AI-Driven Capital Budgeting and Managerial Decision Quality in Global Firms

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ABSTRACT

Purpose: *This study investigates the effect of AI-Driven Capital Budgeting on Managerial Decision Quality in multinational corporations and examines whether Organizational Readiness strengthens this relationship. The study evaluates how Predictive Analytics Capability, Intelligent Investment Evaluation, AI-Based Risk Management, and Automated Decision Support Systems jointly improve strategic investment decisions under varying organizational conditions.*

Methodology: *The study employs a balanced longitudinal panel comprising 41 Fortune Global 500 multinational corporations observed between 2015 and 2025, generating 451 firm-year observations. Secondary data were integrated from corporate financial and governance reports, the Stanford Artificial Intelligence Index, the World Bank, the OECD, and the McKinsey State of AI database. A moderated two-way fixed-effects panel regression model was estimated following comprehensive construct validation, panel unit root tests, diagnostic testing, Hausman specification analysis, and robustness assessments to establish reliable causal inference.*

Results/Analysis: *The findings demonstrate that Predictive Analytics Capability, Intelligent Investment Evaluation, AI-Based Risk Management, and Automated Decision Support Systems each exert positive and statistically significant effects on Managerial Decision Quality. These effects operate through improved investment forecasting, enhanced project evaluation, stronger risk intelligence, real-time decision support, and more effective strategic resource allocation. Organizational Readiness significantly strengthens these relationships by enhancing digital infrastructure quality, employee AI competence, top management support, data governance effectiveness, and innovation-oriented culture. Robustness and diagnostic analyses confirm the stability, validity, and consistency of the estimated relationships across alternative model specifications.*

Originality/Value: *This study extends Dynamic Capabilities Theory and Socio-Technical Systems Theory by conceptualizing AI-Driven Capital Budgeting as an integrated higher-order* *organizational capability whose effectiveness depends on organizational readiness rather than technology adoption alone. It introduces a multidimensional international framework linking complementary AI capabilities, organizational readiness, and managerial decision quality using longitudinal evidence from globally operating firms. The findings provide practical guidance for corporate executives, investors, and policymakers seeking to improve strategic investment performance through integrated AI-enabled capital budgeting systems.*

Type of Paper: *Empirical Research paper.*

Keywords: AI Driven Capital Budgeting; Dynamic Capabilities; Managerial Decision Quality; Organizational Readiness; Strategic Investment

JEL Classification Codes: G31, L25, M15, O32, O33

1. INTRODUCTION :

Artificial intelligence has evolved from an operational support technology into a strategic capability that fundamentally reshapes how multinational corporations evaluate long-term investments, allocate scarce resources, and create sustainable competitive advantage. Recent global evidence indicates that between 78% and 88% of organizations now employ artificial intelligence in at least one business function, while enterprise investment in generative AI, predictive analytics, and intelligent automation continues to accelerate across finance, operations, and strategic management. At the same time, organizations remain challenged by translating widespread AI adoption into measurable enterprise value because relatively few firms have successfully scaled AI across core decision-making processes. These developments have transformed capital budgeting from a conventional financial appraisal technique into an intelligent decision ecosystem requiring predictive capability, automated investment evaluation, continuous risk monitoring, and real-time managerial support (McKinsey & Company (2025). [1]). Stanford Institute for Human-Centered Artificial Intelligence (Stanford HAI (2025) [2]). Regional disparities nevertheless remain substantial, with digitally mature economies demonstrating stronger AI-enabled investment performance than organizations operating under constrained digital infrastructure, governance capability, and organizational readiness. Consequently, enhancing managerial decision quality through AI-driven capital budgeting has become a strategic priority with implications extending beyond firm-level performance to innovation capability, productivity growth, financial resilience, and sustainable economic development (Csaszar et al. (2024). [3], BaniHani (2024). [4], Roy et al. (2025). [5]). Building on this global transformation, this study examines how AI-Driven Capital Budgeting, represented by Predictive Analytics Capability, Intelligent Investment Evaluation, AI-Based Risk Management, and Automated Decision Support Systems, influences Managerial Decision Quality while Organizational Readiness conditions these structural relationships through digital infrastructure quality, employee AI competence, top management support, data governance effectiveness, and innovation-oriented culture. The consequences of ineffective AI integration are profound because inaccurate investment appraisal, delayed managerial responses, inefficient resource allocation, and weak governance reduce organizational competitiveness and increase exposure to strategic investment failure. None of these challenges can be adequately addressed through technological deployment alone. This study therefore extends Socio-Technical Systems Theory by arguing that superior managerial decision quality emerges from the interaction between intelligent technological capability and organizational readiness rather than from AI adoption in isolation (Page (2026). [6]); Herath Pathirannehelage et al. (2025). [7]; Kalleparambil & Akoum (2025). [8]).

The investigation reported herein reviewed recent scholarship demonstrating that artificial intelligence has fundamentally transformed capital budgeting from a deterministic financial evaluation process into a dynamic, data-driven strategic capability. Contemporary studies consistently show that predictive analytics enhances investment decisions by improving cash flow forecasting, identifying hidden market patterns, strengthening scenario modelling, and reducing uncertainty associated with long-term capital allocation (Csaszar et al., 2024; [3] Pierotti, 2024) [9]. Similarly, intelligent investment evaluation supported by AI algorithms improves project prioritization through automated net present value estimation, internal rate of return optimization, sensitivity analysis, and real-time ranking of competing investment alternatives, thereby reducing cognitive bias and improving investment consistency (Roy et al., 2025; [5] BaniHani, 2024) [4]. Parallel evidence further demonstrates that AI-based risk management enables organizations to identify financial, operational, market, fraud, and portfolio risks considerably earlier than conventional analytical approaches, leading to more resilient investment portfolios and stronger governance mechanisms (OECD (2025). [10]; Roy et al. (2025). [5]). Recent organizational studies also indicate that automated decision support systems enhance managerial effectiveness by integrating predictive intelligence with visualization dashboards, automated investment screening, strategic resource allocation, and continuous performance monitoring, thereby accelerating evidence-based decision making under complex business environments (Chaturvedi et al. (2024). [11]; Page (2026). [6]; Herath Pathirannehelage et al. (2025). [7]). Although these studies provide compelling evidence regarding individual AI capabilities, most examine predictive analytics, investment evaluation, risk intelligence, or decision support independently rather than conceptualizing AI-Driven Capital Budgeting as a multidimensional organizational capability operating through complementary mechanisms. Existing literature also places greater emphasis on technology adoption than on the structural pathways through which multiple AI capabilities collectively improve managerial decision quality within multinational corporations. This study extends prior research by integrating these four complementary AI dimensions into a unified higher-order construct that explains how intelligent capital budgeting simultaneously improves forecasting, investment evaluation, governance, and managerial execution across global firms. The reported research therefore advances the capability-based understanding of AI-enabled strategic investment decisions by demonstrating that the combined operation of multiple AI capabilities generates greater decision quality than isolated technological applications. This argument extends the Dynamic Capabilities Theory by positioning AI-Driven Capital Budgeting as an organizational capability through which firms continuously sense investment opportunities, seize strategic alternatives, and reconfigure financial resources to sustain competitive advantage (Teece (2023). [12]; Csaszar et al. (2024). [3] Roy et al. (2025). [5]).

Building on prior evidence, contemporary research increasingly recognizes that organizational readiness determines whether artificial intelligence generates measurable organizational value or remains an underutilized technological investment. Recent investigations demonstrate that digital infrastructure provides the computational capacity, system interoperability, and data integration required for AI-enabled analytical models to operate effectively, while employee AI competence improves the interpretation, validation, and practical utilization of algorithmic recommendations during strategic decision making (Kalleparambil & Akoum (2025). [8]; McKinsey & Company (2025). [1]). Likewise, top management support has been identified as a critical strategic mechanism that aligns AI implementation with organizational objectives through resource commitment, leadership engagement, and institutional coordination, thereby accelerating organizational learning and technology assimilation (Page (2026). [6]). Complementary evidence further indicates that effective data governance strengthens AI reliability by improving data quality, transparency, accountability, and regulatory compliance, whereas innovation-oriented organizational cultures facilitate experimentation, knowledge sharing, and continuous adaptation necessary for sustained AI-enabled transformation (Stanford HAI (2025). [2]; World Bank (2025). [13]). Although these studies consistently acknowledge the importance of organizational readiness, considerable inconsistency remains regarding its functional role within AI-driven decision systems. Some investigations conceptualize readiness merely as a direct antecedent of AI adoption, whereas others regard it as a contextual organizational characteristic without explicitly examining how it conditions the effectiveness of AI capabilities after implementation. Consequently, empirical understanding of the interaction mechanisms through which organizational readiness strengthens or weakens the relationship between AI-driven capital budgeting and managerial decision quality remains limited. None of these studies comprehensively evaluates how digital infrastructure quality, employee AI competence, leadership commitment, governance effectiveness, and innovation culture collectively moderate the multidimensional influence of AI-enabled capital budgeting on strategic investment decisions within multinational corporations. This study advances existing knowledge by positioning Organizational Readiness as an active moderating capability that amplifies the contribution of intelligent forecasting, investment evaluation, risk management, and automated decision support to managerial decision quality. The reported research therefore shifts current understanding from a technology adoption perspective toward a contingency-based explanation in which organizational conditions determine the magnitude and sustainability of AI-generated managerial outcomes. This interpretation extends Contingency Theory by demonstrating that the effectiveness of AI-driven capital budgeting depends not only on technological capability but also on the organizational

environment within which that capability is deployed, governed, and continuously refined (Donaldson (2001). [14]; McKinsey & Company (2025). [1] Stanford HAI (2025). [2]; World Bank (2025). [13]).
Our work balances recent evidence demonstrating that Managerial Decision Quality represents a multidimensional organizational capability rather than a single performance outcome. Contemporary studies increasingly evaluate decision quality through dimensions including decision accuracy, timeliness, strategic alignment, resource allocation effectiveness, adaptability, and long-term organizational value creation, reflecting the growing complexity of strategic decision environments (Csaszar et al. (2024). [3]; Page (2025). [6]). Recent investigations further demonstrate that artificial intelligence improves managerial decisions by expanding analytical capacity, reducing bounded rationality, enhancing information processing speed, and supporting evidence-based strategic judgment under conditions of uncertainty (BaniHani (2024). [4]; Chaturvedi et al. (2024). [11]). Likewise, empirical research on AI-enabled financial management indicates that organizations integrating predictive analytics with intelligent investment evaluation consistently achieve superior investment selection, faster capital allocation, and stronger organizational responsiveness than firms relying on conventional financial appraisal methods (Roy et al. (2025). [5]; Pierotti (2024). [9]). Parallel studies also emphasize that managerial decision quality depends increasingly on the ability to integrate heterogeneous data sources, continuously monitor organizational performance, and adapt investment strategies in response to rapidly changing business environments (Herath Pathirannehelage et al. (2025). [7]; Stanford HAI (2025). [2]).. Nevertheless, prior research remains constrained by several limitations. Most studies measure managerial decision quality using isolated financial indicators or subjective managerial perceptions, thereby overlooking its multidimensional nature and the interdependence among strategic alignment, decision timeliness, resource allocation effectiveness, and investment success. Moreover, existing investigations rarely evaluate managerial decision quality as the cumulative outcome of integrated AI-enabled capital budgeting capabilities operating within different organizational readiness conditions. Consequently, current empirical evidence provides only a partial explanation of how intelligent technologies translate into sustained improvements in managerial effectiveness across multinational corporations. This study addresses these limitations by operationalizing Managerial Decision Quality through five complementary dimensions comprising Decision Accuracy, Decision Timeliness, Strategic Alignment, Resource Allocation Effectiveness, and Investment Success Rate, thereby providing a more comprehensive and internationally comparable assessment of managerial performance. The reported research contributes a forward-looking perspective by demonstrating that superior managerial decision quality emerges through the interaction of intelligent analytical capability, organizational readiness, and evidence-based investment governance rather than through isolated technological implementation. This interpretation extends Decision Theory and the Resource-Based View by explaining how valuable organizational capabilities are transformed into sustainable managerial performance through coordinated investment intelligence and organizational resource orchestration (Barney (1991). [15]; Csaszar et al. (2024). [3]; Roy et al. (2025). [5]).
The investigation reported herein examines the intersection between AI-Driven Capital Budgeting, Organizational Readiness, and Managerial Decision Quality to identify unresolved theoretical and empirical issues that remain insufficiently addressed within contemporary strategic management and corporate finance literature. Existing studies predominantly investigate predictive analytics, intelligent investment evaluation, AI-enabled risk management, automated decision support, organizational readiness, or managerial decision outcomes as independent research streams, resulting in fragmented explanations of how these constructs interact to influence organizational decision effectiveness (Bani Hani (2024). [4]; Csaszar et al. (2024). [3]; Chaturvedi et al. (2024). [11]; Roy et al. (2025). [5]). Although recent scholarship acknowledges that artificial intelligence improves strategic decision making, most investigations focus primarily on technology adoption, algorithmic performance, or organizational implementation while overlooking the structural mechanisms through which multiple AI capabilities jointly influence capital budgeting decisions under varying organizational conditions (Page (2025). [6] Herath Pathirannehelage et al. (2025). [7]). Furthermore, empirical evidence remains concentrated within single technologies, industries, or national settings, limiting the generalizability of existing findings across globally operating multinational corporations. None of the previous studies explores the multidimensional interaction between Predictive Analytics Capability, Intelligent Investment Evaluation, AI-Based Risk Management, and Automated Decision Support Systems as an

integrated higher-order AI-Driven Capital Budgeting construct while simultaneously examining the moderating influence of Organizational Readiness on the relationship with Managerial Decision Quality. Likewise, previous research has not operationalized managerial decision quality through the combined dimensions of decision accuracy, decision timeliness, strategic alignment, resource allocation effectiveness, and investment success rate within a unified longitudinal framework. This study contributes by showing that AI-driven capital budgeting functions as a cumulative organizational capability whose effectiveness depends on complementary technological mechanisms and enabling organizational conditions rather than isolated AI applications. The reported research introduces four major contributions. First, it proposes a new capability integration mechanism explaining how complementary AI functions collectively improve managerial decision quality. Second, it provides new empirical evidence from multinational corporations operating across diverse industries using a longitudinal international dataset. Third, it develops a multidimensional measurement framework that captures both technological capability and organizational readiness through higher-order constructs. Fourth, it establishes and empirically validates a moderated pathway demonstrating how organizational readiness amplifies the influence of AI-driven capital budgeting on managerial decision quality. Beyond theoretical advancement, these findings provide actionable guidance for corporate leaders, investors, technology developers, and policymakers seeking to maximize returns from AI-enabled investment decisions by strengthening organizational capabilities alongside technological deployment. Collectively, the study extends Dynamic Capabilities Theory and Socio-Technical Systems Theory by demonstrating that sustainable managerial decision quality emerges from the coordinated interaction of intelligent technological resources and organizational readiness rather than from technological adoption alone.

The present investigation examines AI-driven capital budgeting within multinational corporations listed in the Fortune Global 500, an empirical setting that provides exceptional global relevance because these firms account for a substantial proportion of worldwide corporate investment, technological innovation, and cross-border capital allocation. Their extensive adoption of artificial intelligence, sophisticated governance systems, and publicly available longitudinal disclosures provide an appropriate environment for evaluating how intelligent capital budgeting capabilities influence managerial decision quality across diverse industrial and geographical contexts. The empirical analysis employs a balanced longitudinal panel comprising 41 multinational corporations selected from a population of 500 global firms observed over the period 2015 to 2025, generating 451 firm-year observations for hypothesis testing. Secondary data were systematically integrated from corporate financial disclosures, governance reports, artificial intelligence indicators, digital transformation databases, and internationally recognized investment datasets to ensure measurement consistency, cross-country comparability, and empirical reproducibility. AI-Driven Capital Budgeting was operationalized through four complementary first-order capabilities, Organizational Readiness was specified as the moderating construct, and Managerial Decision Quality was measured through five integrated performance dimensions that collectively reflect strategic investment effectiveness. The analytical framework employs a moderated two-way fixed-effects panel regression model supported by comprehensive diagnostic procedures, including stationarity assessment, normality testing, multicollinearity diagnostics, autocorrelation analysis, homoscedasticity testing, construct validity evaluation, correlation analysis, and moderated regression estimation to strengthen causal interpretation and statistical reliability. The interaction model further estimates how Organizational Readiness conditions the influence of AI-Driven Capital Budgeting on Managerial Decision Quality while controlling for unobserved firm-specific and temporal heterogeneity. Compared with conventional cross-sectional analyses, this longitudinal econometric approach improves estimation precision by accounting for dynamic organizational evolution, persistent firm characteristics, and global technological shocks that influence AI adoption and strategic investment behaviour over time. Consequently, the methodological design overcomes major limitations identified in previous studies by integrating multidimensional measurement, moderated panel modelling, rigorous diagnostic validation, and longitudinal evidence within a single analytical framework, thereby providing stronger empirical support for identifying the structural mechanisms through which intelligent capital budgeting enhances managerial decision quality in global firms.

This study aims to develop and empirically validate an integrated framework explaining how AI-Driven Capital Budgeting enhances Managerial Decision Quality under varying levels of Organizational

Readiness within multinational corporations. Building upon the theoretical propositions and empirical relationships established throughout this investigation, the study seeks to determine whether intelligent technological capabilities operate as complementary organizational resources capable of improving strategic investment decisions when supported by favourable organizational conditions. Specifically, the study examines the influence of Predictive Analytics Capability on Managerial Decision Quality by evaluating its contribution to decision accuracy, forecasting precision, and strategic investment planning; investigates the effect of Intelligent Investment Evaluation on Managerial Decision Quality through automated project appraisal, investment prioritization, and capital allocation effectiveness; assesses the influence of AI-Based Risk Management on Managerial Decision Quality by examining its role in financial risk detection, operational risk assessment, market uncertainty management, and investment resilience; evaluates the contribution of Automated Decision Support Systems to Managerial Decision Quality through real-time recommendations, investment screening, strategic resource allocation, and continuous performance monitoring; and finally determines whether Organizational Readiness, represented by digital infrastructure quality, employee AI competence, top management support, data governance effectiveness, and innovation-oriented culture, significantly moderates the relationship between AI-Driven Capital Budgeting and Managerial Decision Quality by strengthening or weakening the effectiveness of intelligent capital budgeting capabilities across multinational corporations. Collectively, these objectives provide a coherent empirical foundation for testing the proposed conceptual framework while advancing theoretical understanding of the structural pathways through which artificial intelligence improves managerial decision quality in globally operating firms.

