar, U., Batool, B., Noor, A., Malik, S., & Ullah, A. (2026). Impact of student learning strategies on academic development and psychological well-being among children with autism spectrum disorder. *International Journal of Special Education, 41*(7s), 458–473.
27. Jan, M. F., Khan, I., Kamal, A., & Khan, P. (2026). The impact of corporate social responsibility (CSR) initiatives on employee attraction and retention. *Advance Journal of Econometrics and Finance, 4*(2), 1–7.
28. Jan, M. F., Khan, T., Khan, P., & Zeb, F. (2026). Buffering the dark side of leadership: The role of green human resource management practices in mitigating exploitative leadership and fostering employee green innovative behavior. *Policy Journal of Social Science Review, 4*(1), 144–155.
29. Jan, M. F., & Özyer, K. (2022). The effect of Big Five personality traits on leader member exchange and organization citizenship behavior in Khyber Pakhtunkhwa universities. *Central European Management Journal, 30*(3), 131–155.
30. Jan, M. F., & Shah, M. U. (2021). Connecting corporate social responsibility (CSR) to customer loyalty: A mediation analysis in hoteling industry of Pakistan. *SAGE Open, 11*(4), 21582440211067233.
31. Khan, K. N., Jan, M. F., Wazir, K., Khan, Z., & Safdar, M. Z. (2022). Leading with happiness: Analysing the effect of leaders’ humour styles on employees’ creativity. *Webology, 19*(3).
32. Khan, Q. S., Adnan, A. A., Jan, M. F., & Jamal, W. (2020). The effect of explicit knowledge sharing on human resource performance efficiency: Moderating role of human capacity development. *Abasyn University Journal of Social Sciences, 13*(2).
33. Khan, T. A., Khan, M. M., Jan, M. F., & Safdar, M. Z. (2026). Mediating role of emotional regulation behaviors in the relationship between transformational leadership and project success. *Journal of Business and Management Research, 5*(1), 877–893.
34. Khattak, A., Imran, A., Jamal, S., Jan, M. F., Ellahi, A., Hassan, M., ... Faraz, A. A. (2025). Managing humans and algorithms: The intersection of ESG, green HRM practices, and AI in driving firm performance. *TPM–Testing, Psychometrics, Methodology in Applied Psychology, 32*(S7), 1723–1734.
35. Kline, R. B. (2023). *Principles and practice of structural equation modeling* (5th ed.). Guilford Press.
36. Kraaijenbrink, J., Spender, J. C., & Groen, A. J. (2010). The resource-based view: A review and assessment of its critiques. *Journal of Management, 36*(1), 349–372.

37. Majid, A., Ahmed, S., Rahman, A., Khan, T., & Jan, M. F. (2025). Moderating role of perceived project value in the relationship between perceived service quality and customer satisfaction in Pakistan's hospitality industry. *Pakistan Journal of Social Science Review, 4*(6), 111–137.
38. Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability and competitive performance. *Information Systems Frontiers*.
39. Mikalef, P., Gupta, M., Pappas, I. O., & Krogstie, J. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management, 58*(3).
40. Naeem, M., & Jan, M. F. (2025). Artificial intelligence-augmented decision-making in educational leadership: A state-of-the-art synthesis of cognitive automation and strategic human oversight. *Sarhad Journal of Management Sciences, 11*(2), 103–120.
41. Nagy, H., Sana, S., Ahmad, W., Huseynov, R., Jan, M. F., & Bielik, P. (2021). Factors affecting fast food restaurant image in Peshawar: Moderating role of customer personality traits. *AGRIS on-line Papers in Economics and Informatics, 13*(1), 105–119.
42. Nisar Khan, M. F., & Usman, A. (2021). The impact of investor's personality traits over their investment decisions with the mediating role of financial self-efficacy and emotional biases and the moderating role of [information incomplete in source record]. *Multicultural Education, 7*(8), 766.
43. Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.
44. Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review. *Journal of Applied Psychology, 88*(5), 879–903.
45. Rahman, S., Khan, T., Jan, M. F., & Zeb, F. (2026). Expanding the TQM customer satisfaction model: The role of leadership and external factors in Pakistan's public and private hospitals. *Policy Journal of Social Science Review, 4*(2), 351–365.
46. Rahman, S. U., Jan, M. F., & Iqbal, K. (2018). Determinants of profitability in life and non-life insurance sector of Pakistan: An endogenous and exogenous evaluation. *JISR Management and Social Sciences & Economics, 16*(2), 97–106.
47. Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review, 46*(1), 192–210.
48. Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial least squares structural equation modeling. In *Handbook of market research*. Springer.
49. Saunders, M., Lewis, P., & Thornhill, A. (2023). *Research methods for business students* (9th ed.). Pearson.
50. Saeed, S. A., Jan, F. A., & Jan, M. F. (2011). Problems of advertising agencies in Peshawar. *Journal of Managerial Sciences, 5*(1), 21.
51. Sekaran, U., & Bougie, R. (2020). *Research methods for business: A skill-building approach* (8th ed.). Wiley.
52. Shah, M. U., & Jan, M. F. (2021). Connecting corporate social responsibility (CSR) to customer loyalty: A mediation analysis in hoteling industry of Pakistan. *SAGE Open, 11*(4), 21582440211067233.
53. Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational decision-making structures in the age of AI. *California Management Review, 61*(4), 66–83.

54. Siddiq, A., Baloch, Q. B., Nadeem, A., Ahmad, S., & Jan, M. F. (2015). Emotional intelligence: A driving force towards organizational development. *Journal of Management Research (JMR), 1*(2), 86–104.
55. Siddiq, A., Jan, M. F., Iqbal, K., Ahmed, F., & Adnan, A. (2019). Quality of healthcare services in hospitals of Pakistan: From patients' perspective. *Stratejik Yönetim Araştırmaları Dergisi, 2*(1), 1–20.
56. Soni, V. D. (2020). Emerging roles of AI in business management. *International Journal of Scientific Research and Engineering Development*.
57. Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of sustainable enterprise performance. *Strategic Management Journal*, *28*(13), 1319–1350.
58. Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509–533.
59. Ullah, H., Iqbal, K., Sofwan, M. N., & Jan, F. (2018). Determinants of capital structure of financial firms in Pakistan. *Journal of Management Research, 4*(1), 40–52.
60. Ullah, M. M., Jan, M. F., & Jan, M. F. (2011). Elements of brand salience and its impacts on buying behavior and sales. *Abasyn University Journal of Social Sciences, 4*(2), 381.
61. ul Haq, A., & Jan, M. F. (2026). Corporate governance and ESG controversies: A quantile regression approach: Evidence from Pakistan. *Sarhad Journal of Management Sciences*, *12*(1), 37–55.
62. Verhoef, P. C., Broekhuizen, T., Bart, Y., et al. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, *122*, 889–901.
63. Vial, G. (2019). Understanding digital transformation. *Journal of Strategic Information Systems*, *28*(2), 118–144.
64. Waleed, A., Ahmad, W., Jan, M., Ali, S., Khattak, A., & Nadeem, A. (2021). The effect of team value diversity on team performance: The mediating role of relationship conflict and the moderating effects of organization citizenship behavior and leader-member exchange quality. *Management Science Letters, 11*(8), 2185–2194.
65. Wamba, S. F., et al. (2021). Artificial intelligence capability and firm performance. *International Journal of Production Economics*.
66. Zainab, E., Azam, K., & Jan, M. F. (2025). The impact of influencer advertising on consumer purchase behavior towards products. *Policy Journal of Social Science Review, 3*(11), 389–401.