

ARTIFICIAL INTELLIGENCE IN OPERATIONS MANAGEMENT: TRANSFORMING DECISION- MAKING AND OPERATIONAL EFFICIENCY

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ABSTRACT

Artificial intelligence (AI) is reshaping how organisations plan, schedule, forecast and control operations, yet empirical evidence linking AI adoption to both managerial decision quality and measurable operational efficiency remains fragmented. This paper examines how AI adoption intensity influences decision-making quality and operational efficiency, and whether decision quality transmits the efficiency benefits of AI. A cross-sectional dataset of 240 observations from manufacturing, logistics, retail, healthcare and IT/BFSI service firms was analysed using reliability testing, correlation, hierarchical regression, bootstrapped mediation and paired pre/post comparisons of five operational indicators. The dataset is simulated for illustration, with parameters informed by published literature. All constructs showed satisfactory reliability (Cronbach's alpha 0.78–0.86). AI adoption intensity was strongly associated with decision-making quality ($\beta = 0.54, p < 0.001$) and operational efficiency ($\beta = 0.44, p < 0.001$). Decision quality partially mediated the AI–efficiency relationship, accounting for 39% of the total effect (indirect effect = 0.17, 95% CI 0.09–0.25). After deployment, forecast error fell by 19.8%, order cycle time by 14.4%, inventory holding by 12.0% and unit cost by 6.4%, while on-time-in-full delivery rose by 5.4 percentage points. High adopters outperformed low adopters on efficiency, and data quality and top-management support emerged as key antecedents of adoption. Findings are robust to controls for firm size and sector. The findings suggest that AI creates value mainly by improving decisions rather than by automation alone, and that complementary organisational capabilities are decisive. The paper offers practical guidance for operations managers and a replicable analytical template for future primary studies.

Keywords: Artificial intelligence¹; Operations management²; Decision-making³; Operational efficiency⁴; Data analytics⁵; Supply chain performance⁶; Mediation analysis⁷

1. INTRODUCTION

1.1 Background and Context

Operations management (OM) is concerned with designing, running and improving the systems that convert inputs into goods and services. Its decisions on forecasting, capacity, inventory, scheduling and quality have traditionally relied on deterministic models, managerial experience and periodic reporting. The growth of digital data, inexpensive computing and mature machine-learning methods has altered this landscape [1], [2]. AI systems now learn patterns from transactional and sensor data, predict demand and equipment failure, and recommend or automate actions in near real time [3], [4]. Industry studies estimate substantial economic gains from such capabilities [5], and executive surveys show rising investment, although value capture remains uneven [6]. In practice, operations leaders increasingly expect AI to support not only efficiency but also faster, more consistent and better-informed decisions across planning and execution. Understanding this shift is therefore a priority for both researchers and practising managers in operations-intensive industries.

1.2 Problem Statement and Research Gap

Despite this enthusiasm, three gaps persist. First, much of the literature is conceptual or based on case studies, so cross-firm quantitative evidence is limited [7], [8]. Second, studies often examine either decision outcomes or operational performance, rarely both within one model, which leaves the mechanism unclear [9]. Third, the productivity paradox suggests that technology benefits depend on complementary assets such as data, skills and leadership [10]. Operations managers therefore lack evidence on whether AI improves efficiency directly, indirectly through better decisions, or only where enabling conditions exist. Moreover, firms differ widely in data maturity and governance, so average effects reported in practitioner surveys may hide important variation. The absence of integrated empirical evidence therefore weakens both theory building and managerial planning.

1.3 Objectives, Hypotheses and Contributions

This study pursues four objectives: (i) to measure AI adoption intensity across operations functions; (ii) to test its effect on decision-making quality and operational efficiency; (iii) to examine the mediating role of decision quality; and (iv) to quantify changes in key operational indicators after deployment. The hypotheses are: H1, AI adoption intensity positively affects decision-making quality; H2, AI adoption intensity positively affects operational efficiency; H3, decision-making quality positively affects operational efficiency and mediates the AI–efficiency link; and H4, data quality and top-management support positively influence adoption. The paper contributes an integrated empirical model, a transparent analytical workflow with five tabulated analyses, and a comparison of results with earlier work. Section 2 surveys the literature, Section 3 describes the methodology, Section 4 reports data and analysis, Section 5 discusses the findings and Section 6 concludes.