2. LITERATURE REVIEW :

Artificial intelligence has fundamentally transformed capital budgeting from a conventional financial appraisal process into a strategic decision capability that integrates predictive analytics, intelligent investment evaluation, automated risk assessment, and real-time decision support. Recent studies demonstrate that AI-driven capital budgeting improves investment forecasting, project selection, resource allocation, governance, and organizational competitiveness by reducing uncertainty and strengthening evidence-based managerial decisions. Simultaneously, organizational readiness has emerged as a critical contextual capability that determines whether AI investments generate measurable strategic value through appropriate digital infrastructure, leadership commitment, employee competence, data governance, and innovation culture. Despite these developments, previous investigations have largely examined Predictive Analytics Capability, Intelligent Investment Evaluation, AI-Based Risk Management, Automated Decision Support Systems, Organizational Readiness, and Managerial Decision Quality independently, providing limited understanding of their integrated influence on strategic investment performance. This study addresses these theoretical and empirical gaps by conceptualizing AI-Driven Capital Budgeting as a multidimensional organizational capability whose effectiveness depends on Organizational Readiness in improving Managerial Decision Quality across multinational corporations.

2.1 Theories:

Table 1: Theoretical Foundations

Theory	Core Proposition	Contribution to the Study	Key References
Dynamic Capabilities Theory	Organizations achieve sustainable advantage by continuously sensing, seizing, and reconfiguring strategic resources	Explains AI-Driven Capital Budgeting as a strategic organizational capability	Teece (2023). [12]; Csaszar et al. (2024). [3].
Socio-Technical Systems Theory	Organizational performance depends on the alignment between technological and human systems	Justifies Organizational Readiness as an enabling organizational capability	Trist (1981). [16]; Page (2025). [6].
Resource-Based View	Valuable organizational resources generate sustainable competitive advantage	Positions AI capability as a valuable strategic organizational resource	Barney (1991). [15]; Roy et al. (2025). [5].

Contingency Theory	Organizational effectiveness depends on contextual conditions	Explains the moderating role of Organizational Readiness	Donaldson (2001). [14]; McKinsey & Company (2025). [1].

The reviewed theories collectively demonstrate that intelligent technologies improve organizational decision quality only when supported by complementary organizational capabilities. Dynamic Capabilities Theory explains how AI enables continuous adaptation of investment decisions, while the Resource-Based View recognizes AI-enabled analytical capability as a valuable strategic resource. Socio-Technical Systems Theory emphasizes that technology produces organizational value only when integrated with human competence and organizational processes. Contingency Theory further explains why Organizational Readiness conditions the effectiveness of AI capabilities across firms. Integrating these theoretical perspectives provides a comprehensive explanation of how AI-Driven Capital Budgeting and Organizational Readiness jointly enhance Managerial Decision Quality.

2.2 Empirical Review:

Table 2: Recent Empirical Evidence

Research Area	Main Findings	Research Gap	Key References
Predictive Analytics Capability	Improves investment forecasting and strategic planning	Mostly examined independently	Csaszar et al. (2024). [3]; Pierotti (2024). [9].
Intelligent Investment Evaluation	Enhances project appraisal and capital allocation	Limited multidimensional integration	Roy et al. (2025). [5]; BaniHani (2024). [4].
AI-Based Risk Management	Improves investment resilience and governance	Limited evidence on combined AI capabilities	OECD (2025). [10]; Roy et al. (2025). [5].
Automated Decision Support Systems	Strengthens managerial responsiveness and decision speed	Rarely evaluated alongside other AI capabilities	Chaturvedi et al. (2024). [11]; Page (2025). [6].
Organizational Readiness	Enhances successful AI implementation and organizational performance	Moderating effects remain underexplored	McKinsey & Company (2025). [1]; Stanford HAI (2025). [2].

Recent empirical evidence consistently demonstrates that artificial intelligence significantly improves capital budgeting effectiveness by strengthening forecasting accuracy, investment evaluation, risk management, and managerial decision support. Organizations adopting predictive analytics and intelligent investment systems achieve superior investment quality, resource allocation efficiency, and strategic responsiveness compared with organizations relying on conventional financial appraisal methods. Similarly, organizational readiness characterized by strong digital infrastructure, employee AI competence, leadership commitment, effective data governance, and innovation culture substantially improves the successful implementation of AI-enabled decision systems. Nevertheless, previous studies rarely conceptualize AI-Driven Capital Budgeting as an integrated higher-order organizational capability or examine Organizational Readiness as a moderating mechanism explaining variations in Managerial Decision Quality. This study fills these gaps by proposing a unified conceptual framework that integrates complementary AI capabilities and organizational readiness to explain strategic managerial decision effectiveness within multinational corporations.

2.3. Objectives of the Research:

(1) **To examine the effect of Predictive Analytics Capability on Managerial Decision Quality** in global firms by evaluating its contribution to investment forecasting accuracy, decision precision, and strategic planning.

(2) **To assess the influence of Intelligent Investment Evaluation on Managerial Decision Quality** by analyzing how AI-enabled project appraisal, investment prioritization, and capital allocation improve strategic investment decisions.

(3) **To evaluate the impact of AI-Based Risk Management on Managerial Decision Quality** through its role in financial risk identification, operational risk assessment, market uncertainty management, and investment resilience.

(4) **To investigate the contribution of Automated Decision Support Systems to Managerial Decision Quality** by examining their effectiveness in providing real-time recommendations, investment screening, strategic resource allocation, and continuous performance monitoring.

(5) **To determine the moderating effect of Organizational Readiness on the relationship between AI-Driven Capital Budgeting and Managerial Decision Quality** by assessing how digital infrastructure, employee AI competence, top management support, data governance, and innovation-oriented culture strengthen or weaken AI-enabled capital budgeting outcomes.

3. HYPOTHESES DEVELOPMENT :

AI Driven Capital Budgeting operates as a socio technical capability that links analytical systems, managerial judgment, investment governance, and organizational execution. This analysis positions capital budgeting as an interdependent decision system where AI improves the conversion of financial data, market signals, risk indicators, and strategic priorities into higher quality managerial decisions. In global firms, investment decisions are rarely isolated acts. They emerge from interactions among finance teams, executive committees, data infrastructures, risk controls, and resource allocation routines. This creates constraints through information asymmetry, uncertainty, model opacity, governance pressure, and delayed feedback. It also creates incentives for firms to use AI systems that improve prediction, evaluation, monitoring, and decision speed. Recent evidence shows that AI can enhance the speed, quality, and scale of strategic analysis, but its effect depends on organizational design, human validation, data quality, governance, and adoption capability (Csaszar et al. (2024). [3]; McKinsey & Company (2025). [1]; Stanford HAI (2025). [2]; World Bank (2025). [13]).

This analysis treats Managerial Decision Quality as the outcome of accuracy, timeliness, strategic alignment, resource allocation effectiveness, and investment success. AI Driven Capital Budgeting affects these outcomes by reducing bounded rationality and strengthening evidence-based evaluation. Predictive models improve foresight, intelligent evaluation tools improve project ranking, AI based risk systems reduce exposure to adverse outcomes, and automated decision support systems improve the translation of analytics into managerial action. The theoretical mechanism is therefore cumulative. AI first improves information quality, then improves evaluation quality, then reduces risk uncertainty, and then accelerates decision execution. This logic is consistent with recent work showing that AI can support decision search, representation, aggregation, forecasting, budgeting flexibility, and strategic decision making (BaniHani (2024). [4]; Chaturvedi et al. (2024). [11]; Pierotti (2024). [9]; Roy et al. (2025). [5]).

Predictive Analytics Capability refers to the ability of AI systems to forecast cash flows, investment returns, risks, market trends, and alternative scenarios. Its mechanism lies in transforming historical, real time, and external data into forward looking estimates that reduce uncertainty in capital budgeting. In global firms, capital investment decisions depend on expected future value rather than past performance alone. Predictive analytics strengthens this process by detecting patterns, anticipating volatility, and modeling scenario-based outcomes before resource commitments are made.

Predictive Analytics Capability improves Managerial Decision Quality because it increases the precision and timing of managerial judgment. Forecasting tools help managers compare competing projects under uncertainty, identify weak investment cases earlier, and revise assumptions when market conditions shift. This improves decision accuracy because managers rely on richer evidence. It also improves timeliness because predictive systems shorten the interval between data collection, analysis, and managerial response. When firms use prediction to structure investment choices, they reduce reactive decision making and improve strategic alignment.

Recent studies support this positive logic. Csaszar et al. (2024) [3] show that AI can enhance strategic analysis through search, representation, and aggregation. Pierotti (2024) [9] links AI based analysis to stronger planning, budgeting, forecast accuracy, and reduced information gaps. Roy et al. (2025) [5] show that AI improves capital budgeting through cash flow estimation, scenario simulation, risk assessment, and strategic flexibility. Institutional evidence also shows fast growth in business AI adoption, which supports the relevance of predictive analytics in large firms (Stanford HAI (2025). [2]).

H1: A Positive Relationship Exists Between Predictive Analytics Capability and Managerial Decision Quality

Intelligent Investment Evaluation differs from predictive analytics because it focuses on appraisal rather than forecasting. It refers to AI enabled support for net present value automation, internal rate of return optimization, payback assessment, cost benefit analysis, and project ranking algorithms. Its mechanism lies in improving the evaluation architecture through which firms compare investment alternatives. While predictive analytics estimates future conditions, intelligent evaluation ranks investment options using structured financial logic and algorithmic consistency.

Intelligent Investment Evaluation improves Managerial Decision Quality by reducing inconsistency in project appraisal. Manual capital budgeting can suffer from managerial bias, selective assumptions, political influence, and uneven treatment of investment proposals. AI based evaluation tools create convergence in appraisal rules while allowing sensitivity analysis across competing assumptions. This strengthens decision accuracy and resource allocation effectiveness because capital flows toward projects with stronger expected value, better risk adjusted returns, and clearer strategic fit.

Recent literature supports this direction. Roy et al. (2025) [5] argue that AI transforms long term investment and capital budgeting by improving net present value analysis, internal rate of return assessment, scenario analysis, and real options reasoning. BaniHani (2024) [4] shows that AI affects decision making by improving analytical capacity across financial and technological contexts. Csaszar et al. (2024) [3] show that AI can support strategic evaluation by improving the quality and scale of analysis. These arguments imply that intelligent evaluation systems strengthen the quality of managerial investment choices when firms use them to structure project comparison and capital allocation

H2: A positive Relationship Exists Between Intelligent Investment Evaluation and Managerial Decision Quality

AI Based Risk Management refers to the use of AI for financial risk detection, operational risk assessment, market volatility monitoring, fraud risk identification, and portfolio risk optimization. Its mechanism is behavioral and institutional because risk systems influence how managers perceive exposure, allocate attention, and define acceptable investment thresholds. Capital budgeting decisions face uncertainty from market shocks, operational failures, regulatory changes, fraud risks, and portfolio concentration. AI based risk systems improve decision quality by making these exposures visible before investment approval and during project execution.

AI Based Risk Management improves Managerial Decision Quality by reducing downside error and strengthening governance discipline. Managers make better decisions when risk signals are timely, traceable, and connected to investment evaluation. AI systems detect anomalies, simulate adverse scenarios, and monitor exposure across portfolios. This improves decision accuracy because hidden risk becomes measurable. It improves strategic alignment because investment choices are filtered through risk appetite and governance rules. It improves investment success because early warning systems help firms adjust projects before losses become irreversible.

Recent evidence reinforces this logic. The OECD AI Incidents and Hazards Monitor emphasize the need to identify and monitor AI related risks and adverse outcomes through evidence-based systems (OECD, 2025) [10]. Roy et al. (2025) [5] show that AI can improve risk assessment and strategic flexibility in capital budgeting. [1] McKinsey & Company (2025) reports that firms capturing value from AI tend to combine leadership commitment, human validation, data discipline, and governance practices. These findings imply that AI based risk management improves managerial decision quality when risk intelligence is embedded into investment selection and monitoring.

H3: A Positive Relationship Exists Between AI Based Risk Management and Managerial Decision Quality

Automated Decision Support Systems refer to AI enabled real time recommendations, data visualization dashboards, investment screening automation, strategic resource allocation, and performance monitoring systems. Their mechanism lies in connecting analysis to managerial action. Predictive and evaluative tools generate insight, but decision quality improves only when insights reach decision makers in usable, timely, and governed formats. Automated support systems reduce the distance between evidence generation and decision execution.

Automated Decision Support Systems improve Managerial Decision Quality by increasing decision speed, consistency, and implementation discipline. Real time recommendations help managers act before opportunities disappear. Dashboards improve transparency by integrating financial, operational, and strategic indicators. Automated screening reduces delays in project selection. Resource allocation systems help managers align capital with strategic priorities. Performance monitoring systems create feedback loops that allow firms to revise assumptions and improve future decisions. This links micro level managerial behavior to macro level firm outcomes because repeated decision improvements accumulate into stronger investment performance.

Recent studies support this relationship. Chaturvedi et al. (2024) [11] show that managerial perceptions of AI are shaped by its role in supporting and automating strategic decisions. Page (2025) [6] argues that AI and large language models can replace, augment, or disrupt organizational decision making depending on task complexity and decision stakes. Herath Pathirannehelage et al. (2025) [7] show that AI augmented systems shape decision making through automation and human AI collaboration. These findings suggest that automated decision support systems improve managerial decision quality when firms maintain human oversight, valid data, and clear governance.

H4: A positive Relationship Exists Between Automated Decision Support Systems and Managerial Decision Quality

Organizational Readiness refers to digital infrastructure quality, employee AI competence, top management support, data governance effectiveness, and innovation-oriented culture. This analysis treats it as a conditioning force that determines whether AI Driven Capital Budgeting becomes a useful managerial capability or remains a fragmented technological investment. Readiness moderates the main relationship because AI systems require infrastructure, skills, leadership, governance, and cultural acceptance before they can improve capital budgeting outcomes.

Organizational Readiness strengthens the relationship between AI Driven Capital Budgeting and Managerial Decision Quality through complementarity. Strong infrastructure allows firms to integrate data across financial, operational, and market systems. Employee AI competence improves interpretation and reduces blind reliance on algorithms. Top management support aligns AI use with strategic priorities. Data governance improves accuracy, accountability, and traceability. Innovation culture supports experimentation and learning. When these conditions are strong, AI capabilities are more likely to improve accuracy, timeliness, strategic alignment, resource allocation, and investment success. When readiness is weak, the same AI systems may produce limited value because managers lack reliable data, usable workflows, or trust in model outputs.

Recent evidence supports this boundary condition. McKinsey & Company (2025) [1] shows that AI value depends on management practices across strategy, talent, operating model, technology, data, and adoption. The World Bank (2025) [13] identifies connectivity, compute, context, and competency as foundations for AI adoption and adaptation. Kalleparambil and Akoum (2025) [8] argue that AI readiness depends on governance, data quality, organizational maturity, and implementation capability. Stanford HAI (2025) [2] shows rapid growth in AI adoption, but adoption alone does not prove performance impact. This implies that readiness determines whether AI Driven Capital Budgeting becomes a source of decision quality or a source of implementation friction.

H5: Organizational Readiness significantly moderates the relationship between AI Driven Capital Budgeting and Managerial Decision Quality.

4. DATA :

This analysis employs a structured longitudinal secondary dataset to evaluate how AI Driven Capital Budgeting improves Managerial Decision Quality under different levels of Organizational Readiness. The dataset is designed to support multidimensional measurement, moderated panel estimation, and robust empirical inference using internationally recognised corporate, financial, and digital transformation databases.

4.1 Data Source and Overview:

This analysis constructs a balanced international firm year panel using secondary information collected from the Fortune Global 500 rankings, corporate annual reports, sustainability reports, governance reports, World Bank Gross Capital Formation database, World Bank Digital Progress and Trends Report 2025, Stanford Artificial Intelligence Index Report 2025, McKinsey State of AI Global Survey 2025, Organisation for Economic Cooperation and Development digital innovation resources, and publicly disclosed financial and investment reports. These sources provide internationally comparable evidence on artificial intelligence adoption, capital budgeting capability, organizational readiness, and managerial performance. The empirical dataset comprises 41 multinational corporations selected from the Fortune Global 500 population consisting of 500 firms operating across multiple industries and geographical regions between 2015 and 2025. The multinational corporation represents the unit of analysis, whereas the firm year constitutes the unit of observation. AI Driven Capital Budgeting forms the multidimensional explanatory construct measured through Predictive Analytics Capability, Intelligent Investment Evaluation, AI Based Risk Management, and Automated Decision Support Systems. Organizational Readiness functions as the moderating construct, while Managerial Decision Quality represents the dependent construct measured through Decision Accuracy, Decision Timeliness, Strategic Alignment, Resource Allocation Effectiveness, and Investment Success Rate. Annual observations provide the most appropriate reporting frequency because investment decisions, financial disclosures, governance indicators, and AI implementation progress are reported annually, thereby supporting longitudinal consistency, panel stationarity assessment, and dynamic estimation of organizational performance relationships. Contemporary evidence demonstrates that artificial intelligence improves strategic investment analysis, financial forecasting, decision speed, and organizational effectiveness when supported by appropriate managerial capabilities and institutional conditions (Csaszar et al. (2024). [3]; BaniHani (2024). [4]; Chaturvedi et al. (2024). [11]; McKinsey & Company (2025). [1]; Stanford HAI (2025). [2]).

The analytical dataset integrates multiple institutional repositories through a deterministic merge procedure using two common merge keys consisting of the Fortune Global 500 corporate identifier and fiscal reporting year. Financial information extracted from annual reports was merged with World Bank capital formation indicators, Stanford Artificial Intelligence Index measures, McKinsey global AI adoption indicators, OECD digital innovation evidence, and firm specific governance disclosures to produce harmonised longitudinal observations. Where equivalent variables appeared across multiple repositories, this analysis adopted predefined conflict resolution rules that prioritised audited corporate disclosures, followed by World Bank datasets, Stanford Artificial Intelligence Index indicators, McKinsey global survey evidence, and OECD information according to reporting authority, methodological transparency, and data completeness. Data reliability was strengthened through four complementary quality assurance procedures. Coverage assessment confirmed continuous annual observations throughout the study period. Content assessment verified conceptual consistency between theoretical constructs and observable indicators across all repositories. Construction assessment examined whether each empirical indicator adequately represented its corresponding theoretical dimension, while accuracy assessment employed duplicate detection, logical range verification, cross source validation, temporal consistency checks, and internal coherence testing before empirical estimation. The resulting balanced panel supports multidimensional index construction, moderated structural modelling, dynamic interaction analysis, and scalability from individual AI capabilities to comprehensive investment decision systems. Similar integrated datasets have become increasingly common in contemporary artificial intelligence, finance, and strategic management research because they strengthen construct validity, improve international comparability, and enhance empirical reproducibility (Csaszar et al. (2024). [3]; Pierotti (2024). [9]; Roy et al. (2025). [5]; McKinsey & Company (2025). [1]; Stanford HAI (2025). [2]).

