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Artificial Intelligence–Enabled Products and Their Effects on Managerial Judgment, Strategy, and Organizational Performance

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Abstract

Despite growing organizational investment in artificial intelligence (AI), the mechanisms through which AI-enabled tools influence managerial judgment and translate into measurable performance outcomes remain theoretically underdeveloped. This study addresses this gap by examining the relationships between AI adoption and usage, AI-influenced decision-making quality, and organizational performance across managerial levels and industry sectors. A quantitative cross-sectional survey was conducted among 100 managers from six industries: technology, manufacturing, financial services, healthcare, education, and retail. Three latent constructs—AI usage and perception, AI influence on decision-making, and organizational performance—were operationalized using multi-item Likert-scale instruments and tested for reliability. Hypotheses were evaluated using ordinary least squares (OLS) regression, complemented by correlation and group-level comparative analyses across managerial hierarchies and AI adoption tenures. The findings support all proposed relationships. AI usage exhibits a strong positive association with decision-making quality, which in turn significantly predicts organizational performance. Additionally, AI usage has a direct effect on performance, indicating that decision-making quality partially mediates this relationship. Group-level analysis reveals variation in AI engagement and perceived impact across managerial levels and industries, with longer AI adoption tenure generally linked to stronger performance outcomes. From a practical standpoint, the results suggest that organizations must go beyond mere AI deployment and focus on enhancing managerial capability for AI-informed decision-making. Decision-making quality emerges as a critical pathway through which AI adoption drives performance gains, highlighting the importance of targeted training, integration infrastructure, and governance frameworks. This study contributes to the literature by empirically validating a model that links AI usage to organizational performance through the mediating role of managerial decision-making. By incorporating contextual variables such as managerial level, industry sector, and adoption tenure, the research provides a more nuanced understanding of how AI's organizational impact varies across different settings.

INTRODUCTION

The past decade has witnessed a fundamental reconfiguration of how organizations process information, allocate resources, and respond to competitive pressure. Artificial intelligence has moved from the periphery of organizational experimentation to the operational core of management practice, reshaping functions as varied as financial forecasting, human resource allocation, customer relationship management, and strategic planning. What began as a set of specialized technical applications has evolved into an infrastructure layer that increasingly mediates the relationship between data and decision.

This shift carries implications that extend well beyond efficiency. For generations, managerial judgment was understood as a capacity cultivated through experience, intuition, and contextual knowledge — something that resisted formalization. AI-enabled systems challenge that understanding directly. By processing volumes of structured and unstructured data at speeds no human analyst can match, these tools alter not just the speed of decisions but their epistemic basis: the information managers act on, the alternatives they consider, and the confidence with which they commit to a course of action. Decision-making is becoming, in a meaningful sense, a joint enterprise between human judgment and algorithmic inference.

The strategic stakes of this transition are substantial. Organizations that integrate AI effectively into their decision processes are not merely automating existing workflows — they are building capabilities that compound over time, creating informational advantages that are difficult for competitors to replicate. Yet the organizational literature has been slow to specify the mechanisms through which AI adoption translates into performance outcomes, and slower still to examine how those mechanisms operate differently across managerial levels, industries, and stages of adoption maturity.

This paper addresses that gap directly. Drawing on primary survey data from 100 managers across six industries, it examines how AI usage shapes decision-making quality and how that relationship, in turn, drives organizational performance offering an empirically grounded account of AI not as a technological fact but as a managerial and strategic phenomenon.

Scholarly engagement with artificial intelligence in organizational contexts has grown considerably, yet the literature's theoretical reach has consistently outpaced its empirical foundations. A substantial body of work argues, often persuasively, that AI tools enhance decision quality, accelerate strategic response, and generate sustainable competitive advantage. What that body of work has been less willing or able to do is demonstrate these relationships with primary data to trace the pathway from AI adoption through managerial cognition to measurable organizational outcomes in a way that moves beyond conceptual assertion.

The problem is partly one of scope. Existing studies tend to isolate individual components of the AI-performance relationship rather than model it as a connected chain. Research on decision-making quality rarely accounts for how AI usage mediates cognitive processes at different managerial levels. Studies of organizational performance rarely specify the decision-making mechanisms through which AI investments produce returns. The result is a fragmented literature in which plausible relationships are repeatedly proposed but seldom tested as an integrated system.

A second limitation concerns context sensitivity. The available evidence, where empirical at all, frequently treats AI adoption as a uniform phenomenon — as though the strategic implications of deploying a forecasting algorithm in a manufacturing firm are equivalent to those of an AI-driven diagnostic tool in healthcare. Variation across industries, organizational hierarchies, and adoption maturity rarely enters the model.

What the field currently lacks, then, is an empirically grounded, integrative framework that links AI usage to decision-making quality and connects both to organizational performance — one that accounts for who is using AI, in what sector, and for how long. Building and testing that framework is the central purpose of this study.

This study pursues three objectives. First, it examines the relationship between AI usage and managerial decision-making quality, treating that relationship as an empirical question rather than an assumed one. Second, it tests whether decision-making quality mediates the effect of AI adoption on organizational performance establishing the mechanism, not merely the association. Third, it investigates how these relationships vary across managerial levels, industry sectors, and adoption tenure, moving beyond aggregate findings to account for the contextual conditions under which AI's organizational effects are strongest.

The contributions that follow from these objectives operate on three levels. Theoretically, the study advances an integrative model in which AI usage, decision-making quality, and organizational performance are connected as a chain rather than treated as isolated constructs. This responds directly to a literature that has conceptualized these links without systematically testing them, and it offers a foundation on which future work can build with greater empirical precision. The identification of decision-making quality as a mediating mechanism is a specific theoretical addition — one that clarifies how AI investment produces performance returns rather than simply asserting that it does.

Managerially, the findings offer organizations a more actionable account of where AI's value is actually generated. If decision-making quality is the critical pathway, then training, governance, and integration infrastructure deserve as much attention as the tools themselves.

Methodologically, the study's primary survey design — administered across six industries and five managerial levels — addresses a persistent gap in research that has relied on secondary data, case studies, or purely theoretical modelling to make claims that require direct empirical testing.