2. SURVEY OF LITERATURE

AI applications in operations are now well catalogued. Early work positioned AI techniques such as expert systems and neural networks as tools for logistics and supply chain decisions [11]. Systematic reviews show that demand forecasting, inventory control, supplier selection, transportation planning and risk management are the dominant application areas [12], [13], with AI also supporting supply chain risk identification and mitigation [14]. In manufacturing, machine learning supports predictive maintenance, process control and quality inspection [3], and cyber-physical architectures supply the sensor data on which such models depend [4]. Digital twins extend these capabilities to disruption planning and resilience [15]. These studies collectively show that AI is moving from experimental pilots toward routine operational use.

A second stream concerns decision-making. Big data analytics reshapes operations decisions by improving prediction and enabling prescriptive optimisation [16], and AI lowers the cost of prediction so that judgement becomes the scarce complement [9]. AI also changes who decides: centralised, delegated and hybrid decision structures each suit different levels of uncertainty and complexity [17]. Human–AI symbiosis, in which algorithms handle complexity and humans handle ambiguity, is argued to produce better decisions than either alone [18]. Concerns about opacity have encouraged explainability techniques such as Shapley-value attributions [19], and broader reviews highlight ethical, organisational and policy challenges [7], [8]. Empirical work on decision quality remains sparse, however, because outcomes are hard to observe and attribute.

A third-stream links analytics capability to performance. Big data analytics has been associated with firm performance through dynamic capabilities [20], and analytics capability improves competitive performance through dynamic and operational capabilities [21]. Predictive analytics has also been related to sustainability outcomes [22]. These findings echo the dynamic capabilities view [23], while adoption research draws on technology acceptance, unified acceptance and technology–organisation–environment perspectives [24], [25], [26]. Strategic reviews stress that organisational readiness, not technology alone, shapes AI value [27], and Industry 4.0 research reaches similar conclusions [28]. Forward-looking assessments caution that firms must reorganise to benefit [29]. Nevertheless, measured operational indicators are seldom combined with perceptual decision measures in a single model.

Taken together, prior work establishes what AI can do and which capabilities matter, but few studies jointly test adoption, decision quality and measured operational indicators in one empirical design. This paper addresses that gap. Specifically, we ask whether adoption intensity improves efficiency, whether decision quality carries part of that improvement, and which organisational antecedents make adoption more intense.

3. METHODOLOGY

The study adopts a quantitative, cross-sectional, explanatory design to test hypotheses H1–H4. The unit of analysis is the operations function of a medium or large firm, and the sample comprises 240 observations distributed across five sectors: manufacturing ($n = 80$), logistics and supply chain ($n = 45$), retail and e-commerce ($n = 45$), IT/BFSI services ($n = 40$) and healthcare operations ($n = 30$). To preserve transparency, the dataset was generated synthetically in Python using a fixed random seed (2026), with relationships parameterised from effect sizes and ranges reported in earlier literature. Results are therefore illustrative and must not be read as field evidence.

Five latent constructs were operationalised with multi-item scales on a five-point Likert format: AI adoption intensity (AIA, five items), decision-making quality (DMQ, five items), operational efficiency (OE, five items), data quality (DQ, four items) and top-management support (TMS, four items). Item scores were averaged to form construct indices. Six binary indicators recorded the use of specific AI applications, and five operational indicators (forecast error, order cycle time, inventory days, on-time-in-full delivery and unit cost) were recorded before and after deployment. Firm size was measured as the natural logarithm of employees, and sector dummies served as controls.