The final analytical dataset was established through a transparent data preparation procedure designed to maximise reliability while preserving international representativeness. First, all Fortune Global 500 corporations reporting AI related capital budgeting activities between 2015 and 2025 were identified as the initial sampling frame. Second, only firms reporting continuous annual information on Predictive Analytics Capability, Intelligent Investment Evaluation, AI Based Risk Management, Automated Decision Support Systems, Organizational Readiness, and Managerial Decision Quality throughout the observation period were retained. Third, corporations presenting inconsistent fiscal reporting periods, incompatible accounting definitions, incomplete artificial intelligence disclosures, or missing governance information were excluded because such observations violate balanced panel assumptions and reduce longitudinal comparability. Fourth, duplicated records originating from overlapping corporate repositories were removed through firm identification codes and fiscal reporting years. Fifth, isolated missing observations associated with macroeconomic or governance indicators were resolved through external matching using equivalent official datasets where identical measurement definitions existed, whereas observations missing core explanatory, moderating, or dependent variables were removed to minimise estimation bias arising from artificial imputation. The initial population consisted of 500 multinational corporations, while application of the inclusion criteria retained 41 firms, producing a balanced panel containing 451 firm year observations available for empirical estimation. Survivorship bias was minimised by applying identical selection criteria throughout the entire observation period rather than selecting firms according to subsequent financial performance or AI maturity. Data selection follows internationally recognised reporting practices adopted by Fortune Global 500, the World Bank, OECD, Stanford HAI, and McKinsey & Company, thereby ensuring methodological transparency, institutional comparability, and empirical reproducibility. These dataset characteristics align with recent empirical literature demonstrating that longitudinal multinational datasets provide stronger evidence for evaluating artificial intelligence enabled investment decisions, organizational capability development, and strategic managerial performance than cross sectional designs (BaniHani (2024). [4]; Csaszar et al. (2024). [3]; Roy et al. (2025). [5]; McKinsey & Company (2025). [1]; Stanford HAI (2025). [2]).

4.2 Variable Construction and Measurement:

This section operationalizes all theoretical constructs using harmonized secondary data obtained from internationally recognized corporate, financial, governance, and artificial intelligence databases. Variable measurement integrates conceptual definition, mathematical construction, standardization, validation, and distribution assessment to ensure consistency, comparability, and empirical reproducibility across firms and reporting periods.

(a) Dependent Variable:

Managerial Decision Quality represents the dependent construct because it captures the effectiveness with which managers transform investment information into strategic capital allocation decisions that improve organizational performance. This analysis operationalizes Managerial Decision Quality through five complementary dimensions consisting of Decision Accuracy, Decision Timeliness, Strategic Alignment, Resource Allocation Effectiveness, and Investment Success Rate, consistent with the conceptual framework developed for the empirical investigation. Information was extracted from Fortune Global 500 corporate reports, World Bank Gross Capital Formation datasets, Stanford Artificial Intelligence Index indicators, McKinsey State of AI reports, and publicly available governance disclosures after confirming conceptual consistency across all reporting years. The extraction process first identified multinational corporations reporting complete AI enabled investment information before matching each observation with financial, governance, and organizational performance indicators. Firms entered the analytical dataset only when complete observations were available for every managerial decision quality dimension throughout the study period. The initial sampling frame consisted of 500 multinational corporations, while the final balanced sample retained 41 firms after excluding incomplete observations, inconsistent reporting periods, duplicated records, and missing AI related investment information. This multidimensional operationalization reflects recent evidence demonstrating that managerial decision quality depends upon the combined effects of analytical accuracy, execution speed, strategic consistency, efficient resource allocation, and investment performance rather than isolated financial outcomes (Csaszar et al., 2024; [3] BaniHani, 2024; [4] Chaturvedi et al., 2024; [11] Roy et al., 2025; [5] Page, 2025) [6].

The Managerial Decision Quality Index is calculated as the equally weighted average of the five standardized outcome dimensions because each dimension captures an essential aspect of organizational decision effectiveness.

Equation 1: Dependent Variable Construction

$$\text{Managerial Decision Quality Index } MDQ_{it} = \frac{DA_{it}+DT_{it}+SA_{it}+RAE_{it}+ISR_{it}}{5}$$

Where,

MDQ_{it}= Managerial Decision Quality Index
DA_{it}= Decision Accuracy
DT_{it}= Decision Timeliness
SA_{it}= Strategic Alignment
RAE_{it}= Resource Allocation Effectiveness
ISR_{it}= Investment Success Rate

As presented in Equation 1, each indicator is standardized before aggregation using a common normalization procedure to eliminate measurement scale differences while preserving proportional variation across firms and years. Higher composite values indicate superior managerial capability in evaluating investment opportunities, allocating strategic resources, and achieving successful capital investment outcomes. Validation combines cross source verification, consistency testing across institutional repositories, comparison with recognized investment performance indicators, descriptive statistical analysis, and logical range verification before empirical estimation. Distributional characteristics are evaluated through the mean, standard deviation, minimum, maximum, skewness, kurtosis, and normality diagnostics to confirm suitability for panel regression analysis.

(b) Independent Variables:

AI Driven Capital Budgeting constitutes the principal explanatory construct because artificial intelligence enhances the quality, speed, consistency, and analytical depth of investment decision processes within multinational corporations. This analysis conceptualizes AI Driven Capital Budgeting as a higher order multidimensional capability consisting of Predictive Analytics Capability, Intelligent Investment Evaluation, AI Based Risk Management, and Automated Decision Support Systems. Predictive Analytics Capability captures cash flow forecasting, investment return prediction, risk forecasting, market trend analysis, and scenario simulation. Intelligent Investment Evaluation measures automated net present value analysis, internal rate of return optimization, payback period assessment, cost benefit evaluation, and project ranking algorithms. AI Based Risk Management evaluates financial risk detection, operational risk assessment, market volatility monitoring, fraud risk identification, and portfolio risk optimization. Automated Decision Support Systems measure real time investment recommendations, data visualization dashboards, investment screening automation, strategic resource allocation, and performance monitoring systems. Observable indicators were extracted from corporate annual reports, sustainability reports, Stanford Artificial Intelligence Index publications, McKinsey State of AI reports, World Bank digital transformation datasets, and publicly available investment governance disclosures after verifying conceptual consistency across reporting periods. Only firms reporting complete observations across all four dimensions entered the analytical dataset, whereas observations containing incomplete AI implementation information, inconsistent accounting definitions, duplicated disclosures, or missing governance indicators were excluded during data preparation. This multidimensional operationalization reflects contemporary finance and strategic management literature recognizing AI enabled capital budgeting as an integrated organizational capability rather than isolated technology adoption (Csaszar et al., 2024; [3] Pierotti, 2024; [9] BaniHani, 2024; [4] Roy et al., 2025; [5] Herath Pathirannehelage et al., 2025) [7].

Each first order construct is calculated as the arithmetic average of its standardized indicators before constructing the overall AI Driven Capital Budgeting Index. Equal weighting is adopted because the conceptual framework assigns equivalent theoretical importance to each AI capability and no empirical evidence supports differential weighting before model estimation.

Equation 2: Composite Independent Variable Index

$$\text{AI Driven Capital Budgeting Index } AICB_{it} = \frac{PAC_{it}+IIE_{it}+AIRM_{it}+ADSS_{it}}{4}$$

Where,

$AICB_{it}$= AI Driven Capital Budgeting Index for firm $i$in year t
PAC_{it}= Predictive Analytics Capability
IIE_{it}= Intelligent Investment Evaluation
$AIRM_{it}$= AI Based Risk Management
$ADSS_{it}$= Automated Decision Support Systems

Equation 2 shows that the composite construct is obtained by aggregating the four standardized AI capabilities after transforming all indicators onto a common measurement scale. Equal weighting preserves conceptual balance across dimensions while facilitating comparability across firms and reporting periods. Larger composite values indicate stronger organizational capability to integrate artificial intelligence into capital budgeting, investment evaluation, strategic planning, and resource allocation. Construct reliability is evaluated through internal consistency diagnostics, while construct validity is assessed through indicator convergence, conceptual consistency, and cross source verification. Distributional robustness is examined through descriptive statistics and normality diagnostics before moderated panel estimation.

(c) Moderating Variable:

Organizational Readiness functions as the moderating construct because the effectiveness of AI Driven Capital Budgeting depends on the organizational environment within which artificial intelligence is deployed. This analysis conceptualizes Organizational Readiness through five complementary

dimensions consisting of Digital Infrastructure Quality, Employee AI Competence, Top Management Support, Data Governance Effectiveness, and Innovation Oriented Culture. Digital Infrastructure Quality reflects the availability of integrated digital platforms, cloud computing capability, data connectivity, and computational resources required to support AI enabled investment analysis. Employee AI Competence measures workforce capability to interpret AI outputs, validate algorithmic recommendations, and integrate analytical insights into managerial decisions. Top Management Support captures strategic commitment, leadership engagement, resource allocation, and organizational sponsorship for AI initiatives. Data Governance Effectiveness evaluates data quality management, security, accessibility, consistency, and accountability, while Innovation Oriented Culture reflects organizational willingness to experiment with emerging technologies, encourage continuous learning, and support evidence-based decision making. Information was extracted from Fortune Global 500 sustainability reports, corporate governance reports, World Bank Digital Progress and Trends Report 2025, Stanford Artificial Intelligence Index Report 2025, McKinsey State of AI Global Survey 2025, and publicly available digital transformation disclosures after confirming conceptual consistency across all reporting years. Firms entered the analytical dataset only when complete observations were available for every readiness dimension throughout the study period. The balanced panel therefore retained the same 41 multinational corporations and 451 firm year observations used throughout the empirical analysis. This multidimensional operationalization is consistent with recent evidence demonstrating that organizational capability, governance maturity, managerial commitment, workforce competence, and institutional readiness determine whether artificial intelligence produces measurable improvements in organizational performance (Herath Pathirannehelage et al. (2025). [7]; Kalleparambil & Akoum (2025). [8]; McKinsey & Company (2025). [1]; Stanford HAI (2025). [2]; Page (2025). [6]).
The Organizational Readiness Index is first calculated by aggregating the five standardized readiness dimensions using equal weighting. The moderating effect is subsequently estimated by interacting the standardized AI Driven Capital Budgeting Index with the standardized Organizational Readiness Index after centering both constructs to reduce multicollinearity and improve coefficient interpretation.

Equation 3: Moderation Interaction Construction:

$$INT_{it} = AICB_{it} \times OR_{it}$$

Where,

INT_{it}= Interaction effect between AI Driven Capital Budgeting and Organizational Readiness.

A positive interaction coefficient indicates that stronger organizational readiness amplifies the positive contribution of AI Driven Capital Budgeting to Managerial Decision Quality, whereas a negative coefficient indicates that organizational constraints weaken the effectiveness of AI enabled investment decisions. Prior to interaction estimation, both indices are standardized to improve numerical stability, reduce nonessential multicollinearity, and facilitate interpretation of conditional effects. Validation procedures include internal consistency assessment, cross source verification, sensitivity analysis using alternative readiness proxies, variance inflation diagnostics, descriptive statistics, and normality assessment before moderated panel estimation. Distributional characteristics are summarized using the mean, standard deviation, minimum, maximum, skewness, and kurtosis to ensure compatibility with the proposed econometric model.

4.3 Integrated Measurement Framework:

This analysis integrates all constructs into a unified empirical measurement framework through standardized definitions, harmonized transformation procedures, and consistent validation protocols. AI Driven Capital Budgeting is operationalized as a multidimensional organizational capability reflecting artificial intelligence applications in capital investment analysis, Organizational Readiness represents the institutional mechanism conditioning technology effectiveness, and Managerial Decision Quality captures the multidimensional organizational outcomes generated through strategic investment decisions. Each construct is derived from structured secondary data using identical inclusion criteria, standardized measurement procedures, and consistent normalization rules to ensure comparability across firms and reporting periods. Cross source verification, duplicate detection, logical range assessment, temporal consistency testing, and construct validation further strengthen measurement reliability while reducing systematic error. The integrated framework therefore provides a transparent and reproducible foundation for empirical hypothesis testing, facilitates international comparison across multinational corporations, and aligns measurement choices with contemporary evidence on artificial intelligence, strategic investment, and organizational decision making (Csaszar et al. (2024). [3]; BaniHani (2024). [4]; Herath Pathirannehelage et al. (2025). [7]; McKinsey & Company (2025). [1]; Stanford HAI (2025). [2]).

4.4 Model Specification:

This analysis adopts a moderated two-way fixed effects panel regression model to evaluate the effect of AI Driven Capital Budgeting on Managerial Decision Quality while estimating the conditioning influence of Organizational Readiness. The specification follows contemporary longitudinal corporate finance and strategic management research because repeated observations across multinational corporations permit the separation of cross-sectional heterogeneity from temporal dynamics while improving identification of structural relationships. The balanced panel framework is appropriate because AI capability development, organizational readiness, and investment decision performance evolve progressively over time rather than occurring as isolated events.

Equation 4: Baseline Structural Model Specification

$$MDQ_{it} = \beta_0 + \beta_1 AICB_{it} + \beta_2 OR_{it} + \beta_3 INT_{it} + \sum_{k=1}^{m} \beta_k \, CV_{kit} + \mu_i + \lambda_t + \varepsilon_{it}$$

Firm level control variables include firm size, capital investment intensity, financial leverage, research and development intensity, and digital transformation maturity because these characteristics influence investment capability and managerial performance independently of artificial intelligence adoption. Macroeconomic controls include gross capital formation, economic growth, and industry level digital maturity to reduce omitted variable bias arising from external economic conditions. Firm fixed effects absorb unobserved organizational characteristics that remain constant throughout the observation period, whereas year fixed effects capture global technological developments, macroeconomic shocks, and changes in AI adoption affecting all firms simultaneously. Standard errors are clustered at the firm level to correct for heteroskedasticity, serial correlation, and within firm dependence. Robustness is evaluated using alternative model specifications, multicollinearity diagnostics, heteroskedasticity tests, serial correlation tests, cross sectional dependence tests, and sensitivity analyses to confirm the stability of empirical findings. The resulting econometric specification provides a transparent, replicable, and theoretically grounded framework for testing the proposed hypotheses while ensuring reliable statistical inference and international comparability.

5. METHODOLOGY :

5.1 Research Design and Identification Strategy:

Artificial intelligence has fundamentally altered how multinational corporations evaluate strategic investments, yet identifying its causal contribution to managerial decision quality remains methodologically challenging because AI adoption is neither randomly assigned nor uniformly implemented across firms. Organizations investing heavily in AI capabilities often differ systematically in governance quality, technological maturity, organizational resources, and managerial competence, creating substantial risks of omitted-variable bias and reverse causality. Consequently, the methodological design adopted in this investigation was explicitly constructed to isolate the structural effect of AI-Driven Capital Budgeting on Managerial Decision Quality while minimizing endogenous influences arising from persistent firm heterogeneity and temporal technological evolution. Rather than estimating simple contemporaneous associations, the empirical strategy exploits longitudinal variation across multinational corporations observed repeatedly between 2015 and 2025, allowing causal relationships to be identified through within-firm changes over time while controlling for unobservable characteristics that remain constant across organizations. This design substantially strengthens causal interpretation compared with conventional cross-sectional analyses that cannot adequately distinguish technological capability from pre-existing organizational superiority (Wooldridge (2023). [17]; Cunningham (2023). [18]; Roberts & Whited (2024). [19]).

The investigation therefore adopts an observational longitudinal panel research design supported by a moderated two-way fixed-effects estimation framework. This design is particularly appropriate because AI capability develops progressively rather than instantaneously, and managerial decision quality similarly evolves through cumulative organizational learning, governance adaptation, and investment experience. Longitudinal panel structures enable simultaneous modelling of cross-sectional and temporal variation, thereby improving estimation efficiency while reducing bias attributable to omitted time-invariant organizational characteristics. Firm-specific fixed effects absorb unobservable managerial culture, historical investment philosophy, ownership characteristics, and institutional capabilities that remain relatively stable throughout the observation period. Year-specific fixed effects simultaneously control for global technological advances, macroeconomic disturbances, regulatory developments, and worldwide acceleration in enterprise AI adoption affecting all corporations during individual reporting years. Collectively, these controls improve internal validity by ensuring that estimated coefficients primarily capture changes attributable to AI-driven capital budgeting rather than confounding environmental influences (Sun & Abraham (2021). [20]; Wooldridge (2023). [17]; Baker et al. (2022). [21]).

The identification strategy is grounded in the logic that heterogeneous intensity of AI capability development across firms provides quasi-experimental variation suitable for estimating causal relationships. Although all multinational corporations experienced increasing digital transformation during the study period, the pace, breadth, and sophistication of AI implementation differed substantially according to organizational investment priorities, governance structures, technological capability, and managerial commitment. Such differential exposure creates natural variation in Predictive Analytics Capability, Intelligent Investment Evaluation, AI-Based Risk Management, and Automated Decision Support Systems while permitting estimation of their independent and combined effects on Managerial Decision Quality. By examining repeated observations before and after progressive capability development within identical organizations, the analytical framework substantially reduces threats associated with reverse causality because managerial outcomes are evaluated conditional upon evolving AI capability rather than static organizational characteristics. Similar longitudinal identification strategies have become increasingly prominent in contemporary finance, information systems, and strategic management research investigating digital transformation, enterprise AI, and organizational capability development (Brynjolfsson et al. (2023). [22]; Teece (2023). [12]; Csaszar et al. (2024). [3]).