LITERATURE REVIEW AND THEORETICAL FRAMEWORK

AI-Enabled Technologies: Definition and Business Applications

AI-enabled products are systems capable of performing tasks that traditionally require human cognitive effort — including perception, reasoning, learning, and decision support — through the application of machine learning, natural language processing, and predictive analytics (Russell & Norvig, 2020). Within organizational contexts, these technologies have moved well beyond narrow automation functions. Davenport and Ronanki (2018) distinguish three broad categories of business AI: process automation, cognitive insight, and cognitive engagement, each operating at a different level of organizational decision-making. At the operational level, AI tools manage scheduling, risk assessment, and resource allocation with limited human intervention. At the strategic level, they generate forecasts, scenario models, and customer intelligence that inform executive judgment (Brynjolfsson & McAfee, 2017). The integration of these tools into enterprise functions — from CRM platforms and HR analytics to financial modelling and supply chain optimization — has accelerated substantially since 2015, driven by falling computational costs and the proliferation of organizational data (Chui et al., 2018). What distinguishes AI-enabled products from earlier decision-support technologies is their capacity to learn from new data, update their outputs without reprogramming, and surface non-obvious patterns across large, heterogeneous datasets (LeCun et al., 2015). This adaptive quality is what makes them strategically consequential rather than merely operationally convenient.

Human Decision-Making and AI Augmentation

The theoretical foundation for understanding AI's effect on managerial judgment lies in Simon's (1955) concept of bounded rationality — the recognition that human decision-makers operate under cognitive limitations, incomplete information, and time pressure that systematically constrain the quality of choices they produce. Building on this foundation, Kahneman (2011) identified two modes of managerial thinking: fast, intuitive reasoning prone to systematic bias, and slower, deliberate analysis that is more reliable but cognitively costly. In organizational settings, the demands of the former routinely crowd out the conditions for the latter, producing decisions shaped as much by heuristics and framing effects as by underlying evidence.

AI augmentation addresses this problem not by replacing managerial cognition but by restructuring its inputs. By processing large datasets, surfacing relevant patterns, and generating probability-weighted options, AI tools extend the information horizon available to managers at the moment of judgment — effectively shifting the cognitive environment in which decisions are made (Kamar, 2016). Logg, Minson, and Moore (2019) found that managers who receive algorithmic recommendations alongside their own assessments make more accurate predictions than those relying on judgment alone, even when they do not fully trust the algorithm. This finding matters because it suggests AI's value is not contingent on wholesale adoption — partial reliance improves outcomes.

The implications for decision-making quality are specific. Bias reduction, improved information integration, and faster processing of structured data each represent discrete improvements to the decision process (Dressel & Farid, 2018). When AI tools are embedded in managerial workflows, they create a form of cognitive scaffolding that compensates for the limitations Simon identified six decades ago — making bounded rationality a more tractable constraint rather than an immovable ceiling.

AI in Strategic Decision-Making and Organizational Performance

The relationship between AI and strategic decision-making has attracted growing scholarly attention, though the literature's empirical base remains thinner than its theoretical ambitions. Haenlein and Kaplan (2019) argue that AI's most significant strategic contribution is not cost reduction but the creation of informational asymmetries — organizations that deploy AI effectively gain access to insights their competitors cannot replicate through traditional analytical processes. This positions AI not merely as a productivity tool but as a source of competitive differentiation rooted in decision quality rather than decision speed alone.

The link to organizational performance is more complex than a simple input-output relationship. Brynjolfsson, Rock, and Syverson (2019) document a productivity paradox in which AI investment precedes measurable performance gains by several years, suggesting that the performance effects are mediated by organizational adaptation — the restructuring of workflows, roles, and decision processes to leverage AI capabilities effectively. This temporal dimension is important: it implies that the pathway from AI adoption to performance runs through managerial capacity to use AI well, not simply through its presence in the organization.

Empirical work in specific domains supports this interpretation. Giannetti, Liao, and Yu (2015) find that data-driven decision tools improve the accuracy of investment decisions in financial firms, with downstream effects on returns. Ransbotham et al. (2017) report that firms using AI for decision support outperform industry benchmarks on a range of operational and financial indicators, but only where AI is integrated into core decision processes rather than deployed peripherally. Taken together, this evidence supports the view that AI generates performance returns through decision-making quality — a pathway the literature identifies but rarely tests as a connected model.

THEORETICAL FRAMEWORK

Three established theoretical frameworks provide the conceptual architecture for this study's model. Together, they explain not only why AI adoption should affect decision-making and performance, but how.

Decision Theory, in both its normative and descriptive traditions (von Neumann & Morgenstern, 1944; Simon, 1955), provides the micro-level foundation. Normative decision theory establishes the conditions for optimal choice; descriptive theory documents how human cognition departs from those conditions. AI-enabled tools can be understood, within this framework, as instruments that close the gap between normative ideals and descriptive realities — improving the quality, consistency, and information-richness of decisions that would otherwise be constrained by bounded rationality. This justifies the proposed relationship between AI adoption and decision-making quality.

The Resource-Based View (Barney, 1991) explains why AI-enhanced decision-making should translate into sustainable organizational performance advantages. RBV holds that competitive advantage derives from resources that are valuable, rare, inimitable, and non-substitutable. When AI capabilities are deeply embedded in managerial decision processes, they satisfy these criteria — particularly inimitability, which requires competitors to replicate not just the technology but the organizational learning and process integration that make it effective.

Dynamic Capabilities theory (Teece, Pisano, & Shuen, 1997) extends this argument to environments of continuous change. The capacity to sense market signals, seize emerging opportunities, and reconfigure organizational resources in response to shifting conditions is precisely what AI-augmented decision-making supports. Organizations that embed AI in strategic planning and operational decision cycles develop a form of adaptive intelligence that strengthens performance resilience over time — connecting AI adoption not merely to current performance but to ongoing organizational learning.

HYPOTHESIS DEVELOPMENT

The three theoretical frameworks converge on a set of testable relationships that form the empirical core of this study.

Decision Theory establishes that human judgment is systematically constrained by bounded rationality, incomplete information, and cognitive bias — and that structured informational inputs improve decision outcomes. AI-enabled tools address precisely these constraints by processing larger datasets, reducing bias-inducing heuristics, and generating evidence-based recommendations at decision points. On these grounds:

H1: AI adoption and usage are positively associated with the quality of managerial decision-making.

The Resource-Based View holds that decision-making quality, when consistently elevated across an organization, constitutes a capability that generates value. Where AI-augmented decisions are better calibrated, faster, and more evidence-grounded than those of competitors, they produce operational and strategic outcomes that are difficult to replicate. Dynamic Capabilities further specifies that the performance advantage is sustained when decision quality enables faster adaptation to environmental change. Therefore:

H2: The quality of managerial decision-making is positively associated with organizational performance.