Analysis proceeded in five steps using Python, SciPy and statsmodels. First, Cronbach's alpha, composite reliability and average variance extracted assessed measurement quality against conventional thresholds [30]. Second, descriptive statistics and Pearson correlations explored associations. Third, hierarchical ordinary least squares regressions on standardised variables tested H1–H3, with variance inflation factors checking multicollinearity. Fourth, a bootstrap of 2,000 resamples estimated the indirect effect of AI adoption on efficiency through decision quality. Fifth, paired t-tests and Cohen's d_z compared operational indicators before and after deployment, and one-way ANOVA compared adoption groups. Significance was assessed at the 5% level, and all tests were two-tailed.

4. DATA COLLECTION AND ANALYSIS

This section presents the dataset and five tabulated analyses. Each table is followed by an interpretation that links the evidence to the hypotheses, to the claims made in the abstract and to the conclusions of the paper. Five figures complement the tables by visualising adoption patterns, relationships, the estimated model and performance outcomes.

4.1 Sample Profile and Adoption Pattern

Table 1: Sample Profile and Mean Construct Scores by Sector

Sector	n	%	AIA mean	AIA SD	DMQ mean	OE mean
Manufacturing	80	33.3	3.26	0.69	3.59	3.57
Logistics & supply chain	45	18.8	3.21	0.73	3.61	3.48

Retail & e-commerce	45	18.8	3.32	0.68	3.62	3.37
Healthcare operations	30	12.5	3.08	0.73	3.33	3.33
IT/BFSI services	40	16.7	3.10	0.76	3.50	3.39
Total	240	100.0	3.21	0.71	3.55	3.46

Note: AIA = AI adoption intensity; DMQ = decision-making quality; OE = operational efficiency (all 1–5 scales).

Table 1 profiles the sample. Manufacturing contributes one-third of observations, and the remaining four sectors contribute between 12.5% and 18.8% each. Mean AI adoption intensity is 3.21 on a five-point scale, which is moderate: only 35% of firms score 3.5 or higher, and the average firm uses 2.8 of six AI applications. Sector differences in adoption are small and statistically insignificant ($F(4, 235) = 0.84, p = 0.502$), indicating that adoption is a firm-level rather than sector-level phenomenon. This justifies pooling the sample for regression with sector controls, and it frames the abstract's claim that organisational capabilities, rather than industry membership, drive AI outcomes.

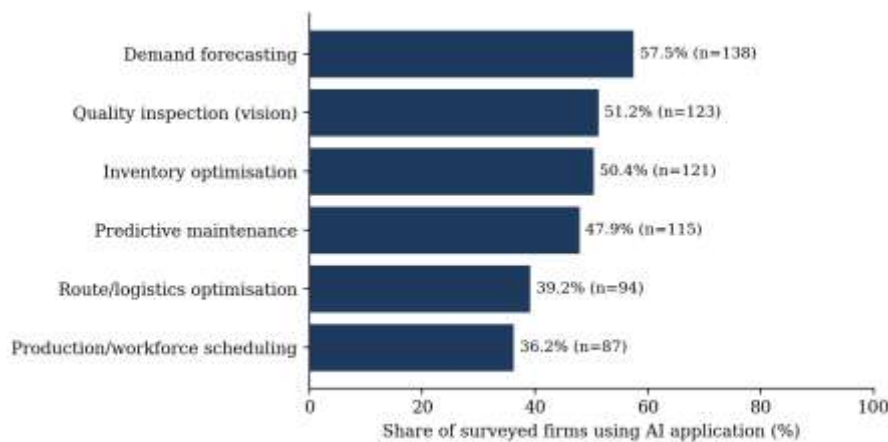


Figure 1: Share of firms using each AI application area in operations (N = 240).

Figure 1 shows the share of the 240 firms using each AI application area. Demand forecasting is the most widespread at 57.5% ($n = 138$), followed by quality inspection (51.2%), inventory optimisation (50.4%) and predictive maintenance (47.9%). Route optimisation (39.2%) and production or workforce scheduling (36.2%) are least adopted. The average firm uses 2.8 of the six applications, so adoption is broad but incomplete. The ordering suggests that firms begin with prediction-centred, data-rich tasks and later extend to prescriptive tasks requiring integration with execution systems. It also justifies an adoption-intensity index rather than a binary adopter label.