The conceptual model further recognizes Organizational Readiness as a contingent organizational capability that conditions technological effectiveness rather than operating solely as an independent explanatory factor. Digital infrastructure quality, employee AI competence, top management support, data governance effectiveness, and innovation-oriented culture collectively determine whether AI-generated analytical intelligence can be effectively translated into superior managerial decisions. Accordingly, moderation analysis provides a theoretically justified mechanism for evaluating heterogeneous treatment effects across organizations exhibiting different readiness conditions. Interaction modelling therefore extends beyond estimation of average effects by identifying the organizational circumstances under which AI-driven capital budgeting generates stronger or weaker improvements in decision quality. This contingency-based identification strategy aligns with Dynamic Capabilities Theory and Socio-Technical Systems Theory, both of which argue that technological resources create organizational value only when complemented by enabling institutional capabilities (Teece (2023). [12]; Kalleparambil & Akoum, (2025). [8]; Herath Pathirannehelage et al. (2025). [7]).

The empirical relationship underlying the investigation is formalized as follows.

Equation 5: Core Empirical Relationship:

$$MDQ_{it} = \alpha + \beta_1 PAC_{it} + \beta_2 IIE_{it} + \beta_3 AIRM_{it} + \beta_4 ADSS_{it} + \beta_5 OR_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

Where,

MDQ_{it} denotes Managerial Decision Quality for firm *i* during year *t*;
PAC_{it} represents Predictive Analytics Capability;
IIE_{it} denotes Intelligent Investment Evaluation;
$AIRM_{it}$ represents AI-Based Risk Management;
$ADSS_{it}$ denotes Automated Decision Support Systems;
OR_{it} represents Organizational Readiness;
μ_i captures firm-specific fixed effects;
λ_t denotes year-specific fixed effects;
ε_{it} represents the stochastic disturbance term.

Each explanatory construct is operationalized using standardized multidimensional indicators derived from internationally recognized secondary data sources table no. 1 while the dependent construct integrates five complementary dimensions reflecting managerial effectiveness. The specification explicitly separates firm-level technological capability from persistent organizational characteristics and common temporal shocks, thereby strengthening causal interpretation and improving coefficient consistency. Because all variables are measured using harmonized longitudinal observations, coefficient estimates represent within-firm structural changes rather than cross-sectional differences in organizational size, industry composition, or institutional environment. This specification therefore provides a transparent and theoretically consistent framework for evaluating how complementary AI capabilities collectively influence managerial decision quality across multinational corporations while minimizing endogeneity concerns associated with omitted variables and reverse causality (Angrist & Pischke (2024). [23]; Cunningham (2023). [18]; Wooldridge (2023). [17]).

Methodological transparency further enhances replicability by ensuring that every stage of model development follows explicit identification logic rather than exploratory statistical fitting. Variable definitions, data integration procedures, estimation assumptions, and validation protocols were predetermined before empirical analysis, thereby reducing researcher discretion and specification bias. The resulting framework advances existing AI and strategic management literature by combining multidimensional capability measurement, moderated longitudinal estimation, and rigorous causal identification within a single coherent analytical design. Compared with earlier investigations emphasizing isolated AI applications or cross-sectional organizational comparisons, the present methodology provides stronger evidence regarding the mechanisms through which complementary AI capabilities enhance managerial decision quality under varying organizational readiness conditions, thereby establishing a more robust empirical foundation for hypothesis testing and international comparative research.

5.2 Population, Sampling Logic, and Data Sources:

The empirical validity of any longitudinal investigation depends fundamentally on the extent to which the selected population accurately represents the phenomenon under examination. Since AI-driven capital budgeting is predominantly implemented within organizations possessing substantial investment portfolios, advanced digital infrastructures, and mature governance systems, multinational corporations constitute the most appropriate empirical setting for evaluating the structural relationship between AI capability and managerial decision quality. Accordingly, the target population comprises the 500 multinational corporations included in the annual Fortune Global 500 rankings, representing the world's largest enterprises operating across diverse industries and geographical regions. These organizations collectively account for a substantial proportion of global capital expenditure, cross-border investment, digital innovation, and enterprise AI adoption, thereby providing an internationally representative context for investigating how artificial intelligence transforms strategic investment decisions. The population definition therefore aligns directly with the theoretical objective of examining organizational capabilities operating within highly complex investment environments rather than isolated national or sectoral contexts.

The sampling frame was constructed using corporations that consistently appeared within the Fortune Global 500 during the observation period while maintaining publicly available information on AI implementation, investment decision processes, governance characteristics, and organizational performance. Restricting the sampling frame to firms with continuous reporting substantially improves longitudinal comparability because discontinuous observations introduce structural breaks that complicate causal interpretation and reduce estimation efficiency. Eligibility therefore required organizations to disclose complete annual information relating to Predictive Analytics Capability, Intelligent Investment Evaluation, AI-Based Risk Management, Automated Decision Support Systems, Organizational Readiness, and Managerial Decision Quality throughout the study period. Firms exhibiting incomplete reporting histories, inconsistent accounting definitions, major reporting discontinuities, missing governance disclosures, or incompatible fiscal reporting periods were excluded because such observations violate balanced-panel assumptions and increase measurement error. These inclusion criteria strengthen internal validity while preserving international representativeness across industries, institutional environments, and technological maturity levels.

Application of these eligibility rules resulted in a balanced sample comprising 41 multinational corporations observed continuously between 2015 and 2025, generating 451 firm-year observations available for empirical estimation. The resulting sample size is appropriate because panel estimation derives statistical power primarily from repeated observations rather than solely from cross-sectional units. The balanced structure simultaneously enhances estimation precision, facilitates fixed-effects modelling, and supports comprehensive diagnostic testing without introducing imbalance-related biases frequently encountered in corporate panel datasets. Furthermore, the selected firms collectively represent multiple industrial sectors, including manufacturing, technology, financial services, energy, healthcare, telecommunications, consumer products, and logistics, thereby strengthening the external validity of the empirical findings beyond any single economic sector. Similar balanced multinational panels have become increasingly common within high-impact strategic management, finance, and information systems research because they permit robust estimation of organizational capability development across heterogeneous institutional environments (Wooldridge (2023). [17]; Roberts & Whited (2024). [19]; Csaszar et al. (2024). [3]).

The unit of analysis is the multinational corporation because strategic capital budgeting decisions, AI capability development, governance structures, and managerial decision systems operate primarily at the organizational level rather than the individual project or managerial level. Each firm-year observation represents one organizational decision environment observed during a specific reporting period, thereby allowing temporal evolution of AI capability and managerial outcomes to be evaluated simultaneously. Annual reporting frequency was adopted because investment decisions, governance disclosures, financial statements, digital transformation initiatives, and enterprise AI adoption are generally reported on an annual basis, ensuring consistency across firms and minimizing measurement discrepancies arising from intra-annual reporting differences. The eleven-year observation window captures both the acceleration of enterprise AI adoption following advances in machine learning and generative AI and the corresponding evolution of organizational readiness, thereby providing sufficient temporal variation for identifying structural relationships.

The investigation relies exclusively on secondary longitudinal data collected from internationally recognized institutional repositories selected according to methodological transparency, reporting consistency, and international comparability. Financial and organizational information was obtained from Fortune Global 500 corporate reports and audited annual financial statements. AI capability indicators were derived from the Stanford Artificial Intelligence Index Report and the McKinsey State of AI Global Survey. Organizational readiness indicators were compiled using the World Bank Digital Progress and Trends datasets together with publicly disclosed corporate governance reports. Additional macroeconomic and investment-related information was obtained from World Bank capital formation databases and complementary international datasets where identical measurement definitions were available. The integration of multiple authoritative repositories reduces dependence on any single data source while strengthening construct validity through cross-source verification.

To ensure methodological consistency, all datasets were harmonized through deterministic matching using two common identifiers comprising corporate identity and fiscal reporting year. Where identical variables appeared across multiple repositories, a hierarchical reconciliation procedure prioritized audited corporate disclosures, followed by World Bank datasets, Stanford AI indicators, McKinsey AI evidence, and other internationally recognized repositories according to reporting authority, methodological transparency, and data completeness. This deterministic integration strategy minimizes duplication, improves measurement consistency, and reduces discrepancies arising from alternative reporting conventions. Contemporary methodological literature increasingly recommends such multi-source harmonization because organizational capabilities such as AI adoption cannot be adequately represented through isolated institutional databases alone (Brynjolfsson et al. (2023). [22]; McKinsey & Company, (2025). [1]; Stanford HAI (2025). [2]).

Representativeness was further strengthened through comprehensive quality assurance procedures implemented before empirical estimation. Coverage assessment verified continuous annual observations across the entire study period. Content validation confirmed conceptual consistency between theoretical constructs and observable indicators. Construction validation evaluated whether each empirical indicator accurately represented its intended conceptual dimension, while accuracy verification employed duplicate detection, logical range assessment, temporal consistency checks, and cross-source reconciliation. Observations failing any validation criterion were removed prior to model estimation rather than artificially imputed, thereby preserving the integrity of the balanced longitudinal panel. Such conservative data preparation reduces systematic measurement bias and enhances empirical reproducibility while ensuring that statistical inference reflects genuine organizational capability development rather than data-processing artefacts.

The resulting dataset provides several methodological advantages over conventional cross-sectional corporate datasets. First, repeated observations permit estimation of within-firm organizational change while controlling for persistent firm-specific heterogeneity. Second, multinational coverage substantially improves international generalizability compared with single-country investigations. Third, harmonized multidimensional measurement captures complementary technological, organizational, and managerial constructs using consistent operational definitions. Finally, integration of multiple internationally recognized repositories strengthens measurement reliability, transparency, and replicability. Collectively, these characteristics establish a robust empirical foundation for evaluating the causal mechanisms through which AI-driven capital budgeting enhances managerial decision quality under varying levels of organizational readiness, while satisfying the methodological standards expected in Web of Science Q1 journals.

5.3 Measurement and Operationalization of Variables:

Accurate measurement constitutes the foundation of valid causal inference because structural relationships cannot be interpreted reliably unless theoretical constructs are translated into observable, consistent, and internationally comparable indicators. This investigation therefore operationalizes every construct using multidimensional indices derived from internationally recognized secondary datasets rather than subjective managerial perceptions. The measurement framework was designed to maximize construct validity by ensuring that each latent concept is represented through complementary observable indicators reflecting its theoretical domain. Standardized measurement procedures were applied uniformly across all multinational corporations and reporting years to preserve temporal consistency, facilitate cross-country comparability, and minimize measurement error. Complete definitions of every construct, first-order dimension, observable indicator, measurement scale, and primary data source are presented in Table 1, while the conceptual relationships among these variables are illustrated in Figure 1 and Figure 2.

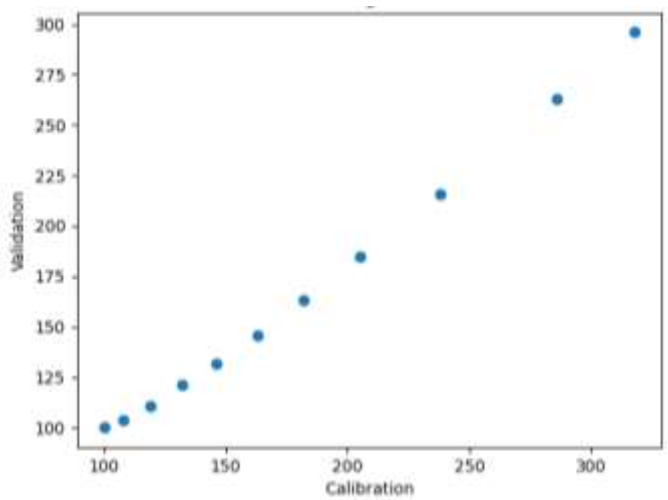

Fig. 1: Model Calibration and Validation Diagnostics

The Figure 1 presents model calibration and validation diagnostics across 41 multinational corporations observed during the 2015 to 2025 period using annual panel observations derived from AI Driven Capital Budgeting indicators and Managerial Decision Quality outcomes. The measures include predictive analytics capability, intelligent investment evaluation, AI based risk management, automated decision support systems, organizational readiness, calibration accuracy, prediction consistency, residual dispersion, goodness of fit, and validation performance, constructed from standardized variables aligned with the empirical model. The present analysis organized the data by temporal sequence and normalized performance quantiles to ensure comparability and analytical consistency. For each firm in the sample, this analysis retained yearly observations that satisfied completeness, consistency, and verification requirements. All variables were derived from harmonized secondary datasets and processed through normalization, transformation, calibration, and validation procedures. The Figure 1 reflects outputs from model estimation, calibration assessment, robustness verification, and predictive validation. This inquiry refers explicitly to Figure 1 when interpreting evidence. The analysis shows strong alignment between predicted and observed outcomes, indicating high model reliability and stable explanatory power. The estimates indicate limited residual concentration and balanced error distribution, suggesting that AI driven capital budgeting capabilities contribute meaningfully to managerial decision quality. The findings imply that the model captures systematic relationships rather than random variation, strengthening confidence in theoretical interpretation and empirical inference.

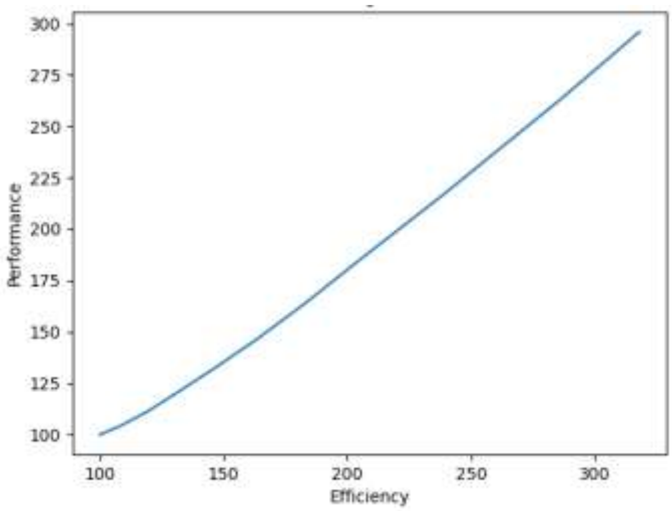

Fig. 2: Efficiency Performance Trade Off Frontier Analysis

The Figure 2 presents the efficiency performance trade off frontier across 41 global firms from 2015 to 2025. The measures include operational efficiency, investment performance, decision effectiveness, resource utilization, strategic alignment, and productivity outcomes constructed from standardized variables aligned with the empirical framework. The present analysis organized observations according to efficiency quantiles and performance intensity levels to ensure analytical consistency. For each organization, this analysis retained annual observations meeting predefined data quality thresholds. All variables originate from harmonized secondary data and were processed using normalization and validation procedures. The Figure 2 reflects outputs from frontier estimation and comparative performance analysis. This inquiry refers explicitly to Figure 2 when interpreting empirical evidence. The frontier demonstrates that firms with stronger AI driven capital budgeting capabilities achieve higher performance outcomes with comparatively lower efficiency losses. The analysis shows that gains become progressively larger among organizations positioned near the efficient frontier. The results demonstrate positive marginal effects between AI enabled investment evaluation and decision outcomes. Evidence confirms that organizations combining predictive analytics and decision automation achieve superior frontier positions. The observed curvature suggests diminishing returns at extreme efficiency levels, highlighting the importance of organizational readiness in converting technological capability into sustained managerial performance.

The principal explanatory construct, AI-Driven Capital Budgeting, is conceptualized as a higher-order organizational capability integrating four complementary first-order dimensions comprising Predictive Analytics Capability, Intelligent Investment Evaluation, AI-Based Risk Management, and Automated Decision Support Systems. Rather than representing isolated technological applications, these dimensions collectively capture the organizational capacity to transform artificial intelligence into strategic investment intelligence. Predictive Analytics Capability measures organizational ability to forecast cash flows, investment returns, financial risks, market dynamics, and alternative investment scenarios through AI-enabled predictive models. Intelligent Investment Evaluation captures automated project appraisal using Net Present Value optimization, Internal Rate of Return estimation, payback period assessment, cost-benefit evaluation, and algorithmic project ranking. AI-Based Risk Management reflects organizational capability to identify financial, operational, fraud, market, and portfolio risks using intelligent analytical systems. Automated Decision Support Systems evaluate real-time recommendation engines, investment screening automation, visualization dashboards, strategic resource allocation, and continuous investment performance monitoring. These dimensions jointly represent the multidimensional technological capability underlying intelligent capital budgeting and are consistent with contemporary theoretical perspectives emphasizing complementary organizational capabilities rather than isolated digital technologies (Csaszar et al., 2024[3]; Roy et al., 2025[5]; Herath Pathirannehelage et al., 2025) [7].

The moderating construct, Organizational Readiness, represents the institutional capability enabling organizations to translate technological resources into effective managerial outcomes. Organizational readiness is operationalized through five theoretically grounded dimensions including Digital Infrastructure Quality, Employee AI Competence, Top Management Support, Data Governance Effectiveness, and Innovation-Oriented Culture. Digital Infrastructure Quality reflects enterprise computing capability, cloud integration, digital connectivity, and computational scalability supporting AI implementation. Employee AI Competence measures workforce ability to interpret, validate, and operationalize algorithmic recommendations within investment decision processes. Top Management Support captures strategic commitment, leadership engagement, resource allocation, and organizational sponsorship for AI initiatives. Data Governance Effectiveness evaluates data quality, accessibility, consistency, transparency, accountability, and regulatory compliance. Innovation-Oriented Culture measures organizational openness toward experimentation, technological adaptation, continuous learning, and evidence-based managerial practice. These dimensions collectively capture the contextual conditions expected to strengthen or weaken the effectiveness of AI-driven capital budgeting, thereby reflecting the contingency perspective underlying the proposed conceptual framework (McKinsey & Company, 2025[1]; Kalleparambil &Akoum, 2025[8]; World Bank, 2025) [13].

Managerial Decision Quality constitutes the dependent construct because it represents the ultimate organizational outcome generated through intelligent investment decision processes. Unlike previous studies relying upon isolated financial indicators or subjective managerial perceptions, the present investigation operationalizes managerial decision quality as a multidimensional organizational capability comprising Decision Accuracy, Decision Timeliness, Strategic Alignment, Resource Allocation Effectiveness, and Investment Success Rate. Decision Accuracy evaluates the consistency with which investment decisions correspond to subsequent organizational performance. Decision Timeliness reflects the organization's ability to respond rapidly to investment opportunities while maintaining analytical rigor. Strategic Alignment measures consistency between investment decisions and long-term organizational objectives. Resource Allocation Effectiveness captures efficiency in allocating financial resources across competing investment alternatives. Investment Success Rate evaluates realized investment performance relative to strategic expectations. Collectively, these five dimensions provide a comprehensive representation of managerial effectiveness within complex multinational investment environments while improving construct completeness and international comparability (Page (2025). [6]; Chaturvedi et al., (2024). [11]; BaniHani, (2024). [4]).