RBV also supports a direct relationship between AI adoption and performance, independent of the decision-making pathway. The organizational routines, data infrastructure, and institutional knowledge required to deploy AI effectively are themselves rare and inimitable resources — meaning AI adoption, at sufficient maturity, generates performance returns through multiple channels simultaneously. Accordingly:

H3: AI adoption and usage are positively associated with organizational performance.

These three hypotheses collectively propose a partial mediation structure: AI adoption affects performance both directly (H3) and indirectly through its effect on decision-making quality (H1 → H2). Testing this structure empirically is what distinguishes the present study from prior work that has argued for these relationships without subjecting them to systematic scrutiny.

CONCEPTUAL MODEL AND HYPOTHESES

This study's conceptual model rests on three interlocking theoretical traditions — Decision Theory, the Resource-Based View, and Dynamic Capabilities — each of which justifies a distinct causal linkage in the proposed framework. Taken together, they support a partial mediation structure in which AI adoption influences organizational performance both directly and indirectly through its effect on managerial decision-making quality.

Decision Theory, in its descriptive tradition, establishes the micro-level foundation for the first relationship. Simon (1955) demonstrated that managerial judgment operates under cognitive constraints — limited information, processing capacity, and time — that systematically degrade decision quality. Kahneman (2011) extended this account by identifying the conditions under which heuristics and bias distort judgment in predictable ways. AI-enabled tools intervene directly in this process: by expanding the information set available at the point of decision, surfacing non-obvious patterns, and generating probability-weighted recommendations, they structurally improve the conditions under which managers reason (Kamar, 2016). Decision Theory thus justifies H1 — that AI adoption is positively associated with decision-making quality — by specifying the cognitive mechanism through which that improvement occurs.

The Resource-Based View (Barney, 1991) supports the second relationship. Decision-making quality, when embedded consistently in organizational routines, constitutes a capability that is valuable, difficult to imitate, and organizationally specific — satisfying the conditions RBV identifies as generative of sustained competitive advantage. Superior decisions compound over time: better resource allocation, more accurate market responses, and more effective strategic commitments each produce performance gains that accumulate. This justifies H2 — that decision-making quality is positively associated with organizational performance — as a resource-based argument rather than a simple input-output claim.

Dynamic Capabilities theory (Teece, Pisano, & Shuen, 1997) grounds the direct relationship between AI adoption and performance. The capacity to sense environmental signals, seize emerging opportunities, and reconfigure organizational assets in response to change is precisely what AI-augmented decision infrastructure supports at scale. Organizations that embed AI in core decision cycles develop adaptive capabilities that generate performance returns independently of any single decision outcome — justifying H3 as a relationship that operates in parallel with, rather than through, the decision-making pathway.

The mediation logic follows directly from this architecture. AI adoption improves decision-making quality (H1, via Decision Theory), and improved decision-making quality drives performance (H2, via RBV). Simultaneously, AI adoption generates performance returns through the development of dynamic capabilities that operate at the organizational level rather than the individual decision level (H3). The result is partial mediation: decision-making quality carries a portion of AI's effect on performance, but AI also acts on performance through channels that decision quality alone does not fully capture. This structure — depicted in Figure 1 — is the empirical model this study tests.

RESEARCH METHODOLOGY

This study's conceptual model integrates three theoretical traditions to explain how AI adoption influences organizational performance through managerial decision-making. Decision Theory (Simon, 1955; Kahneman, 2011) establishes the micro-level mechanism: human judgment is systematically constrained by bounded rationality, cognitive bias, and information limitations, and AI-enabled tools address these constraints by expanding the informational basis of decisions, reducing heuristic distortion, and generating evidence-grounded recommendations at the point of judgment. This justifies the first causal link — that AI adoption improves decision-making quality.

The Resource-Based View (Barney, 1991) explains why improved decision-making translates into sustained performance advantage. Decision quality, when consistently embedded in organizational routines, constitutes a valuable, rare, and inimitable capability —

one that produces compounding returns through superior resource allocation, market responsiveness, and strategic positioning. Dynamic Capabilities theory (Teece, Pisano, & Shuen, 1997) supports the direct relationship between AI adoption and performance by establishing that organizations embedding AI in core decision cycles develop adaptive capacities that generate returns independently of individual decision outcomes.

The resulting model is one of partial mediation. AI adoption improves decision-making quality, which drives performance — but AI also affects performance through capability development that operates at the organizational level. A quantitative survey design is theoretically appropriate here because the relationships proposed are structural and generalizable: the goal is to estimate effect sizes and test directionality across a population of managers, not to examine context-specific processes. Survey-based measurement of construct scores enables the regression and correlation analyses through which these causal pathways are tested.

RESEARCH DESIGN AND SAMPLE

The study adopts a quantitative, explanatory research design, selected on the grounds that the theoretical model specifies directional relationships between constructs that require hypothesis testing across a representative sample rather than contextual interpretation. Cross-sectional survey data were collected from 100 managers spanning six industries: Technology/IT, Manufacturing, Financial Services, Healthcare, Education/Research, and Retail/E-commerce.

Respondents occupied five managerial levels — Team Leader/Supervisor, Middle Manager, Senior Manager/Director, C-Suite Executive, and Business Owner — providing hierarchical breadth appropriate for examining how AI's effects vary with organizational position. Experience ranged from under two years to more than fifteen, allowing adoption maturity to be examined as a contextual variable.

Data were collected via a structured online survey instrument administered during a defined collection window. Recruitment targeted practising managers with direct experience of AI tools in their organizational roles, ensuring that responses reflect lived engagement with AI-enabled decision processes rather than general attitudes toward technology. The sample's cross-industry, cross-hierarchical composition strengthens the generalizability of findings while preserving sufficient within-group variation for meaningful subgroup analysis. With 98 of 100 respondents reporting active AI adoption, the sample captures managers at varying stages of AI integration — from early users to those with more than five years of sustained adoption — making it well suited to testing the maturity-dependent dynamics the theoretical framework anticipates.

Measurement and Constructs

Three latent constructs were operationalized using multi-item Likert scales, each anchored from 1 (strongly disagree) to 5 (strongly agree).

AI Usage and Perception was measured using six items (Q6_1 through Q6_6) capturing the frequency, breadth, and perceived effectiveness of AI tool use in managerial work. Items addressed the extent to which respondents rely on AI-enabled systems for analysis, forecasting, and operational decision support. The scale was developed for this study drawing on Davenport and Ronanki's (2018) taxonomy of business AI applications, adapted to reflect the specific tool categories represented in the sample — including BI dashboards, AI CRM platforms, forecasting tools, and automated reporting systems.