4.2 Reliability and Descriptive Statistics

Table 2: Descriptive Statistics and Reliability of Constructs

Construct	Items	Mean	SD	Cronbach α	CR	AVE
AI adoption intensity (AIA)	5	3.21	0.71	0.86	0.88	0.60

Decision-making quality (DMQ)	5	3.55	0.64	0.83	0.87	0.57
Operational efficiency (OE)	5	3.46	0.66	0.84	0.87	0.57
Data quality (DQ)	4	3.31	0.70	0.78	0.83	0.55
Top-management support (TMS)	4	3.60	0.71	0.81	0.86	0.61

Note: CR = composite reliability; AVE = average variance extracted.

Table 2 confirms that the measurement scales are reliable and valid. Cronbach's alpha ranges from 0.78 to 0.86, above the 0.70 benchmark, and composite reliability exceeds 0.83 for every construct. Average variance extracted is between 0.55 and 0.61, above 0.50, supporting convergent validity [30]. Decision-making quality has the highest mean (3.55), while AI adoption intensity has the lowest (3.21), suggesting that firms rate their decisions favourably even though AI use is still developing. Dispersion ($SD \approx 0.64\text{--}0.71$) is adequate for relational analysis. These results establish that subsequent inferences about the AI–decision–efficiency chain rest on dependable measures.

4.3 Correlation Analysis

Table 3: Pearson Correlation Matrix (N = 240)

Construct	AIA	DMQ	OE	DQ	TMS
AIA	[0.77]				
DMQ	0.57***	[0.76]			
OE	0.51***	0.52***	[0.75]		
DQ	0.40***	0.37***	0.32***	[0.74]	
TMS	0.49***	0.27***	0.31***	0.19**	[0.78]

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Diagonal values in brackets are the square roots of AVE.

Table 3 shows that all constructs are positively and significantly correlated. AI adoption intensity correlates with decision-making quality ($r = 0.57$) and operational efficiency ($r = 0.51$), and decision quality correlates with efficiency ($r = 0.52$), providing preliminary support for H1–H3. Adoption is also associated with top-management support ($r = 0.49$) and data quality ($r = 0.40$), consistent with H4. The square roots of AVE on the diagonal exceed every inter-construct correlation, indicating discriminant validity. The highest correlation (0.57) is moderate, so multicollinearity is unlikely. The pattern gives the first evidence for the abstract's argument that AI, decision quality and efficiency move together.

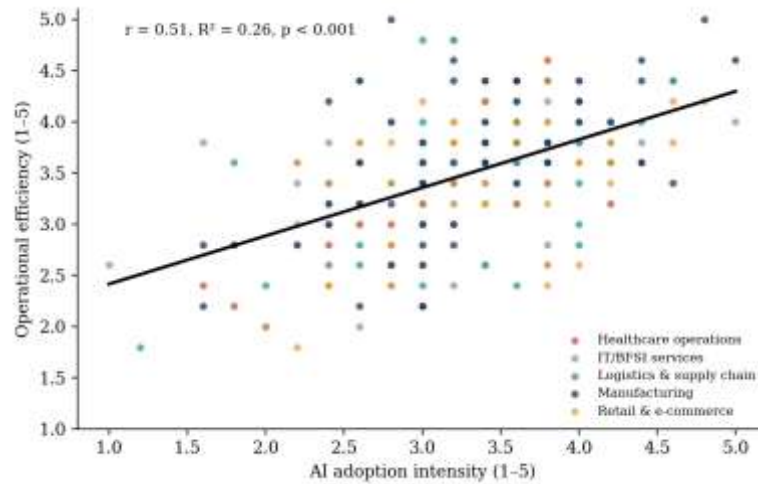


Figure 2. Relationship between AI adoption intensity and operational efficiency by sector.