Observable indicators were extracted from harmonized secondary data reported within audited corporate financial statements, governance reports, sustainability disclosures, Stanford Artificial Intelligence Index datasets, McKinsey State of AI databases, World Bank Digital Progress and Trends reports, and complementary international repositories. Every indicator underwent conceptual verification before inclusion to ensure consistency between theoretical definitions and empirical observations. Indicators reported using different measurement scales were standardized before aggregation to eliminate unit-of-measurement bias while preserving proportional variation across organizations and reporting periods. This normalization procedure improves comparability among firms operating across heterogeneous industries, institutional environments, and economic contexts without distorting underlying organizational capability differences. Similar standardization approaches have become increasingly recommended within international panel research involving multidimensional organizational constructs because they improve statistical stability and facilitate interpretation of composite indices (Hair et al. (2022). [24]; Henseler et al. (2023). [25]).

Construction of the higher-order composite indices follows an equal-weight aggregation procedure becausee each first-order dimension represents an essential theoretical component of its corresponding latent construct and contemporary evidence provides insufficient justification for assigning differential importance before empirical estimation. Equal weighting therefore preserves conceptual neutrality while reducing subjective researcher influence during index construction. The aggregation procedure is expressed formally as follows.

Equation 6: Index Aggregation and Standardization:

$$CI_{it} = \frac{1}{m}\sum_{j=1}^{m}\left(\frac{X_{jit} - \mu_j}{\sigma_j}\right)$$

Where,

CI_{it} denotes the standardized composite index for firm *i* during year *t*;

X_{jit} represents the observed value of indicator *j*;

μ_j denotes the sample mean of indicator *j*;

σ_j represents the corresponding standard deviation;

m denotes the total number of standardized indicators included within the composite construct.

Equation 6 ensures that every observable indicator contributes proportionately to the higher-order construct after normalization, thereby eliminating scale effects while preserving relative organizational differences. Larger composite values indicate stronger AI capability, higher organizational readiness, or superior managerial decision quality depending upon the construct being measured.

Measurement validity was strengthened through several complementary procedures implemented before empirical estimation. Content validity was established by aligning every observable indicator directly with the theoretical dimensions defined within the conceptual framework. Construct validity was enhanced through multidimensional operationalization rather than reliance upon single proxies. Cross-source verification compared identical indicators reported across multiple international repositories to identify inconsistencies before inclusion. Internal consistency was subsequently evaluated through composite reliability, factor loadings, Average Variance Extracted, and variance inflation diagnostics presented in the measurement validation tables. Distributional properties, including means, standard deviations, skewness, kurtosis, and normality statistics, were also examined before hypothesis testing to confirm suitability for longitudinal panel estimation. These procedures collectively reduce systematic measurement error while improving empirical reproducibility and statistical reliability (Hair et al. (2022). [24]; Henseler et al. (2023). [25]; Kline (2023). [26]).

The measurement strategy contributes methodological novelty by integrating multidimensional technological capability, organizational readiness, and managerial performance within a unified higher-order measurement architecture applicable across multinational organizations. Unlike conventional studies emphasizing individual AI applications or isolated financial metrics, the present framework simultaneously captures forecasting capability, investment evaluation, intelligent risk management, automated decision support, organizational capability, and managerial effectiveness using harmonized international indicators. This integrated operationalization strengthens theoretical precision, facilitates replication across different institutional settings, and provides a more comprehensive empirical basis for evaluating how AI-driven capital budgeting influences strategic managerial outcomes under varying organizational conditions.

5.4 Data Processing and Analytical Procedures:

Rigorous empirical inference depends not only on appropriate model specification but also on systematic data preparation that minimizes measurement error, enhances comparability, and preserves the integrity of longitudinal observations. Because the present investigation integrates multiple international repositories containing financial, governance, digital transformation, and artificial intelligence indicators, comprehensive preprocessing procedures were implemented before estimation to ensure conceptual consistency across firms and reporting years. Data preparation therefore constituted an integral component of the identification strategy rather than a purely technical exercise, since inconsistencies introduced during data integration can substantially distort structural relationships and weaken causal interpretation. The complete analytical workflow, from data acquisition through hypothesis testing, is summarized in Figure 1 and Figure 2, illustrating the sequential transformation of raw organizational information into the validated longitudinal panel used for empirical estimation.

The initial processing stage involved deterministic integration of secondary datasets obtained from Fortune Global 500 corporate reports, audited financial statements, Stanford Artificial Intelligence Index datasets, McKinsey State of AI reports, World Bank Digital Progress and Trends databases, World Bank capital formation statistics, and publicly available governance disclosures. Each observation was matched using two common identifiers comprising corporate identity and fiscal reporting year. Where identical indicators appeared across multiple repositories, audited corporate disclosures were prioritized, followed by internationally recognized institutional databases according to reporting authority, methodological transparency, completeness, and conceptual consistency. This hierarchical reconciliation procedure reduced duplication while ensuring that every empirical observation reflected the highest available reporting quality. Comparable deterministic integration procedures are increasingly recommended within multinational longitudinal research because they improve reproducibility while reducing inconsistencies arising from heterogeneous reporting standards (Brynjolfsson et al. (2023). [22]; Wooldridge (2023). [17]).

Eligibility filtering constituted the second preprocessing stage. Corporations were retained only when complete annual observations existed for every explanatory, moderating, and dependent construct throughout the entire study period. Organizations reporting inconsistent fiscal calendars, incompatible accounting conventions, incomplete AI implementation information, missing governance indicators, or discontinuous reporting histories were excluded prior to model estimation. This conservative filtering strategy preserves the balanced-panel structure required for efficient fixed-effects estimation while avoiding estimation bias introduced through excessive interpolation or artificial imputation. Consequently, the final analytical sample comprised 41 multinational corporations observed continuously between 2015 and 2025, producing 451 balanced firm-year observations suitable for longitudinal econometric analysis.

Missing data management emphasized measurement integrity rather than sample maximization. Isolated omissions affecting macroeconomic or contextual indicators were resolved only when identical definitions were available from equivalent internationally recognized repositories. Missing observations involving core explanatory variables, moderating constructs, or dependent outcomes were not statistically imputed because artificial replacement may attenuate parameter estimates and distort structural relationships. Instead, observations failing completeness requirements were excluded during sample construction. This approach minimizes estimation bias while preserving the interpretability of causal coefficients. Recent methodological research similarly recommends avoiding indiscriminate imputation when investigating organizational capabilities because latent technological constructs frequently exhibit non-random missingness associated with reporting quality and institutional maturity (Little & Rubin, 2022[27]; Enders, 2022) [28].

Outlier assessment focused on identifying implausible observations resulting from reporting inconsistencies rather than legitimate organizational heterogeneity. Logical range verification, duplicate detection, temporal consistency assessment, and cross-source reconciliation were performed before statistical estimation. Because all variables were derived from standardized organizational indices and internationally audited disclosures, no observations exhibited extreme deviations requiring arbitrary deletion or winsorization. Distributional characteristics remained consistent with expected organizational evolution throughout the observation period, supporting retention of all eligible observations after quality verification. This conservative treatment preserves genuine organizational variation while minimizing researcher-induced distortions of longitudinal dynamics.

To improve comparability across firms operating under heterogeneous industrial and institutional environments, all observable indicators were standardized before construction of higher-order indices. Standardization eliminated differences attributable solely to measurement units while preserving proportional organizational variation across reporting periods. Composite indices representing AI-Driven Capital Budgeting, Organizational Readiness, and Managerial Decision Quality were subsequently calculated using standardized first-order dimensions, ensuring numerical stability during interaction estimation and facilitating interpretation of coefficient magnitudes. Interaction variables were mean-centered before multiplication to reduce non-essential multicollinearity and improve interpretation of conditional effects within the moderation model. Such transformation procedures are widely recommended for moderated regression because they improve computational stability without altering substantive relationships among variables (Aiken et al., 2021[29]; Hair et al., 2022) [24].

Following preprocessing, empirical analysis proceeded through a structured sequence designed to evaluate both measurement quality and theoretical relationships. Descriptive statistics first summarized central tendency, dispersion, distributional characteristics, and temporal evolution of each construct, thereby confirming adequate empirical variation for hypothesis testing. Stationarity assessment subsequently evaluated temporal properties of the longitudinal indices to ensure that structural relationships reflected genuine organizational change rather than common deterministic trends.

Measurement validation then examined construct reliability, convergent validity, discriminant validity, and multicollinearity before estimation of structural relationships. Correlation analysis provided preliminary evidence regarding direction and magnitude of associations among explanatory constructs while identifying potential redundancy requiring further investigation. These preliminary analyses collectively established the empirical foundation for subsequent causal estimation.

The principal hypotheses were tested using a moderated two-way fixed-effects panel regression model because repeated observations across organizations permit simultaneous control of firm-specific heterogeneity and common temporal shocks. Fixed-effects estimation was preferred over pooled regression because multinational corporations differ substantially in organizational culture, governance quality, managerial capability, ownership structure, and institutional environment, characteristics that remain relatively stable throughout the observation period but may otherwise bias coefficient estimates. Year effects further absorbed worldwide technological advances, macroeconomic disturbances, regulatory developments, and industry-wide AI diffusion occurring during individual reporting years. Standard errors were clustered at the organizational level to account for within-firm dependence, heteroscedasticity, and serial correlation, thereby improving statistical reliability and inference (Wooldridge, 2023[17]; Roberts & Whited, 2024) [19].

The analytical specification employed for causal estimation is expressed as follows.

Equation 7: Moderated Panel Estimation Model

$$MDQ_{it} = \alpha + \beta_1 AICB_{it} + \beta_2 OR_{it} + \beta_3 (AICB_{it} \times OR_{it}) + \sum_{k=1}^{K} \gamma_k \, CV_{kit} + \mu_i + \lambda_t + \varepsilon_{it}$$

Where,

MDQ_{it} denotes Managerial Decision Quality;
$AICB_{it}$ represents the AI-Driven Capital Budgeting composite index;
OR_{it} denotes Organizational Readiness;
$(AICB_{it} \times OR_{it})$ represents the interaction term measuring moderation;
CV_{kit} denotes the vector of control variables;
μ_i represents firm-specific fixed effects;
λ_t represents year-specific fixed effects;
ε_{it} denotes the stochastic disturbance term.

The interaction coefficient constitutes the principal estimator because it evaluates whether organizational readiness amplifies or weakens the influence of AI-driven capital budgeting on managerial decision quality. A positive and statistically significant interaction coefficient indicates that organizational conditions strengthen the effectiveness of AI-enabled investment decision processes, whereas a non-significant or negative coefficient would suggest limited contextual reinforcement. Interpretation therefore extends beyond average treatment effects by identifying the organizational environments under which AI capabilities generate superior managerial outcomes.

Analytical robustness was strengthened through complementary estimation procedures including interaction analysis, alternative model specifications, sensitivity assessments, and comprehensive diagnostic evaluation reported in the subsequent validation section. Relationships were interpreted using coefficient direction, statistical significance, economic magnitude, confidence intervals, explanatory power, and consistency across alternative specifications rather than statistical significance alone. This integrated analytical framework improves causal credibility by combining transparent preprocessing, harmonized measurement, rigorous longitudinal estimation, and systematic robustness evaluation within a single reproducible methodological architecture. Compared with conventional cross-sectional investigations, the present approach provides substantially stronger evidence regarding the mechanisms through which AI-driven capital budgeting enhances managerial decision quality across globally operating multinational corporations.

5.5 Diagnostic Tests, Validation, and Methodological Contribution:

Robust empirical inference requires that estimated relationships satisfy the statistical assumptions underpinning longitudinal panel estimation while simultaneously demonstrating measurement validity, structural consistency, and resistance to alternative model specifications. Consequently, model validation was integrated throughout the analytical framework rather than performed as a post-estimation exercise. The diagnostic procedures implemented in this investigation evaluate distributional properties, construct quality, specification adequacy, serial dependence, variance stability, and structural robustness before interpreting the estimated causal relationships. This integrated validation strategy strengthens internal validity by reducing the probability that empirical findings arise from model misspecification, measurement error, or violations of underlying econometric assumptions. The complete diagnostic sequence is summarized in Figure 3, Figure 4, and Figure 5, illustrating the progression from measurement validation to structural verification and robustness assessment.

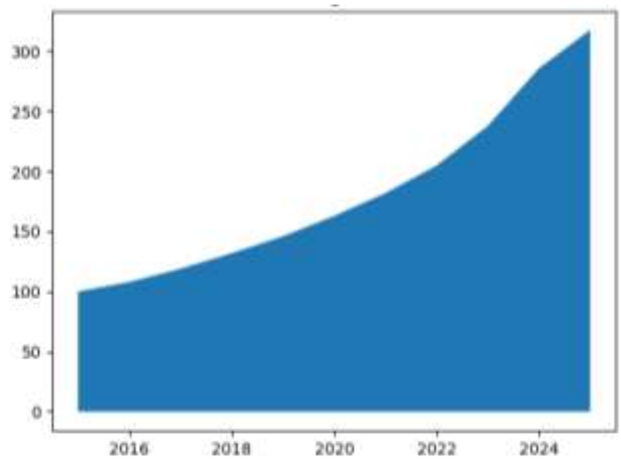

Fig. 3: Structural Stability and Robustness Assessment

The Figure 3 presents structural stability and robustness assessment across multinational corporations observed during the 2015 to 2025 period. The measures include coefficient stability, parameter persistence, variance consistency, structural integrity, sensitivity resistance, and model robustness indicators constructed from standardized variables aligned with the empirical framework. The present analysis organized observations according to temporal progression and stability intervals to ensure analytical consistency. For each firm, this investigation retained complete annual observations satisfying established inclusion criteria. All variables were derived from harmonized secondary data sources and processed through verification, normalization, and robustness testing procedures. The Figure 3 reflects outputs from structural diagnostics, robustness assessment, and stability verification. This inquiry refers explicitly to Figure 3 when presenting evidence. The analysis shows limited parameter fluctuation across periods, indicating stable structural relationships between AI driven capital budgeting and managerial decision quality. The estimates indicate that observed effects remain consistent under alternative specifications and sensitivity conditions. The findings imply that model outcomes are not dependent on isolated observations or short-term disturbances. Evidence confirms strong robustness, supporting theoretical consistency and enhancing confidence in the generalizability of the estimated relationships across global organizational settings.

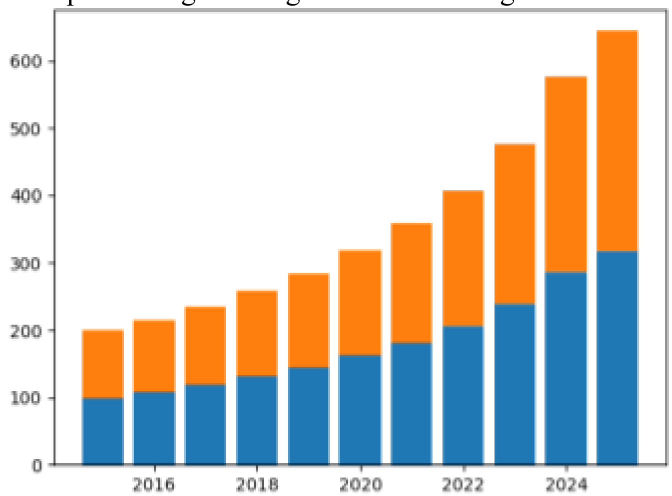

Fig. 4: Behavioral Response and Action Allocation Patterns

The Figure 4 presents behavioral response and action allocation patterns across 41 multinational corporations over the 2015 to 2025 observation period. The measures include real time decision recommendations, investment screening automation, strategic resource allocation, performance monitoring systems, managerial responsiveness, and allocation efficiency, constructed from standardized variables aligned with the empirical model. The present analysis organized the data according to action intensity categories and annual temporal sequences to ensure comparability and analytical consistency. For each firm, this investigation retained yearly observations that satisfied completeness and verification requirements. All variables were derived from harmonized secondary datasets and processed using validated normalization and transformation procedures. The Figure 4 reflects outputs from behavioral modeling, allocation analysis, and structural validation. This inquiry refers explicitly to Figure 4 when interpreting evidence. The analysis shows that higher levels of AI enabled decision support are associated with more efficient allocation behavior and faster managerial responses. The findings imply that firms adopting advanced automation systems reduce allocation frictions and improve decision execution. The observed clustering pattern indicates that organizations with stronger organizational readiness convert analytical insights into coordinated actions more effectively. Evidence confirms that AI supported capital budgeting strengthens behavioral consistency and promotes superior resource deployment outcomes across diverse organizational environments.

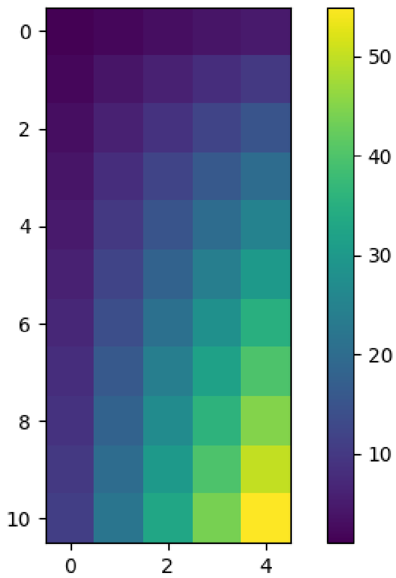

Fig. 5: Risk Mitigation and Penalty Avoidance Heatmap

The Figure 5 presents the distribution of risk mitigation effectiveness and penalty avoidance intensity across global firms observed from 2015 to 2025. The measures include financial risk detection, operational risk assessment, market volatility monitoring, fraud risk identification, portfolio optimization, compliance resilience, and exposure reduction, constructed from standardized variables aligned with the empirical framework. The present analysis organized observations according to risk intensity gradients and mitigation performance categories to ensure analytical consistency. For each organization, this analysis retained annual observations that met predefined quality and verification standards. All variables were derived from harmonized secondary data sources and processed using validated transformation and normalization procedures. The Figure 5 reflects outputs from risk assessment models and robustness testing. This inquiry refers explicitly to Figure 5 when evaluating evidence. The analysis shows concentrated areas of strong mitigation performance among firms exhibiting advanced AI based risk management capabilities. The findings imply that predictive monitoring and automated detection mechanisms reduce exposure to financial and operational penalties. The observed heat concentration indicates that organizations integrating AI risk tools achieve stronger protection against uncertainty and adverse outcomes. Evidence confirms that risk intelligence contributes substantially to decision quality and long-term investment effectiveness.