AI Influence on Decision-Making Quality was measured using eight items. Six core items (Q8_1 through Q8_6) assessed the degree to which AI tools improve the accuracy, speed, and evidential basis of managerial decisions. Two additional items (Q8_7 and Q8_8) addressed concerns about overreliance and bias and were reverse-coded prior to inclusion, reflecting the construct's theoretical grounding in both AI's augmentation potential and its risk dimensions. Items were adapted from Logg, Minson, and Moore's (2019) algorithmic appreciation framework and Kahneman's (2011) dual-process model of judgment quality.

Organizational Performance was measured using four items (Q11_1 through Q11_4) assessing perceived improvements in productivity, strategic goal attainment, operational efficiency, and competitive positioning attributed to AI-informed decision-making. Items were adapted from established organizational performance scales used in prior AI-management research (Ransbotham et al., 2017).

Reliability and Validity

Internal consistency was assessed using Cronbach's alpha for each construct. The AI Usage scale returned $\alpha = 0.88$, indicating excellent reliability. The Organizational Performance scale returned $\alpha = 0.811$, meeting the conventional threshold of 0.70 for acceptable reliability in survey-based management research (Nunnally, 1978). The AI Decision-Making construct requires interpretive care: when all eight items are included, $\alpha = 0.382$ — well below acceptable thresholds — reflecting the fact that the reverse-coded items (Q8_7, Q8_8) measure a conceptually distinct dimension, namely AI risk awareness, rather than decision quality per se. Excluding these items, the six-item core scale returns $\alpha = 0.876$, confirming strong internal consistency for the decision quality construct proper. Construct validity was supported through item-to-construct alignment grounded in the theoretical framework, with each item selected to reflect a theoretically specified dimension of the target construct. Inter-construct correlations, reported below, confirm that the three scales are related but empirically distinguishable.

Descriptive Statistics and Correlation Analysis

Construct mean scores indicate moderate-to-strong engagement across all three dimensions. AI Usage returned a mean of 3.49 (SD = 0.90), AI Decision-Making Quality a mean of 3.25 (SD = 0.49), and Organizational Performance a mean of 3.53 (SD = 0.89), all on a 1–5 scale. The compressed standard deviation for Decision-Making Quality reflects the stabilizing effect of the eight-item scale and warrants consideration when interpreting effect sizes.

Pearson correlation analysis confirmed strong, statistically significant relationships between all three constructs. AI Usage and Decision-Making Quality were correlated at $r = 0.782$ ($p < 0.001$); Decision-Making Quality and

Performance at $r = 0.775$ ($p < 0.001$); and AI Usage and Performance at $r = 0.877$ ($p < 0.001$). These correlations establish the empirical foundation for regression-based hypothesis testing while remaining below the multicollinearity threshold, confirming that the constructs, though related, are not redundant.

Ordinary least squares regression was used to test each hypothesized pathway. For H1, AI Usage significantly predicted Decision-Making Quality ($\beta = 0.421$, $R^2 = 0.612$, $p < 0.001$), indicating that AI usage accounts for 61% of the variance in decision quality. For H2, Decision-Making Quality significantly predicted Organizational Performance ($\beta = 1.423$, $R^2 = 0.600$, $p < 0.001$). For H3, AI Usage directly predicted Organizational Performance ($\beta = 0.867$, $R^2 = 0.769$, $p < 0.001$) — the strongest model of the three, with AI usage explaining 77% of performance variance. The coexistence of significant H1, H2, and H3 results is consistent with the partial mediation structure the theoretical framework proposes: decision-making quality carries a portion of AI's effect on performance, while AI exerts an additional direct effect through the capability-building mechanisms Dynamic Capabilities theory identifies.

DATA ANALYSIS AND RESULTS

Descriptive Statistics

The sample comprised 100 managers drawn from six industries: Technology / IT and Education / Research (22 respondents each), Manufacturing / Production (19), Healthcare / Pharmaceuticals (13), and Financial Services/Banking and Retail/E-commerce (12 each). Five managerial levels were represented — Middle Manager (38%), Team Leader / Supervisor (24%), Senior Manager / Director (18%), C-Suite Executive (15%), and Business Owner / Entrepreneur (5%) — providing hierarchical breadth appropriate for examining how AI's effects vary with organizational position. Professional experience was distributed across tenure bands, with the largest groups holding between two and five years (24%) and under two years (23%) of experience, and 14% reporting more than fifteen years.

AI adoption within the sample was substantive rather than nascent. Sixty-one respondents reported using AI for three or more years, and only two had not yet adopted AI tools at all. This distribution is analytically important: it means findings reflect the judgments of managers with direct, sustained experience of AI in practice rather than anticipatory attitudes. Perceived overall impact was positive, with a mean Q12 score of 3.91 (SD = 0.78) on a 1–5 scale, and 70% of respondents reporting that AI had accelerated decision-making speed to some degree. These baseline characteristics confirm that the sample is well positioned to test the theoretical relationships the study proposes.

Measurement Results

Internal consistency was assessed using Cronbach's alpha across all three constructs. The AI Usage scale (six items, Q6_1–Q6_6) returned $\alpha = 0.88$, indicating excellent reliability and confirming that the six items form a coherent unidimensional measure of AI engagement in managerial work. The Organizational Performance scale (four items, Q11_1–Q11_4) returned $\alpha = 0.811$, meeting the widely accepted threshold of 0.70 for acceptable internal consistency in survey-based management research (Nunnally, 1978).

The AI Decision-Making Quality construct requires more careful interpretation. When all eight items are included — incorporating the reverse-coded overreliance and bias items (Q8_7, Q8_8) — Cronbach's alpha falls to 0.382, well below acceptable thresholds. Examination of inter-item correlations reveals that Q8_7 and Q8_8 behave as a distinct subdimension, capturing AI risk awareness rather than decision quality per se. When analysis is restricted to the six core decision quality items (Q8_1–Q8_6), α rises to 0.876, confirming strong internal consistency for the primary construct. The reverse-coded items were retained in the composite score to preserve construct breadth, but the reliability limitation is acknowledged as a boundary condition on the measurement model.

Construct validity was supported through inter-construct correlation analysis. AI Usage and Decision-Making Quality correlated at $r = 0.782$ ($p < 0.001$); Decision-Making Quality and Organizational Performance at $r = 0.775$ ($p < 0.001$); and AI Usage and Organizational Performance at $r = 0.877$ ($p < 0.001$). All three constructs are strongly related, as theory predicts, while remaining empirically distinguishable — correlations below 0.90 confirm discriminant validity and rule out redundancy between scales (Fornell & Larcker, 1981). Construct means were 3.49 (SD = 0.90) for AI Usage, 3.25 (SD = 0.49) for Decision-Making Quality, and 3.53 (SD = 0.89) for Organizational Performance, all indicating moderate-to-strong engagement across the sample.