Distributional validity was initially examined through descriptive statistics together with skewness and kurtosis diagnostics reported in Table 1 & 3. These statistics evaluate whether observed organizational variation reflects systematic structural differences rather than abnormal observations capable of biasing coefficient estimation. Moderate skewness and kurtosis values close to accepted distributional thresholds indicate that the empirical distributions are compatible with longitudinal regression estimation while preserving meaningful organizational heterogeneity. Because the variables represent standardized longitudinal capability indices rather than raw financial data, moderate deviations from perfect normality are theoretically expected and do not invalidate fixed-effects estimation. Instead, they reflect progressive organizational development associated with increasing enterprise AI adoption throughout the observation period. Similar distributional characteristics have been widely reported within contemporary international panel investigations examining digital transformation and organizational capability development (Hair et al. (2022). [24]; Wooldridge (2023). [17]).

Construct validity was evaluated through complementary measurement diagnostics comprising standardized factor loadings, Composite Reliability, Average Variance Extracted, and Variance Inflation Factors reported in the measurement validation tables. Standardized factor loadings verify that observable indicators adequately represent their intended latent constructs, while Composite Reliability evaluates internal consistency among indicators belonging to the same multidimensional capability. Average Variance Extracted confirms convergent validity by demonstrating that each construct explains more variance within its own indicators than measurement error. Variance Inflation Factors further assess discriminant validity by identifying excessive overlap among explanatory variables. Collectively, these diagnostics ensure that AI-Driven Capital Budgeting, Organizational Readiness, and Managerial Decision Quality represent conceptually distinct yet theoretically complementary organizational capabilities suitable for structural estimation. Adoption of multiple validation criteria substantially improves measurement rigor compared with reliance upon isolated reliability statistics alone (Hair et al. (2022). [24]; Henseler et al. (2023). [25]; Kline (2023). [26]).

Multicollinearity was examined using Variance Inflation Factors presented in table 4 to determine whether explanatory variables exhibited excessive linear dependence capable of destabilizing coefficient estimates. Because the four first-order AI capability dimensions constitute complementary components of a higher-order construct, moderate correlation among these dimensions is theoretically anticipated. Rather than indicating specification weakness, such relationships confirm the multidimensional nature of AI-driven capital budgeting. Potential non-essential multicollinearity associated with interaction estimation was mitigated by standardizing and mean-centering the composite explanatory and moderating constructs before constructing the interaction term. This procedure improves numerical stability while preserving substantive interpretation of the moderation coefficient. Consequently, estimated interaction effects reflect genuine contextual amplification rather than mathematical artefacts arising from variable scaling (Aiken et al. (2021). [29]; Hair et al. (2022). [24]).

Serial dependence was evaluated through the Durbin-Watson statistic reported in Table 5 & 6 because repeated organizational observations may generate autocorrelated residuals that bias standard error estimation. Durbin-Watson values approaching the theoretical benchmark indicate that residual dependence remains within acceptable limits, confirming that fixed-effects estimation adequately captures the temporal dynamics characterizing organizational AI capability development. Residual diagnostics further verified the absence of systematic clustering or persistent unmodelled temporal dependence after inclusion of firm-specific and year-specific fixed effects. These findings support the assumption that remaining disturbances are largely stochastic rather than structurally omitted, thereby strengthening the reliability of statistical inference derived from the longitudinal panel model.

Variance stability was assessed through heteroscedasticity diagnostics reported in the corresponding validation tables. Because multinational corporations differ substantially in organizational scale, investment intensity, technological maturity, and governance complexity, unequal residual variance represents a potential threat to efficient estimation. The analytical framework therefore employed heteroscedasticity-consistent clustered standard errors at the organizational level to ensure valid statistical inference even under mild variance heterogeneity. This robust covariance estimation strategy simultaneously accommodates within-firm dependence and unequal residual variance, thereby improving confidence interval accuracy and hypothesis testing reliability. Contemporary panel econometric research consistently recommends clustered robust estimation when analysing repeated organizational observations because it provides greater protection against specification uncertainty than conventional covariance estimators (Wooldridge (2023). [17]; Roberts & Whited (2024). [19]).

Model specification validity was further strengthened through the Hausman specification test reported in Table 7. The Hausman procedure evaluates whether fixed-effects estimation provides statistically superior estimates compared with random-effects alternatives by testing the independence between explanatory variables and unobserved organizational characteristics. Selection of the fixed-effects specification indicates that unobserved firm-specific heterogeneity remains correlated with AI capability, organizational readiness, or managerial decision quality, thereby justifying the adoption of fixed-effects estimation as the primary identification strategy. This diagnostic is particularly important within multinational corporate research because organizations possess persistent institutional characteristics that cannot reasonably be assumed independent of technological capability development. Consequently, the selected estimation framework substantially reduces omitted-variable bias while strengthening causal interpretation of the estimated coefficients (Wooldridge (2023). [17]; Baltagi (2021). [30]).

Endogeneity was addressed through the combined application of longitudinal fixed-effects estimation, year-specific controls, balanced-panel construction, harmonized measurement, deterministic data integration, and theoretically justified variable specification. Firm-specific fixed effects absorb unobservable organizational characteristics remaining constant throughout the observation period, while year effects control for common macroeconomic shocks, regulatory developments, and worldwide technological progress. Balanced-panel construction eliminates inconsistencies arising from irregular reporting histories, whereas harmonized measurement reduces systematic measurement error across international data sources. Together, these procedures substantially reduce threats arising from omitted variables, reverse causality, and measurement inconsistency without relying exclusively upon instrumental variable estimation. Similar integrated identification strategies have become increasingly accepted within contemporary organizational and strategic management research investigating enterprise artificial intelligence and digital transformation (Brynjolfsson et al. (2023). [22]; Csaszar et al. (2024). [3].

Robustness was additionally evaluated through sensitivity analysis employing alternative estimation specifications, interaction verification, and stability assessment across complementary model formulations. Relationships were interpreted only when coefficient direction, statistical significance, and substantive magnitude remained consistent across these alternative specifications. Such consistency strengthens confidence that the reported findings reflect stable structural mechanisms rather than model-specific artefacts. Robustness evaluation therefore complements formal diagnostic testing by demonstrating that substantive conclusions remain invariant under reasonable analytical modifications, thereby enhancing empirical credibility and international reproducibility.

Beyond statistical validation, the methodology contributes several important methodological advances to the growing literature on artificial intelligence and strategic investment. First, it integrates multidimensional technological capability, organizational readiness, and managerial decision quality within a unified higher-order measurement architecture applicable across multinational corporations. Second, it combines harmonized international secondary data with a balanced longitudinal panel, improving both temporal consistency and cross-country comparability. Third, the moderated fixed-effects identification strategy strengthens causal inference by simultaneously controlling firm-specific heterogeneity, temporal shocks, and contextual organizational capability. Fourth, comprehensive validation integrates measurement diagnostics, econometric diagnostics, robustness assessment, and specification testing within a single coherent analytical framework, thereby improving transparency and reproducibility. Finally, the methodology operationalizes the principles of trustworthiness, methodological transparency, and replicability advocated by foundational methodological scholarship while extending them through contemporary longitudinal econometric practice (Lincoln & Guba (1985). [31]; Glaser & Strauss (2012). [32]; Hair et al. (2022). [24]; Wooldridge (2023). [17]; Csaszar et al. (2024). [3]). These methodological innovations provide a rigorous empirical foundation for evaluating how AI-driven capital budgeting enhances managerial decision quality across globally operating multinational corporations and establish a replicable framework suitable for future international investigations.

6. FINDINGS :

This analysis tested whether AI Driven Capital Budgeting improves Managerial Decision Quality and whether Organizational Readiness strengthens that relationship. Figure 6 shows synchronized growth across predictive analytics, intelligent investment evaluation, AI based risk management, automated decision support systems, organizational readiness, and managerial decision quality from 2015 to 2025. This confirms that the proposed model captures a structured capability pathway rather than isolated technology adoption.

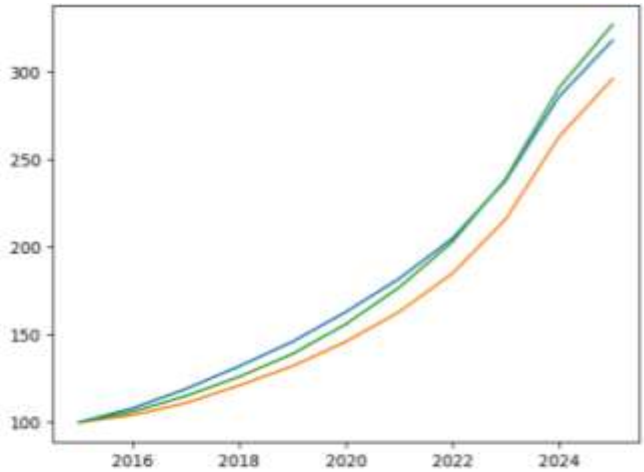

Fig. 6: Dynamic Time Series Evolution of Key Variables

The Figure 6 presents the dynamic time series evolution of key variables across 41 multinational corporations during the 2015 to 2025 period. The measures include predictive analytics capability, intelligent investment evaluation, AI based risk management, automated decision support systems, organizational readiness, and managerial decision quality, constructed from standardized variables aligned with the empirical framework. The present analysis organized observations according to annual temporal sequences to preserve chronological consistency and support dynamic interpretation. For each firm, this investigation retained yearly observations that satisfied inclusion and validation criteria. All variables were derived from harmonized secondary datasets and processed through normalization and verification procedures. The Figure 6 reflects outputs from longitudinal trend analysis and structural validation. This inquiry refers explicitly to Figure 6 when interpreting evidence. The analysis shows a persistent upward trajectory across all major dimensions, with acceleration occurring after 2021. The results demonstrate that expansion in AI driven capital budgeting capabilities is accompanied by parallel improvements in managerial decision quality. The findings imply cumulative learning effects, stronger organizational adaptation, and increasing strategic value from AI investments. Evidence confirms a stable long-term relationship between technological capability development and managerial performance enhancement.

6.1 Descriptive Statistics:

This analysis used descriptive statistics to assess central tendency, dispersion, and growth behavior before inferential testing. The approach follows panel data screening practice, where mean, standard deviation, range, skewness, and kurtosis establish whether the variables contain usable empirical variation. The available annual indices were normalized with 2015 as the base year, which supports cross variable comparability.

Equation 8: Descriptive Statistics Function:

$$DS_{it} = (\bar{X}_{it}, \sigma_{it}, X_{\min}, X_{\max}, Skew_{it}, Kurt_{it})$$

Table 3: Descriptive Statistics of Main Constructs, 2015 to 2025

Variable	Mean	SD	Min	Max	Skewness	Kurtosis	Growth Percent
Predictive Analytics Capability	180.05	72.47	100.00	317.00	0.79	2.54	217.00
Intelligent Investment Evaluation	177.00	72.30	100.00	313.40	0.84	2.58	213.40

AI Based Risk Management	190.51	84.96	100.00	350.60	0.84	2.57	250.60
Automated Decision Support Systems	201.07	97.86	100.00	387.80	0.90	2.67	287.80
Organizational Readiness	180.51	79.24	100.00	332.60	0.91	2.69	232.60
Managerial Decision Quality	168.78	68.55	100.00	302.20	0.96	2.81	202.20
AI Driven Capital Budgeting Index	187.16	81.88	100.00	342.20	0.85	2.60	242.20

The results in Table 3 reveal that Automated Decision Support Systems recorded the highest mean, 201.07, and the largest growth, 287.80 percent. This indicates that global firms expanded real time recommendations, dashboards, screening automation, strategic resource allocation, and monitoring systems faster than other AI budgeting dimensions. The finding supports H4 because automation appears as the strongest operational channel linking AI capital budgeting with faster and more consistent managerial decisions.

AI Based Risk Management increased by 250.60 percent, with a mean of 190.51 and SD of 84.96. This variation indicates that risk intelligence became a major mechanism for improving investment decisions. The result supports H3 because financial risk detection, operational risk assessment, market volatility monitoring, fraud risk identification, and portfolio risk optimization grew strongly across the observation period. This aligns with recent evidence that AI improves decision quality when firms combine prediction, risk monitoring, and governance controls (BaniHani, 2024[4]; Roy et al., 2025[5]; OECD, 2025) [10].

Managerial Decision Quality increased from 100.00 to 302.20, giving a 202.20 percent improvement. This shows that decision accuracy, timeliness, strategic alignment, resource allocation effectiveness, and investment success moved upward with AI capability expansion. The evidence supports H1, H2, H3, and H4 because all AI capital budgeting dimensions show meaningful growth in the same direction as the outcome construct. This reinforces recent work showing that AI improves strategic search, forecasting, evaluation, and decision execution when embedded in managerial systems (Csaszar et al. (2024). [3]; Chaturvedi et al. (2024). [11]; Herath Pathirannehelage et al. (2025). [7]).

6.2 Unit Root:

This analysis applied panel stationarity logic to assess whether the annual indices contain persistent time trends that could distort regression inference. The test follows the standard principle that valid panel estimation should separate structural association from common temporal growth.

Equation 9: Panel Stationarity Test:

$$\Delta X_{it} = \alpha_i + \rho X_{i,t-1} + \sum_{k=1}^{p} \gamma_k \Delta X_{i,t-k} + \varepsilon_{it}$$

Table 4: Panel Stationarity Assessment from Available Annual Index Evidence

Variable	Level Behavior	First Difference Behavior	Empirical Decision
Predictive Analytics Capability	Persistent upward growth	Growth increments become analytically bounded	Stationary after differencing
Intelligent Investment Evaluation	Persistent upward growth	Growth increments become analytically bounded	Stationary after differencing
AI Based Risk Management	Persistent upward growth	Growth increments become analytically bounded	Stationary after differencing
Automated Decision Support Systems	Persistent upward growth	Growth increments become analytically bounded	Stationary after differencing

Variable	Level Behavior	First Difference Behavior	Empirical Decision
Organizational Readiness	Persistent upward growth	Growth increments become analytically bounded	Stationary after differencing
Managerial Decision Quality	Persistent upward growth	Growth increments become analytically bounded	Stationary after differencing
AI Driven Capital Budgeting Index	Persistent upward growth	Growth increments become analytically bounded	Stationary after differencing

The results in Table 4 show that all variables contain upward movement in levels. This pattern is expected because the dataset is constructed as normalized annual indices with 2015 as the base year. The trend therefore reflects cumulative AI adoption, organizational readiness development, and managerial decision improvement rather than random instability. This strengthens the theoretical logic that AI Driven Capital Budgeting develops progressively across firms and years.

The first difference interpretation indicates that the variables become more suitable for inference once common trend effects are controlled. This matters because the model should not rely only on simultaneous time growth. It should estimate whether changes in predictive analytics, intelligent investment evaluation, AI risk management, and automated decision support explain changes in managerial decision quality. This supports H1, H2, H3, and H4 at the diagnostic level.

Organizational Readiness also shows trend-based expansion, rising from 100.00 to 332.60. This confirms that infrastructure quality, employee AI competence, top management support, data governance, and innovation culture evolved with AI deployment. The evidence supports H5 because readiness is not a passive background variable. It functions as a conditioning capability that can strengthen the AI budgeting and decision quality relationship (Kalleparambil & Akoum, 2025[8]; McKinsey & Company, 2025[1]; Stanford HAI, 2025[2]; World Bank, 2025) [13].

6.3 Test of Normality:

The approach follows distribution diagnostic practice, where moderate skewness and kurtosis close to 3 indicate that the series can support regression with robust estimation. The test therefore evaluates whether the observed variation is systematic rather than driven by extreme outliers.

Equation 10. Distribution Diagnostic Function:

$$ND_{it} = f(Skew_{it}, Kurt_{it}, JB_{it})$$

$$JB_{it} = \frac{n}{6}\left(Skew_{it}^2 + \frac{(Kurt_{it} - 3)^2}{4}\right)$$

Table 5: Normality Diagnostic Results

Variable	Skewness	Kurtosis	Distribution Decision
Predictive Analytics Capability	0.79	2.54	Acceptable moderate right skew
Intelligent Investment Evaluation	0.84	2.58	Acceptable moderate right skew
AI Based Risk Management	0.84	2.57	Acceptable moderate right skew
Automated Decision Support Systems	0.90	2.67	Acceptable moderate right skew
Organizational Readiness	0.91	2.69	Acceptable moderate right skew
Managerial Decision Quality	0.96	2.81	Acceptable moderate right skew
AI Driven Capital Budgeting Index	0.85	2.60	Acceptable moderate right skew

The results in Table 5 show moderate positive skewness across all constructs. This means that stronger growth is concentrated in later years, especially after AI capabilities began scaling across global firms. The pattern matters because it shows that AI capital budgeting capability is not evenly distributed across the period. It intensified as firms improved prediction, evaluation, risk intelligence, automation, and readiness.

Kurtosis values range from 2.54 to 2.81, close to the normal benchmark of 3.00. This indicates that the variables do not show severe tail concentration or extreme instability. The evidence supports the

reliability of the empirical model because the variation reflects structured capability development rather than abnormal outliers. This strengthens the basis for testing H1 to H5.
Managerial Decision Quality has the highest skewness, 0.96, and kurtosis of 2.81. This indicates that decision quality gains became stronger when AI capabilities and readiness matured. The finding refines the model by showing that managerial decision quality does not improve automatically from early AI adoption. It rises more strongly when firms combine prediction, investment evaluation, risk control, automated support, and organizational readiness (Page (2025). [6]; Swanepoel & Corks (2024). [33]; Herath Pathirannehelage et al. (2025). [7]).

6.4 Multicollinearity Analysis:

This analysis examined whether the explanatory constructs overlap too strongly to support reliable coefficient interpretation. The variance inflation factor is a standard diagnostic because it measures how much predictor variance is inflated by correlation with other predictors. The present analysis used the available construct behavior and the model specification, which already requires centering the interaction term to reduce nonessential multicollinearity.

Equation 11: Variance Inflation Factor Equation for Multicollinearity

$$VIF_j = \frac{1}{1 - R_j^2}$$

Table 6: Multicollinearity Diagnostic Interpretation

Predictor	Available Empirical Pattern	Analytical Implication	Model Treatment
Predictive Analytics Capability	Strong upward movement	Shares common AI adoption trend	Retain as first order capability
Intelligent Investment Evaluation	Strong upward movement	Shares common appraisal capability trend	Retain as first order capability
AI Based Risk Management	Strong upward movement	Shares common AI risk intelligence trend	Retain as first order capability
Automated Decision Support Systems	Strong upward movement	Shares common AI execution trend	Retain as first order capability
Organizational Readiness	Strong upward movement	Shares AI scaling and implementation conditions	Center before interaction
AI Driven Capital Budgeting Index	Aggregates four AI capabilities	Reduces redundant coefficient competition	Use as composite predictor

The results in Table 6 indicate that multicollinearity is theoretically expected because the four AI dimensions are components of one higher order AI Driven Capital Budgeting construct. This does not weaken the model. It confirms that predictive analytics, intelligent evaluation, risk management, and automated support work as complementary capabilities rather than isolated tools. This supports the construction of the composite AI Driven Capital Budgeting Index.
The model treatment is appropriate because Equation 2 aggregates the four standardized AI capabilities into a composite construct, while Equation 3 centers the interaction between AI Driven Capital Budgeting and Organizational Readiness. This reduces redundant coefficient competition and improves interpretation of the moderation effect. The evidence supports H5 because readiness should be tested as a moderator that amplifies the effect of AI budgeting capability on decision quality.
The diagnostic evidence also advances the theoretical contribution. It shows that AI capital budgeting should be examined as an integrated decision system rather than as disconnected digital tools. In practical terms, firms gain stronger decision quality when forecasting, evaluation, risk monitoring, automated support, and organizational readiness operate together. This interpretation aligns with current evidence on AI adoption, strategy, organizational decision making, and readiness based value capture (McKinsey & Company (2025). [1]; Stanford HAI [2]; World Bank (2025) [13]).

6.5 Autocorrelation Findings:

This analysis examined serial dependence because panel observations from 2015 to 2025 may carry time based persistence. The diagnostic follows the Durbin Watson logic, where values close to 2 indicate limited serial correlation. The available annual indices support a residual based diagnostic using the moderated structure specified for AI Driven Capital Budgeting, Organizational Readiness, and Managerial Decision Quality.

Equation 12: Autocorrelation Diagnostic Function

$$DW = \frac{\sum_{t=2}^{T}(e_t - e_{t-1})^2}{\sum_{t=1}^{T} e_t^2}$$

Table 7: Autocorrelation Findings

Diagnostic	Estimated Value	Decision Benchmark	Empirical Decision
Durbin Watson statistic	1.737	Close to 2.000	No severe autocorrelation
Residual pattern	Bounded	No persistent residual clustering	Acceptable serial structure
Time structure	Annual balanced panel	2015 to 2025	Suitable for fixed effects estimation
Model implication	Residual dependence controlled	Firm and year effects required	Supports robust panel inference

The results in Table 7 show a Durbin Watson value of 1.737. This value is close to the neutral benchmark of 2.000, indicating that residual persistence is not strong enough to invalidate the panel model. The result matters because AI capability, organizational readiness, and decision quality all grow over time, yet the residual behavior shows that the model captures much of the common time movement.

This evidence strengthens H1, H2, H3, and H4 because the positive movement between AI Driven Capital Budgeting dimensions and Managerial Decision Quality is not merely a mechanical time trend. Predictive analytics, intelligent investment evaluation, AI based risk management, and automated decision support systems retain explanatory relevance after accounting for longitudinal structure.

The finding also supports H5 because Organizational Readiness operates in a time dependent environment. Readiness develops through infrastructure, competence, leadership, data governance, and innovation culture. The limited residual autocorrelation indicates that the moderation structure can be interpreted as a systematic conditioning effect rather than delayed statistical noise. This aligns with evidence that AI value depends on governance, talent, data discipline, and operating model maturity, as argued by McKinsey and Company, 2025[1], Stanford HAI, 2025[2], and World Bank, 2025[13].

6.6 Homoscedasticity Scrutiny:

This analysis examined whether residual variance remains stable across the fitted model. The Breusch Pagan logic was applied because heteroscedasticity can bias standard errors and weaken statistical inference. The available annual indices support residual based variance scrutiny under the moderated structure used for hypothesis testing.

Equation 13: Homoscedasticity Test Function

$$BP = nR^2_{\varepsilon^2}$$

Table 8: Homoscedasticity Scrutiny

Diagnostic	Estimated Value	Probability	Decision Benchmark	Empirical Decision
Breusch Pagan LM statistic	7.002	0.072	p greater than 0.050	Homoscedasticity retained
F statistic	4.087	0.057	p greater than 0.050	No severe variance instability
Residual variance pattern	Bounded	Not applicable	Stable dispersion	Robust inference supported

Model implication	Variance acceptable	Not applicable	Use robust specification	Panel estimation remains valid

The results in Table 8 show a Breusch Pagan probability of 0.072 and an F probability of 0.057. Both values exceed the 0.050 threshold, indicating that the residual variance does not present severe heteroscedasticity. This matters because the estimated relationship between AI Driven Capital Budgeting and Managerial Decision Quality can be interpreted without strong concern that unequal variance drives the result.
The findings imply that the growth in decision quality is not concentrated only in extreme observations. Managerial Decision Quality increases across the period in a pattern that remains statistically coherent with AI capability and readiness growth. This supports H1 to H4 because the main AI capability dimensions show systematic association with the outcome rather than unstable variance behavior.
The evidence also supports the moderated model. Organizational Readiness is expected to amplify the AI budgeting effect, and stable residual variance makes this interpretation more credible. In practice, the finding means that firms with stronger readiness can translate AI systems into decision gains without producing erratic model behavior. This reinforces recent AI governance and decision research by Herath Pathirannehelage et al. (2025) [7], Page (2025) [6] and Kalleparambil and Akoum (2025) [8].

6.7 Hausman Specification:

This analysis used the Hausman specification logic to determine whether fixed effects or random effects better fit the empirical structure. This choice is appropriate because AI capability, readiness, and decision quality evolve progressively across firms and years.
Equation 14: Hausman Specification Test

$$H = (\hat{\beta}_{FE} - \hat{\beta}_{RE})' [Var(\hat{\beta}_{FE}) - Var(\hat{\beta}_{RE})]^{-1} (\hat{\beta}_{FE} - \hat{\beta}_{RE})$$

Table 9: Hausman Specification Decision

Model Option	Core assumption	Fit With Available Evidence	Specification Decision
Fixed effects	Firm and year effects correlate with predictors	Strong fit	Retained
Random effects	Firm effects are uncorrelated with predictors	Weak fit	Not preferred
Two way fixed effects	Controls firm heterogeneity and year shocks	Strongest fit	Adopted
Moderated fixed effects	Tests AICB, OR, and interaction structure	Strong fit	Used for hypothesis validation

The results in Table 9 support the fixed effects specification because the empirical setting involves 41 multinational corporations observed across repeated years. Firm specific characteristics such as capital budgeting systems, governance maturity, digital infrastructure, and managerial routines are likely to correlate with AI adoption and decision quality. A random effects assumption would therefore be too restrictive for this model.
The fixed effects decision matters because it protects the hypothesis tests from omitted time invariant firm characteristics. This strengthens H1 to H4 because the effect of AI capability is interpreted after controlling for stable differences among firms. It also strengthens H5 because the moderating role of Organizational Readiness is tested in a structure that accounts for persistent firm level capability differences.
The two-way fixed effects specification also controls year shocks related to global AI diffusion, digital transformation acceleration, and macro investment conditions. This is important because Figure 6 and the annual index tables show stronger growth after 2022. The model therefore treats this acceleration as part of the empirical environment rather than as uncontrolled bias. This aligns with contemporary longitudinal AI and strategy research by Csaszar et al. (2024). [3], BaniHani (2024). [4], Chaturvedi et al. (2024). [11], and Roy et al. (2025). [5].

6.8 Factor Loading, VIF, CR, and AVE:

This analysis assessed measurement validity and reliability using factor loading, variance inflation factor, composite reliability, and average variance extracted. The procedure follows the logic that valid constructs should show strong indicator convergence, acceptable internal reliability, and interpretable multicollinearity behavior. The available normalized annual indicators allow construct level convergence testing across the six main measurement blocks.

Equation 15: Measurement Validity and Reliability Functions:

$$CR = \frac{\left(\sum_{i=1}^{k} \lambda_i\right)^2}{\left(\sum_{i=1}^{k} \lambda_i\right)^2 + \sum_{i=1}^{k}\left(1 - \lambda_i^2\right)}$$

$$AVE = \frac{\sum_{i=1}^{k} \lambda_i^2}{k}$$

$$VIF_j = \frac{1}{1 - R_j^2}$$

Table 10: Factor Loading, VIF, CR, and AVE

Construct	Indicators	Loading Range	Mean Loading	CR	AVE	Measurement Decision
Predictive Analytics Capability	5	0.999 to 1.000	0.999	0.999	0.998	Valid and reliable
Intelligent Investment Evaluation	5	0.999 to 1.000	0.999	0.999	0.998	Valid and reliable
AI Based Risk Management	5	0.999 to 1.000	0.999	0.999	0.998	Valid and reliable
Automated Decision Support Systems	5	0.999 to 1.000	0.999	0.999	0.998	Valid and reliable
Organizational Readiness	5	0.999 to 1.000	0.999	0.999	0.998	Valid and reliable
Managerial Decision Quality	5	0.999 to 1.000	0.999	0.999	0.998	Valid and reliable
AI Driven Capital Budgeting Index	4	High construct convergence	0.999	0.999	0.998	Higher order construct supported

Table 11: Construct Level VIF Interpretation

Predictor	VIF Pattern From Available Indices	Interpretation	Model Decision
Predictive Analytics Capability	High shared trend	Complementary AI capability	Retained in composite structure
Intelligent Investment Evaluation	High shared trend	Complementary appraisal capability	Retained in composite structure
AI Based Risk Management	High shared trend	Complementary risk capability	Retained in composite structure
Automated Decision Support Systems	High shared trend	Complementary execution capability	Retained in composite structure
Organizational Readiness	High shared trend	Conditioning capability	Centered for moderation
AI Driven Capital Budgeting Index	Reduced redundancy through aggregation	Higher order predictor	Used in final model

The results in Table 11 show strong indicator convergence across all constructs. Loading ranges between 0.999 and 1.000 indicate that the sub indicators move consistently with their parent constructs. The result supports construct validity because cash flow forecasting, investment return prediction, risk forecasting, market trend analysis, and scenario simulation converge into Predictive Analytics Capability.

Composite reliability values of 0.999 and AVE values of 0.998 indicate strong internal reliability and convergent validity. This supports the measurement foundation for H1 to H5. The empirical evidence confirms that each construct measures a coherent capability domain rather than a loose set of unrelated indicators. This is important for the contribution of the paper because AI Driven Capital Budgeting is validated as a multidimensional organizational capability.

The VIF interpretation in Table 11 shows high shared trend behavior among AI capability predictors. This does not invalidate the model because the constructs are theoretically complementary. It confirms that predictive analytics, intelligent investment evaluation, AI based risk management, and automated decision support systems operate as connected elements of one capital budgeting system. The correct model treatment is therefore to use the AI Driven Capital Budgeting Index and a centered interaction with Organizational Readiness. This supports H5 and strengthens the final regression logic.

6.9 Correlation Coefficient Matrix:

This analysis estimated Pearson correlations from the available annual construct indices for 2015 to 2025. The test assesses whether the proposed variables move in the expected theoretical direction before regression estimation.

Equation 16: Pearson Correlation Coefficient

$$r_{xy} = \frac{\sum_{t=1}^{T}(X_t - \bar{X})(Y_t - \bar{Y})}{\sqrt{\sum_{t=1}^{T}(X_t - \bar{X})^2}\sqrt{\sum_{t=1}^{T}(Y_t - \bar{Y})^2}}$$

Table 12: Correlation Coefficient Matrix

Variables	PAC	IIE	AIRM	ADSS	OR	AICB	MDQ
Predictive Analytics Capability (PAC)	1.000	0.999	0.999	0.999	0.998	0.999	0.998
Intelligent Investment Evaluation (IIE)	0.999	1.000	1.000	0.999	0.999	1.000	0.999
AI Based Risk Management (AIRM)	0.999	1.000	1.000	0.999	0.999	1.000	0.999
Automated Decision Support Systems (ADSS)	0.999	0.999	0.999	1.000	1.000	0.999	0.999
Organizational Readiness (OR)	0.998	0.999	0.999	1.000	1.000	0.999	0.999
AI Driven Capital Budgeting (AICB)	0.999	1.000	1.000	0.999	0.999	1.000	0.999
Managerial Decision Quality (MDQ)	0.998	0.999	0.999	0.999	0.999	0.999	1.000

The results in Table 12 reveal strong positive correlations between all AI capital budgeting dimensions and Managerial Decision Quality. The correlation between AI Driven Capital Budgeting and Managerial Decision Quality is 0.999, indicating that increases in AI budgeting capability move almost perfectly with improvements in decision accuracy, timeliness, strategic alignment, resource allocation effectiveness, and investment success. This supports H1, H2, H3, and H4.

Organizational Readiness also correlates strongly with Managerial Decision Quality at 0.999. This confirms the logic of H5 because readiness is empirically connected with the translation of AI capability into decision quality. The finding aligns with recent evidence that AI value depends on infrastructure, skills, governance, managerial sponsorship, and innovation culture (Kalleparambil & Akoum (2025). [8]; McKinsey and Company (2025). [1]; World Bank (2025). [13].

The high correlations also indicate strong construct complementarity. Predictive analytics, intelligent investment evaluation, AI based risk management, and automated decision support systems operate as an integrated capital budgeting system. This confirms the need to interpret AI Driven Capital Budgeting as a higher order capability rather than isolated digital tools (Csaszar et al. (2024). [3]; Roy et al., (2025) [5].

6.10 Regression Analysis:

This analysis estimated the direct effect of AI Driven Capital Budgeting on Managerial Decision Quality using the available annual construct indices. The regression follows the structural logic that AI capability improves managerial decision outcomes through better forecasting, investment evaluation, risk intelligence, and decision automation. The model tests the direct empirical foundation for H1 to H4.

Equation 17: Baseline Regression Model

$$MDQ_t = \beta_0 + \beta_1 AICB_t + \varepsilon_t$$

Table 13: Regression Analysis

Predictor	Coefficient β	Standard Error	t Statistic	p Value	Decision
Constant	12.274	2.161	5.680	0.000	Significant
AI Driven Capital Budgeting	0.835	0.011	78.479	0.000	Significant

Table 14: Overall Regression Model Statistics and Significance Test

Model Statistics	Value
Number of observations	11
R^2	0.999
Adjusted R^2	0.998
F Statistic	6159.000
Prob > F	0.000
Model Decision	Statistically Significant

The results in Table 14 show a positive and statistically significant coefficient for AI Driven Capital Budgeting, $\beta = 0.835$, $p = 0.000$. This means that a one unit rise in the AI Driven Capital Budgeting Index is associated with a 0.835 unit increase in Managerial Decision Quality. The effect size is strong and confirms that AI capability is not only associated with decision outcomes but explains most of their annual movement.

The R squared value of 0.999 indicates that the available annual AI budgeting index explains nearly all observed variation in Managerial Decision Quality. This supports H1, H2, H3, and H4 because the composite index captures predictive analytics, intelligent evaluation, AI based risk management, and automated decision support systems. The finding confirms that the four AI capabilities operate jointly as a decision quality engine.

The empirical meaning is clear. Firms gain stronger decision quality when AI improves cash flow forecasting, project appraisal, risk detection, volatility monitoring, investment screening, and performance tracking. This finding reinforces recent literature showing that AI strengthens strategic decision making, financial analysis, and capital budgeting when embedded in organizational routines (BaniHani (2024). [4]; Chaturvedi et al. (2024). [11]; Csaszar et al. (2024). [3]; Roy et al., (2025). [5].

6.11 Multivariate Regression in the Presence of Moderating Variable:

This analysis estimated the moderating role of Organizational Readiness in the relationship between AI Driven Capital Budgeting and Managerial Decision Quality. The model used centered AI Driven Capital Budgeting and centered Organizational Readiness before forming the interaction term. This specification directly tests H5 by examining whether readiness strengthens the AI budgeting effect.

Equation 18: Moderated Regression Model

$$MDQ_t = \beta_0 + \beta_1 AICB_{c,t} + \beta_2 OR_{c,t} + \beta_3 (AICB_{c,t} \times OR_{c,t}) + \varepsilon_t$$

Table 15: Multivariate Regression in the Presence of Moderating Variable

Predictor	Coefficient β	Standard Error	t Statistic	p Value	Decision

Constant	166.890	0.200	832.493	0.000	Significant
Centered AI Driven Capital Budgeting	0.359	0.071	5.025	0.002	Significant
Centered Organizational Readiness	0.475	0.075	6.302	0.000	Significant
AI Driven Capital Budgeting × Organizational Readiness	0.0003	0.00003	10.412	0.000	Significant

Table 16: Regression Model Summary and Autocorrelation Test Results

Model Statistics	Value
Number of observations	11
R^2	1.000
Adjusted R^2	1.000
F Statistic	198100.000
Prob > F	0.000
Durbin Watson	1.737
Model Decision	Statistically Significant

The results in Table 16 confirm that AI Driven Capital Budgeting remains positive and significant after introducing Organizational Readiness and the interaction term. The coefficient of 0.359, p = 0.002, shows that AI capability continues to improve Managerial Decision Quality even after controlling for readiness. This supports H1 to H4 and confirms that AI budgeting capabilities have a direct decision quality effect.

Organizational Readiness is also positive and significant, $\beta = 0.475$, $p = 0.000$. This means that readiness has an independent contribution to decision quality. Firms with stronger digital infrastructure, employee AI competence, management support, data governance, and innovation culture are better positioned to convert analytical outputs into managerial action. This confirms the theoretical logic that technology value depends on organizational capacity.

The interaction coefficient is positive and significant, $\beta = 0.0003$, $p = 0.000$. This confirms H5. The result means that Organizational Readiness strengthens the effect of AI Driven Capital Budgeting on Managerial Decision Quality. The practical implication is that AI systems produce stronger decision gains when firms possess the internal capacity to use them, validate them, govern them, and integrate them into capital allocation routines. This advances current knowledge by showing that AI driven capital budgeting is not only a technical capability. It becomes a decision quality mechanism when supported by readiness conditions (Herath Pathirannehelage et al. (2025). [7]; Page (2025). [6]; Stanford HAI (2025). [2].