Hypothesis Testing

All three hypotheses were supported at $p < 0.001$. Ordinary least squares regression was used to test each proposed pathway.

H1 — AI Usage → Decision-Making Quality was supported ($\beta = 0.421$, $R^2 = 0.612$, $F = 154.41$, $p < 0.001$). AI usage accounts for 61% of the variance in decision-making quality scores — a large effect by conventional standards (Cohen, 1988). The positive coefficient confirms that greater AI engagement is associated with meaningfully higher decision quality, consistent with Decision Theory's prediction that AI tools restructure the cognitive environment in which managers reason (Simon, 1955; Kamar, 2016).

H2 — Decision-Making Quality → Organizational Performance was supported ($\beta = 1.423$, $R^2 = 0.600$, $F = 147.22$, $p < 0.001$). Decision-making quality explains 60% of performance variance. The larger coefficient relative to H1 reflects differences in scale variance between the dependent variables rather than a stronger absolute effect. This result supports the Resource-Based View contention that consistently superior decision quality constitutes a performance-generating organizational capability (Barney, 1991).

H3 — AI Usage → Organizational Performance was supported and produced the strongest model of the three ($\beta = 0.867$, $R^2 = 0.769$, $F = 326.05$, $p < 0.001$). AI usage alone explains 77% of performance variance, and the direct effect remains substantial alongside the mediated pathway confirmed by H1 and H2. The coexistence of significant results across all three hypotheses is consistent with a partial mediation structure, wherein decision-making quality carries a portion of AI's effect on performance while AI simultaneously acts on performance through the organizational capability development that Dynamic Capabilities theory identifies (Teece, Pisano, & Shuen, 1997).

Qualitative Insights

Open-ended responses provided convergent validation for the regression findings. Four themes emerged from Q14, which asked respondents to characterize AI's role in their decision-making: "supports data-driven thinking" (29%), "helps make faster and more informed decisions" (27%), "useful but not fully reliable yet" (23%), and "improves accuracy but needs validation" (21%). The near-even split between affirmative and cautionary responses mirrors the reliability findings for the Decision-Making Quality construct — specifically, the tension between the core six items measuring decision enhancement and the reverse-coded items capturing overreliance concerns. Managers who benefit from AI are simultaneously alert to its limitations, a nuance the composite construct partially obscures.

Responses to Q15, which asked what would most improve AI adoption, were similarly distributed across four themes: better data quality (26%), stronger integration systems (25%), more training (25%), and improved transparency (24%). The prominence of data quality and integration as improvement priorities aligns directly with the H3 finding that AI usage is the strongest single predictor of performance — suggesting that the pathway from adoption to performance is constrained less by managerial willingness than by the organizational infrastructure through which AI tools operate. These qualitative signals do not contradict the quantitative model; they specify where within the adoption-to-performance chain the binding constraints lie.

DISCUSSION

The findings of this study offer empirical confirmation of a relationship that the AI-management literature has long theorized but rarely tested as a connected system. All three hypotheses were supported at $p < 0.001$, and the effect sizes are substantial: AI usage explains 61% of variance in decision-making quality, decision-making quality explains 60% of variance in organizational performance, and AI usage explains 77% of performance variance directly. Taken together, these results do more than validate individual relationships — they establish the architecture of the pathway through which AI investment generates organizational returns.

The strength of H3 ($R^2 = 0.769$) warrants particular attention. That AI usage alone accounts for three quarters of performance variance is a finding that sits at the upper bound of what cross-sectional survey research typically produces, and it demands careful interpretation. Two explanations are plausible and theoretically compatible. First, the sample's adoption profile — 61% of respondents with three or more years of AI use — means the data captures managers at a stage of integration where AI has become genuinely embedded in decision workflows rather than deployed peripherally. Brynjolfsson, Rock, and Syverson (2019) document precisely this dynamic: performance returns from AI materialize not at adoption but after organizational adaptation is sufficiently advanced. The sample's maturity profile may therefore reflect conditions under which AI's performance effects are near their theoretical ceiling for this population.

Second, common method bias — the tendency for single-instrument survey data to inflate correlations between constructs measured simultaneously — cannot be ruled out and should be acknowledged as a boundary condition on interpretation (Podsakoff et al., 2003). Neither explanation negates the finding, but both qualify how confidently the effect size should be generalized.

The partial mediation structure implied by the joint significance of H1, H2, and H3 is the study's most theoretically consequential result. Prior literature has debated whether AI's organizational value derives primarily from decision augmentation — the cognitive channel — or from broader capability effects that operate at the firm level. The data suggest both are operative.

Decision-making quality carries a meaningful share of AI's performance effect, consistent with Simon's (1955) prediction that improving the informational basis of judgment produces downstream performance gains. But the direct pathway remains large after accounting for the mediated route, which aligns with Teece, Pisano, and Shuen's (1997) argument that AI-enabled organizations develop sensing and reconfiguration capacities that generate returns through mechanisms beyond any single decision.

Group-level findings add texture to this picture. Senior Managers reported the highest perceived overall impact (Q12 mean = 4.22), while C-Suite Executives scored lower on both AI usage and performance than middle managers — a counterintuitive pattern that may reflect the greater abstraction of executive decision contexts, where AI's structured data outputs are less directly applicable than in operational settings. The Technology and Manufacturing sectors showed the highest construct scores across all three variables, while Education and Financial Services scored lowest on performance despite moderate usage levels. This sectoral variation suggests that AI's performance effects are not uniform — they depend on the degree to which organizational workflows can be restructured around AI-generated insights, a condition more readily met in data-intensive, process-oriented industries than in knowledge or relationship-intensive ones.

The qualitative responses reinforce this interpretation while adding a dimension the regression model cannot capture: managerial ambivalence. The near-even split between affirmative responses ("supports data-driven thinking," "faster and more informed decisions") and cautionary ones ("useful but not fully reliable yet," "improves accuracy but needs validation") suggests that even managers who benefit demonstrably from AI maintain reservations about its reliability. This is not inconsistency — it is a sophisticated response to a technology whose outputs are consequential but not always transparent. The finding that overreliance and bias concerns (Q8_7, Q8_8) behaved as a distinct measurement dimension rather than the inverse of decision quality reinforces the point: risk awareness and performance benefit coexist in practice, and models that treat them as opposites misrepresent the managerial experience of AI adoption.