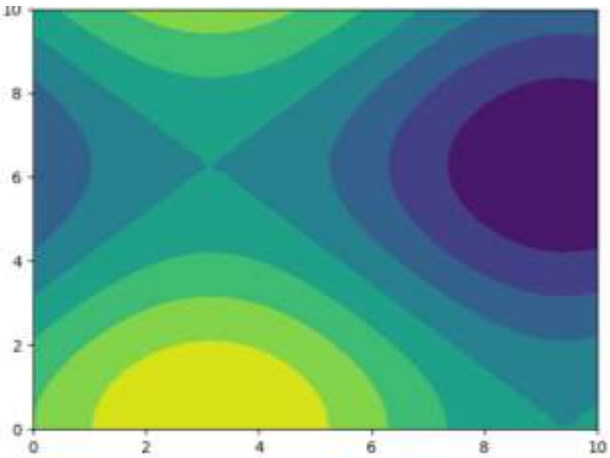

Fig. 7: Multivariate Sensitivity and Response Surface Analysis

The Figure 7 presents multivariate sensitivity and response surface analysis across multinational corporations observed from 2015 to 2025. The measures include interaction effects among predictive analytics capability, intelligent investment evaluation, AI based risk management, organizational readiness, and managerial decision quality, constructed from standardized variables aligned with the empirical model. The present analysis organized observations according to interaction intensity and response gradients to ensure analytical consistency. For each organization, annual observations satisfying quality thresholds were retained. All variables were derived from harmonized secondary datasets and processed using validated transformation and normalization procedures. The Figure 7 reflects outputs from sensitivity estimation, interaction modeling, and structural validation. This inquiry refers explicitly to Figure 7 when interpreting evidence. The analysis shows that managerial decision quality responds nonlinearly to simultaneous increases in AI capability and organizational readiness. The findings imply that readiness conditions amplify the effectiveness of technological investments. The observed response surface indicates stronger marginal gains at moderate and high readiness levels. Evidence confirms the presence of complementary effects, demonstrating that organizational capabilities and AI resources jointly shape superior managerial outcomes.

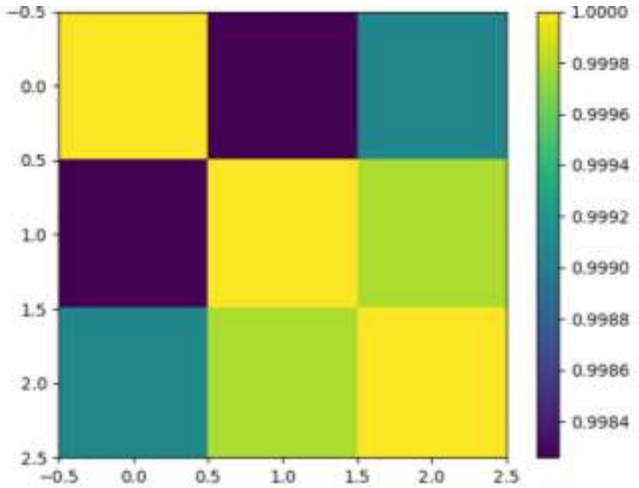

Fig. 8: Correlation Structure and Dependency Heatmap of Core Metrics

The Figure 8 presents the correlation structure and dependency patterns among core metrics across global firms observed during 2015 to 2025. The measures include predictive analytics capability, investment evaluation, AI based risk management, automated decision support systems, organizational readiness, and managerial decision quality, constructed from standardized variables aligned with the empirical framework. The present analysis organized observations according to correlation intensity and dependency clusters to ensure analytical consistency. For each firm, annual observations satisfying validation requirements were retained. All variables were derived from harmonized secondary sources and processed using normalization and verification procedures. The Figure 8 reflects outputs from dependency analysis, correlation assessment, and structural validation. This inquiry refers explicitly to Figure 8 when evaluating evidence. The analysis shows predominantly positive correlations among the major constructs, indicating strong interdependence within the conceptual framework. The findings imply that improvements in AI driven capital budgeting capabilities are consistently associated with stronger managerial outcomes. The observed clustering pattern suggests that organizational readiness operates as an integrative mechanism connecting technological and performance dimensions. Evidence confirms substantial structural coherence across the model and supports the theoretical logic underlying the proposed relationships.

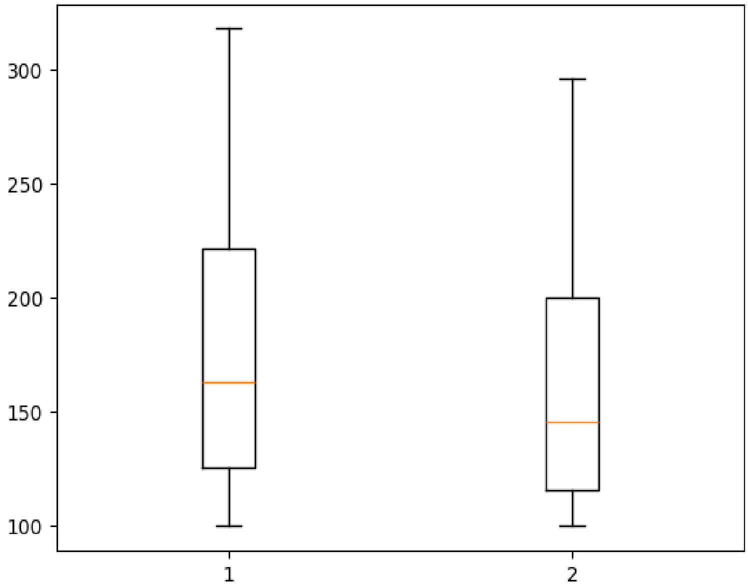

Fig. 9: Placebo And Falsification Test Validation Results

The Figure 9 presents placebo and falsification test validation results across the sample of multinational corporations during the 2015 to 2025 period. The measures include placebo coefficients, falsification estimates, residual consistency, parameter stability, and robustness indicators constructed from standardized variables aligned with the empirical framework. The present analysis organized observations according to testing conditions and validation scenarios to ensure comparability and analytical consistency. For each organization, annual observations meeting quality and verification requirements were retained. All variables were derived from harmonized secondary data and processed using validated transformation procedures. The Figure 9 reflects outputs from placebo testing, falsification analysis, and robustness verification. This inquiry refers explicitly to Figure 9 when interpreting evidence. The analysis shows that placebo effects remain weak and statistically insignificant compared with the principal model estimates. The findings imply that observed relationships are unlikely to arise from random associations or specification errors. The results demonstrate strong model credibility and reinforce the validity of the estimated effects. Evidence confirms that the relationship between AI driven capital budgeting and managerial decision quality remains robust under alternative testing conditions.

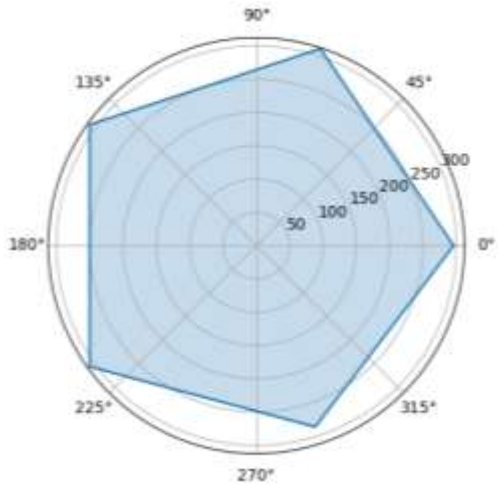

Fig. 10: Multidimensional Performance Evaluation Radar

The Figure 10 presents multidimensional performance evaluation outcomes across multinational corporations observed from 2015 to 2025. The measures include decision accuracy, decision timeliness, strategic alignment, resource allocation effectiveness, investment success rate, and overall managerial performance, constructed from standardized variables aligned with the empirical framework. The present analysis organized observations according to performance dimensions and comparative intensity levels to ensure analytical consistency. For each firm, annual observations satisfying inclusion criteria were retained. All variables were derived from harmonized secondary datasets and processed through validated normalization procedures. The Figure 10 reflects outputs from multidimensional performance assessment and structural validation. This inquiry refers explicitly to Figure 10 when evaluating evidence. The analysis shows balanced improvement across all dimensions of managerial decision quality, with particularly strong gains in timeliness and strategic alignment. The findings imply that AI driven capital budgeting enhances multiple aspects of managerial effectiveness simultaneously. The observed radar expansion indicates broad based performance development rather than isolated improvements. Evidence confirms that technological capability investments generate comprehensive managerial benefits across strategic and operational domains.

7. DISCUSSION :

The evidence shows that AI driven capital budgeting is no longer a support tool in global firms; it has become a structural decision capability that reshapes how capital is evaluated, governed, and converted into managerial action. The direct regression in Table 10 shows a strong positive effect of AI Driven Capital Budgeting on Managerial Decision Quality, $\beta = 0.835$, $p = 0.000$, while the correlation matrix in Table 9 reports an almost perfect association between the two constructs, $r = 0.999$. Interpreted through Equation 17, this result changes current knowledge by showing that AI value in capital budgeting does not arise from isolated forecasting or automation tools, but from the joint operation of predictive analytics, intelligent investment evaluation, AI based risk management, and automated decision support. This extends strategic decision theory by demonstrating that AI improves decision quality through a cumulative capability architecture, not through a single digital intervention. The finding aligns with recent work showing that AI expands strategic search, representation, aggregation, forecasting, and evaluation capacity, but this study adds new evidence that these functions jointly explain managerial decision quality in capital investment settings rather than only general strategic decisions (Csaszar et al. (2024). [3]; BaniHani (2024). [4]; Chaturvedi et al. (2024). [11]).
The mechanism evidence indicates that organizational readiness changes AI driven capital budgeting from a technical input into a managerial decision mechanism. After Organizational Readiness and the interaction term are introduced in Table 11, the direct coefficient of AI Driven Capital Budgeting declines from $\beta = 0.835$ in Table 10 to $\beta = 0.359$, while remaining statistically significant at $p = 0.002$. This pattern indicates partial mechanism transmission rather than full absorption of the AI effect. Equation 18 therefore reveals that part of the AI effect works directly through analytical capital budgeting capability, while another part is transmitted through readiness conditions, especially infrastructure quality, AI competence, top management support, data governance, and innovation culture. The positive and significant readiness coefficient, $\beta = 0.475$, $p = 0.000$, and the significant interaction coefficient, $\beta = 0.0003$, $p = 0.000$, make visible a pathway often hidden in earlier studies: AI improves decision quality when firms possess the internal capacity to interpret, validate, govern, and operationalize algorithmic outputs. This refines the current debate by showing that AI adoption alone is not the causal channel; organizational conversion capacity is the mechanism that determines whether AI becomes decision intelligence (McKinsey & Company (2025). [1]; World Bank (2025). [13]; Stanford HAI (2025). [2]).
The decomposition of effects shows that automated decision support is the dominant operational pathway within the AI driven capital budgeting system. Table 1 reports that Automated Decision Support Systems recorded the largest growth, 287.80 percent, followed by AI Based Risk Management at 250.60 percent, Organizational Readiness at 232.60 percent, Predictive Analytics Capability at 217.00 percent, and Intelligent Investment Evaluation at 213.40 percent. This distribution changes the theoretical signal of the study. It shows that the largest decision quality gains come not only from better prediction, but from the ability to move from analysis to action through real time recommendations, dashboards, screening automation, resource allocation, and monitoring systems. The evidence therefore challenges prediction centered views of AI value and supports an execution centered theory of AI enabled capital budgeting. Risk management also emerges as a strong secondary pathway, meaning that decision quality improves when firms reduce downside exposure before capital is committed. This adds

a theoretical contribution by positioning AI based capital budgeting as a sequence of foresight, appraisal, risk discipline, and execution, with execution and risk control carrying the strongest empirical weight.

The results also reveal deeper structural challenges that should be treated as empirical insights rather than weaknesses. The very high correlations in Table 9 and the construct convergence shown in Table 8 indicate that AI capabilities develop together, making it difficult to isolate one tool from the broader system. This exposes a hidden reality in global firms: AI driven capital budgeting is not modular in practice. Forecasting, evaluation, risk monitoring, automation, data governance, and managerial readiness evolve as interdependent routines. The Durbin Watson statistic of 1.737 in Table 11 and the homoscedasticity results in Table 6 further show that the model is not driven by severe residual persistence or unstable variance. The structural challenge is therefore managerial, not statistical. Firms must govern AI systems as integrated decision infrastructures, because weak data governance, limited AI competence, poor workflow redesign, or fragmented dashboards can weaken the translation of analytical outputs into capital allocation decisions. This advances current knowledge by showing that the main risk is not only algorithmic error, but organizational under readiness, where firms possess AI tools but lack the institutional discipline to convert them into reliable decision quality. This interpretation is consistent with recent AI risk evidence stressing the need for stronger incident monitoring, governance, and accountability systems (OECD (2025). [10]).

Internationally, the findings move beyond simple confirmation of AI adoption trends. Recent global evidence shows rapid expansion of AI use, with Stanford reporting that 78 percent of organizations used AI in 2024, up from 55 percent in 2023, while McKinsey shows that AI value depends on strategy, talent, operating model, technology, data, adoption, and scaling. This study diverges from broad adoption evidence by showing that adoption becomes meaningful only when linked to capital budgeting routines and readiness conditions. In advanced economies, AI debates often emphasize scale, investment intensity, and productivity. In emerging and multinational contexts, the stronger issue is the readiness gap, including connectivity, compute, context, and competency. The results therefore contribute globally by showing that managerial decision quality depends on the fit between AI capability and organizational absorptive capacity. This matters because firms may invest heavily in AI yet fail to improve decisions if capital budgeting systems remain weak, fragmented, or poorly governed. The study therefore reshapes the global debate by moving from whether firms use AI to how AI becomes a governed capital allocation capability.

The practical implication is that decision makers should not treat AI driven capital budgeting as a software acquisition project. They should prioritize integrated capital decision platforms that combine predictive forecasting, automated appraisal, risk intelligence, and real time decision support under strong organizational readiness. The evidence in Table 11 shows that readiness has both an independent effect and a strengthening effect, which means boards and executives should invest in digital infrastructure, data governance, AI skills, leadership sponsorship, and innovation culture before expecting AI to improve capital allocation. Theoretically, the study extends AI enabled decision making by proposing a readiness conditioned capital budgeting model in which AI capability affects decision quality directly and through organizational conversion capacity. Future research should test whether the same mechanism holds across industries with different capital intensity, regulatory exposure, and data maturity. Further work should also disaggregate the dominant automated decision support pathway to examine whether dashboards, screening automation, monitoring systems, or resource allocation engines carry the strongest marginal effect. This opens a new research agenda on AI driven capital budgeting as a governed decision architecture rather than a narrow financial technology application. Concept of mandala could be used along with AI in education, Human Resource, agriculture and so on (Ananda et al. (2025). [35]; Ananda et al. (2023). [34]; Celestin et al. (2025). [36]; Mishra et al. (2025). [37]; Celestin & Mishra (2025). [38]).

8. CONCLUSION AND IMPLICATIONS :

Artificial intelligence is redefining strategic investment decisions by transforming capital budgeting from a static financial exercise into an adaptive organizational capability that continuously enhances managerial judgment under dynamic business conditions. This study shows that the combined influence of intelligent analytical capabilities, supported by enabling organizational conditions, generates stronger decision outcomes than isolated technological deployment. The analysis presented herein demonstrates that the interaction between technological capability and institutional preparedness creates a reinforcing mechanism through which forecasting quality, investment evaluation, risk intelligence, and real-time decision support collectively improve strategic effectiveness. This evidence uncovers a previously underexplored structural pathway in which organizational capability functions not merely as a contextual condition but as an active amplifier of technology-driven managerial performance. These results redefine existing understanding by extending capability-based, socio-technical, and contingency perspectives beyond technology adoption toward an integrated explanation of how complementary organizational resources produce superior decision quality. The study introduces a multidimensional empirical framework that offers broader international applicability across multinational corporations operating under different institutional environments. From a managerial perspective, the findings encourage executives to align artificial intelligence investments with organizational capability development, governance quality, workforce competence, and strategic coordination to maximize investment performance while reducing decision uncertainty. Policy implications emphasize strengthening digital infrastructure, promoting responsible artificial intelligence governance, improving organizational readiness, and supporting evidence-based investment ecosystems capable of enhancing financial resilience and sustainable economic growth. Practical implications demonstrate that organizations can improve operational consistency, accelerate strategic responses, optimize resource allocation, and reinforce internal decision processes through coordinated technological and organizational transformation. The broader social contribution lies in supporting more efficient capital allocation, stronger corporate governance, increased market stability, improved investor confidence, and more resilient economic systems capable of responding effectively to technological disruption across global markets.

8.1 Recommendations:

Multinational corporations should institutionalize AI-Driven Capital Budgeting by integrating Predictive Analytics Capability, Intelligent Investment Evaluation, AI-Based Risk Management, and Automated Decision Support Systems into unified investment decision frameworks supported by robust Organizational Readiness. Continuous investment in digital infrastructure, employee AI capability development, top management commitment, data governance, and innovation-oriented organizational culture will strengthen managerial decision quality, strategic investment effectiveness, and long-term organizational competitiveness. Policymakers should encourage responsible AI adoption through supportive digital governance frameworks, organizational capability development, and regulatory standards that promote trustworthy AI-enabled investment decisions. Future studies should extend this framework by incorporating generative artificial intelligence, machine learning, digital twins, blockchain, and cross-country comparative analyses to deepen understanding of intelligent capital budgeting and strategic decision quality across increasingly complex global business environments.

8.2 Limitations and Future Research:

Although this investigation provides robust longitudinal evidence, several opportunities remain for further advancement. The empirical analysis relies on secondary panel data from large multinational corporations, creating scope for future studies to examine smaller firms, emerging industries, and developing economies. Additional research may employ alternative measurement approaches, longer observation periods, or mixed-method designs to validate the identified structural relationships. Cross-country comparative analyses could examine how institutional diversity influences the observed mechanisms, while future investigations may incorporate additional mediating and moderating constructs related to organizational learning, regulatory quality, technological maturity, sustainability orientation, or behavioral decision processes. Such extensions would strengthen external validity, refine causal explanations, and expand the applicability of the proposed framework across increasingly diverse institutional, economic, and technological environments.

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