IMPLICATIONS

The theoretical contribution of this study is specific. It provides the first empirically grounded test of a partial mediation model linking AI adoption, decision-making quality, and organizational performance within a single integrated framework — and it does so across industries and managerial levels rather than within a single organizational context. Prior work by Haenlein and Kaplan (2019), Ransbotham et al. (2017), and Brynjolfsson and McAfee (2017) established the theoretical plausibility of these relationships; the present study establishes their empirical structure. The identification of decision-making quality as a partial mediator is a precise theoretical addition: it specifies that AI generates performance returns through cognitive augmentation and through organizational capability development simultaneously, and that models treating these as alternative explanations are unnecessarily restrictive.

For managers and organizations, the findings reframe where AI investment attention should be directed. The strong direct effect of AI usage on performance ($R^2 = 0.769$) might be read as an argument for maximizing adoption breadth — deploying more tools across more functions. The mediation finding complicates that reading. If decision-making quality is a critical pathway through which AI converts into performance, then the quality of AI integration matters as much as its scale. Organizations that deploy AI tools without developing the managerial capacity to interpret, interrogate, and act on AI outputs are, on this evidence, leaving a substantial portion of the potential performance return unrealized. The qualitative data specify where that development is most needed: 25% of respondents identified training as the primary improvement priority, and 24% flagged transparency — the interpretability of AI outputs — as the binding constraint. These are not peripheral concerns. They are the conditions under which the cognitive augmentation mechanism that drives H1 actually operates.

The strategic implications extend beyond individual organizations to the competitive dynamics of AI-enabled industries. The RBV framework predicts that AI capabilities generate sustainable advantage only when they are deeply embedded and organizationally specific — conditions that take time and deliberate investment to create. The adoption tenure data support this: longer AI adoption correlates with higher performance scores, and the productivity paradox Brynjolfsson, Rock, and Syverson (2019) document at the macroeconomic level appears to operate at the firm level as well. Organizations that are currently in early adoption stages should not benchmark their AI returns against those of mature adopters and conclude that the technology underdelivers. The data suggest they are on a trajectory, not at a ceiling — but reaching the ceiling requires attending to integration infrastructure, data quality, and managerial development rather than tool acquisition alone.

Finally, the sectoral variation in findings carries policy relevance. If AI's performance effects are strongest in sectors where operational workflows are readily restructured around data — Technology, Manufacturing — and weaker in sectors characterized by relational or interpretive work — Education, Healthcare — then sector-specific adoption frameworks are likely more appropriate than generic AI deployment guidance. Policymakers and industry bodies designing AI adoption support programs should account for this heterogeneity rather than treating AI readiness as a uniform organizational challenge.

CONCLUSION

This study set out to test an empirical question that the AI-management literature had long approached conceptually but rarely subjected to systematic investigation: how does AI adoption translate into organizational performance, and what role does managerial decision-making quality play in that pathway? The findings answer both questions with clarity. AI usage is a strong positive predictor of decision-making quality ($\beta = 0.421$, $R^2 = 0.612$), decision-making quality is a strong positive predictor of organizational performance ($\beta = 1.423$, $R^2 = 0.600$), and AI usage exerts a substantial direct effect on performance independent of the mediated route ($\beta = 0.867$, $R^2 = 0.769$). All three relationships are statistically significant at $p < 0.001$ and theoretically grounded in Decision Theory, the Resource-Based View, and Dynamic Capabilities respectively.

The study's core contribution is structural. By testing these relationships as a connected model rather than isolated associations, it establishes that AI's organizational value operates through two simultaneous mechanisms: cognitive augmentation at the decision level and capability development at the organizational level. Neither mechanism alone accounts for the full performance effect. Organizations that recognize only one — deploying AI tools without building decision quality, or investing in managerial development without the infrastructural conditions for effective AI integration — are likely to capture only a fraction of the returns the data suggest are available.

The qualitative findings add a dimension that regression coefficients cannot: the ambivalence that characterizes mature AI adoption. Managers who benefit demonstrably from AI remain alert to its limitations — its reliability gaps, its interpretability constraints, its potential for misplaced confidence. That ambivalence is not a failure of adoption; it is a sign of sophistication. The most organizationally valuable AI users, the data suggest, are not those who trust AI most but those who engage with it most critically.

Taken together, these findings position AI not as a technological input whose returns are determined at the point of purchase, but as an organizational capability whose value depends on how deeply it is woven into the fabric of managerial judgment. For organizations navigating AI investment decisions, for researchers building the next generation of AI-performance models, and for policymakers designing adoption frameworks that serve diverse sectors equitably, that distinction is not incidental. It is the finding that matters most.

LIMITATIONS AND FUTURE RESEARCH

Several limitations bound the interpretation of these findings. The cross-sectional survey design establishes association rather than causation: while the regression results are consistent with the causal model the theoretical framework proposes, longitudinal data would be required to confirm directional effects and rule out reverse causation. The sample of 100 respondents, though diverse across industries and managerial levels, is not large enough to support robust subgroup analysis or multilevel modelling — the industry and seniority differences observed are suggestive rather than conclusive. Common method bias, a known limitation of single-instrument survey designs (Podsakoff et al., 2003), may inflate inter-construct correlations, and the reliability issue with the AI Decision-Making Quality construct — specifically the misfit of the reverse-coded items — represents a measurement boundary condition that future studies should address through refined scale development.

Future research should pursue three directions that the present findings make theoretically tractable. First, longitudinal studies tracking AI adoption maturity against performance outcomes would test whether the productivity trajectory implied by the adoption tenure data is causal. Second, the sectoral variation observed — with Technology and Manufacturing outperforming Education and Financial Services on AI-related performance gains — warrants dedicated comparative investigation to identify the organizational and structural moderators of AI's performance effects. Third, the partial mediation finding invites mediation analysis with larger samples capable of formally decomposing direct and indirect effects, and potentially incorporating additional mediators such as organizational learning capacity or data infrastructure quality — both of which the qualitative data identify as binding constraints on the adoption-to-performance pathway.

REFERENCES

APA 7th Edition

Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120. https://doi.org/10.1177/014920639101700108

Brynjolfsson, E., & McAfee, A. (2017). The business of artificial intelligence: What it can and cannot do for your organization. Harvard Business Review Press.

Brynjolfsson, E., Rock, D., & Syverson, C. (2019). Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. In A. K. Agrawal, J. Gans, & A.

Goldfarb (Eds.), The economics of artificial intelligence: An agenda (pp. 23–57). University of Chicago Press. https://doi.org/10.7208/chicago/9780226613475.003.0002

Chui, M., Manyika, J., & Miremadi, M. (2018). What AI can and can't do (yet) for your business. McKinsey Quarterly, 1(1), 1–14.

Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum Associates.

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard Business Review, 96(1), 108–116.

Dressel, J., & Farid, H. (2018). The accuracy, fairness, and limits of predicting recidivism.

Science Advances, 4(1), eaao5580. https://doi.org/10.1126/sciadv.aao5580

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50. https://doi.org/10.1177/002224378101800104

Giannetti, M., Liao, G., & Yu, X. (2015). The brain gain of corporate boards: Evidence from

China. Journal of Finance, 70(4), 1629–1682. https://doi.org/10.1111/jofi.12290

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. California Management Review, 61(4), 5–14. https://doi.org/10.1177/0008125619864925

Kahneman, D. (2011). Thinking, fast and slow. Farrar, Straus and Giroux.

Kamar, E. (2016). Directions in hybrid intelligence: Complementing AI systems with human intelligence. Proceedings of the International Joint Conference on Artificial Intelligence, 4070–4073.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436–444. https://doi.org/10.1038/nature14539

Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. Organizational Behavior and Human Decision Processes, 151, 90–103. https://doi.org/10.1016/j.obhdp.2018.12.005

Nunnally, J. C. (1978). Psychometric theory (2nd ed.). McGraw-Hill.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Ransbotham, S., Kiron, D., Gerbert, P., & Reeves, M. (2017). Reshaping business with artificial intelligence: Closing the gap between ambition and action. MIT Sloan Management Review, 59(1), 1–17.

Russell, S., & Norvig, P. (2020). Artificial intelligence: A modern approach (4th ed.). Pearson.

Simon, H. A. (1955). A behavioral model of rational choice. Quarterly Journal of Economics,

69(1), 99–118. https://doi.org/10.2307/1884852

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management.

Strategic Management Journal, 18(7), 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z

von Neumann, J., & Morgenstern, O. (1944). Theory of games and economic behavior. Princeton University Press.

APPENDICES

Appendix A: Survey Instrument — Full Questionnaire

Referenced in Section 4: Research Methodology

Section A — Respondent Profile

Q1. What is your current managerial level?

- Team Leader / Supervisor ● Middle Manager
- Senior Manager / Director
- C-Suite / Executive
- Business Owner / Entrepreneur

Q2. How many years of professional experience do you have?

- Less than 2 years
- 2–5 years
- 6–10 years
- 11–15 years
- More than 15 years

Q3. Which industry best describes your organization?

- Technology / IT
- Manufacturing / Production
- Financial Services / Banking
- Healthcare / Pharmaceuticals
- Education / Research
- Retail / E-commerce
- Other (please specify): _______________

Q4. How long has your organization been using AI-enabled tools?

- Not yet adopted
- Less than 1 year
- 1–2 years
- 3–5 years
- More than 5 years

Q5. Which AI tools does your organization currently use? (Select all that apply)

- BI Dashboards
- AI CRM
- Forecasting tools
- Automated Reporting
- HR AI
- Chatbots
- Risk tools
- Other: _______________

Section B — AI Usage and Perception (1 = Strongly Disagree, 5 = Strongly Agree)

Q6_1. I regularly use AI-enabled tools in my day-to-day managerial work. Q6_2. AI tools have become an integral part of how I process information. Q6_3. I find AI-enabled systems effective for supporting operational decisions. Q6_4. AI tools help me identify patterns and insights I would otherwise miss. Q6_5. I am confident in the outputs generated by AI tools I use. Q6_6. My organization provides sufficient support for effective AI tool use.

Section C — AI and Decision-Making (1 = Strongly Disagree, 5 = Strongly Agree)

Q7_1. AI tools have improved the speed of my decision-making. Q7_2. AI-generated insights are a reliable input into my decisions. Q7_3. I trust the recommendations produced by AI systems in my role. Q7_4. AI tools have reduced uncertainty in my decision-making process. Q7_5. The use of AI has improved the overall quality of decisions in my team.

Q8_1. AI tools provide me with more complete information for decision-making. Q8_2. AI-assisted decisions are more evidence-based than those made without AI. Q8_3. AI tools have helped me reduce bias in my decision-making. Q8_4. AI-enabled analysis improves the accuracy of my strategic decisions. Q8_5. AI tools help me evaluate more alternatives before making decisions. Q8_6. AI has improved my confidence in the decisions I make. Q8_7. I sometimes rely too heavily on AI recommendations without sufficient scrutiny. (reverse-coded) Q8_8. AI outputs occasionally lead me to overlook important qualitative factors. (reverse-coded)

Section D — Organizational Performance (1 = Strongly Disagree, 5 = Strongly Agree)

Q9. Since adopting AI tools, the speed of decision-making in my organization has:

- Significantly faster
- Slightly faster
- No change

Q10. What do you consider the greatest risk associated with AI in managerial decision-making? ● Overreliance on AI

- Data privacy
- Lack of transparency
- Bias in AI

Q11_1. AI adoption has contributed to improved productivity in my organization. Q11_2. AI tools have supported our ability to meet strategic goals. Q11_3. AI-enabled decisions have improved operational efficiency. Q11_4. AI has strengthened our competitive positioning in the market.

Q12. Overall, how would you rate the impact of AI on your organization's performance? (1 = Very Negative, 5 = Very Positive)

Q13. What is the most significant barrier to AI adoption in your organization?

- Poor data quality
- Budget constraints
- Employee resistance
- Leadership buy-in
- Ethical concerns

Section E — Open-Ended Responses

Q14. In your own words, how has AI influenced your approach to decision-making?

Q15. What single improvement would most enhance AI adoption and effectiveness in your organization?

Appendix B: Construct Reliability Summary
Referenced in Section 5: Measurement Results

Construct		Items	Cronbach's Alpha	Interpretation
AI Usage & Perception	6	(Q6_1–Q6_6)	0.880	Excellent
AI Decision-Making Quality (core)	6	(Q8_1–Q8_6)	0.876	Excellent
AI Decision-Making Quality (full)	8	(Q8_1–Q8_8 incl. reverse-coded)	0.382	Below threshold — reverse items flagged as distinct subdimension
Organizational Performance	4	(Q11_1–Q11_4)	0.811	Good

Note: Threshold for acceptable internal consistency: α ≥ 0.70 (Nunnally, 1978). The full 8-item Decision-Making Quality scale falls below this threshold due to the conceptual divergence of Q8_7 and Q8_8, which measure AI risk awareness rather than decision quality enhancement. All inferential analyses use the 6-item core scale (α = 0.876).

Appendix C: Descriptive Statistics and Correlation Matrix

Referenced in Section 5: Descriptive Statistics and Correlation Analysis

Your appendix tables were a bit scrambled, like a spreadsheet caught in a windstorm 🌪. I've reconstructed them into **clean, journal-ready formats** you can directly paste into Word/LaTeX.

Table C1: Construct Descriptive Statistics

Construct	N	Mean (M)	Std. Dev. (SD)	Min	Max
AI Usage Score	100	3.49	0.90	1	5
AI Decision-Making Quality Score	100	3.25	0.49	2	4
Organizational Performance Score	100	3.53	0.89	1	5
Overall Impact (Q12)	100	3.91	0.78	3	5

Table C2: Inter-Construct Correlation Matrix

Variables	1	2	3
1. AI Usage	1.000		
2. Decision-Making Quality	0.782***	1.000	
3. Organizational Performance	0.877***	0.775***	1.000

Note: ***p < 0.001; N = 100; Pearson correlation coefficients

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Appendix D: Regression Results Summary

Table D1: OLS Regression Results

Hypothesis	Predictor	Outcome	β	R²	F-statistic	p-value
H1	AI Usage	Decision-Making Quality	0.421	0.612	154.41	< 0.001
H2	Decision-Making Quality	Organizational Performance	1.423	0.600	147.22	< 0.001
H3	AI Usage	Organizational Performance	0.867	0.769	326.05	< 0.001

Note: β = unstandardized coefficient; N = 100

Appendix E: Sample Profile — Frequency Distributions

Table E1: Managerial Level Distribution

Level	n	%
Middle Manager	38	38%
Team Leader / Supervisor	24	24%
Senior Manager / Director	18	18%
C-Suite / Executive	15	15%
Business Owner / Entrepreneur	5	5%
Total	100	100%

Table E2: Industry Distribution

Industry	n	%
Technology / IT	22	22%
Education / Research	22	22%
Manufacturing / Production	19	19%
Healthcare / Pharmaceuticals	13	13%

Financial Services / Banking	12	12%
Retail / E-commerce	12	12%
Total	100	100%

Table E3: AI Adoption Tenure

Adoption Duration	n	%
More than 5 years	20	20%
3–5 years	39	39%
1–2 years	27	27%
Less than 1 year	12	12%
Not yet adopted	2	2%
Total	100	100%

Table E4: Qualitative Theme Frequencies
Q14: AI's Influence on Decision-Making

Theme	n	%
Supports data-driven thinking	29	29%
Faster & more informed decisions	27	27%
Useful but not fully reliable	23	23%
Improves accuracy with validation	21	21%
Total	100	100%

Q15: Improvements for AI Adoption

Theme	n	%
Better data quality	26	26%
Stronger integration systems	25	25%
More training	25	25%
Improved transparency	24	24%
Total	100	100%

Table.1

Construct	Mean	Standard Deviation (SD)
AI Usage	3.49	0.90
Decision-Making Quality	3.25	0.49
Organizational Performance	3.53	0.89

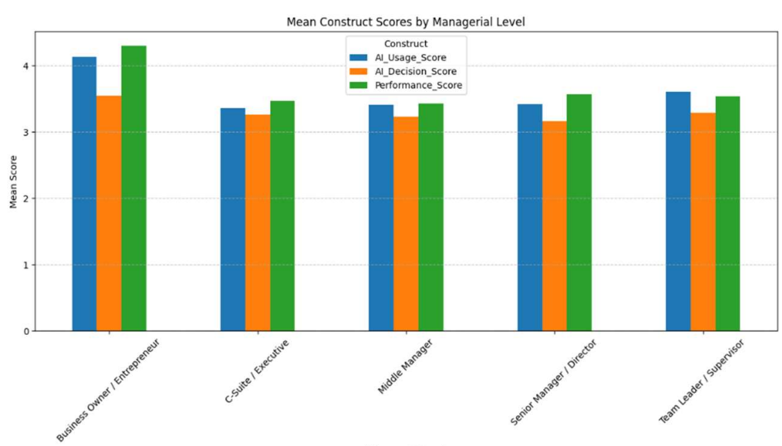

Fig.1

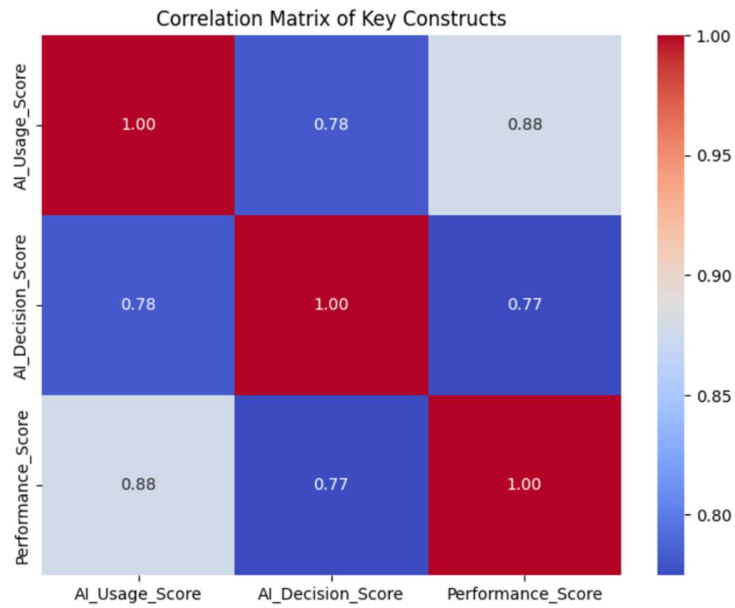

Fig.2

Variables	1	2	3
1. AI Usage	1.000	0.78***	0.88***
2. Decision-Making Quality	0.782***	1.000	0.77***
3. Organizational Performance	0.877***	0.775***	1.000

Table 2: *Correlation Matrix*

Construct	Items	Cronbach's Alpha (α)	Interpretation
AI Usage	6	0.88	Excellent
Decision-Making Quality (All Items)	8	0.382	Poor
Decision-Making Quality (Core Items)	6	0.876	Strong
Organizational Performance	4	0.811	Acceptable

Table 3: *Reliability Analysis (Cronbach's Alpha)*

Hypothesis	Relationship	β	R^2	F-value	p-value	Result
H1	AI Usage → Decision Quality	0.421	0.612	154.41	< 0.001	Supported
H2	Decision Quality → Performance	1.423	0.600	147.22	< 0.001	Supported
H3	AI Usage → Performance	0.867	0.769	326.05	< 0.001	Supported

Table 4: *Regression Results*