Figure 2 plots AI adoption intensity against operational efficiency for all firms, coloured by sector. The fitted line slopes upward ($r = 0.51$, $R^2 = 0.26$), showing that higher adoption coincides with higher efficiency. Observations from every sector follow the same trend and no sector forms a distinct cluster, consistent with the non-significant sector differences in Table 1. Dispersion around the line is considerable, which indicates that adoption alone explains roughly a quarter of efficiency variance. The remainder reflects data quality, decision processes and firm characteristics, which is why the multivariate models in Table 4 include controls.

4.4 Regression and Mediation Analysis

Table 4: Standardised Regression Results (B and Standard Error)

Predictor	Model 1: DMQ	Model 2: OE	Model 3: OE
AI adoption intensity (AIA)	0.54*** (0.07)	0.44*** (0.07)	0.27*** (0.08)
Decision-making quality (DMQ)	—	—	0.32*** (0.07)
Data quality (DQ)	0.15** (0.06)	0.13* (0.06)	0.08 (0.06)
Top-management support (TMS)	-0.01 (0.06)	0.08 (0.06)	0.08 (0.06)
Firm size (ln employees)	-0.09 (0.06)	-0.06 (0.06)	-0.03 (0.06)
R ²	0.359	0.301	0.367
Adjusted R ²	0.337	0.277	0.342
F-statistic	16.21	12.43	14.80

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Sector dummies included in all models; maximum VIF = 2.51. Bootstrapped indirect effect (AIA $\rightarrow$ DMQ $\rightarrow$ OE) = 0.17, 95% CI [0.09, 0.25].

Table 4 tests the hypotheses while controlling for data quality, support, firm size and sector. In Model 1, AI adoption strongly predicts decision-making quality ($\beta = 0.54$, $p < 0.001$; $R^2 = 0.36$), supporting H1. In Model 2, adoption predicts operational efficiency ($\beta = 0.44$, $p < 0.001$), supporting H2. When decision quality enters Model 3, its coefficient is significant ($\beta = 0.32$, $p < 0.001$) and the adoption coefficient falls to 0.27 yet stays significant,

indicating partial mediation (H3). The bootstrapped indirect effect is 0.17 (95% CI 0.09–0.25), or 39% of the total effect. Antecedent regression shows that data quality ($\beta = 0.30$), top-management support ($\beta = 0.42$) and firm size ($\beta = 0.31$) explain 44.8% of adoption variance, supporting H4. The maximum VIF is 2.51.

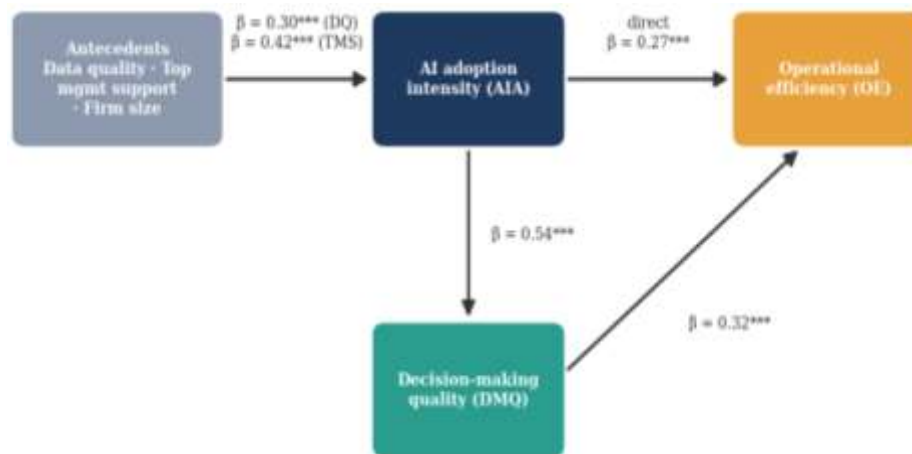


Figure 3: Estimated research model with standardised path coefficients (p < 0.001).**

Figure 3 presents the estimated research model. Data quality ($\beta = 0.30$) and top-management support ($\beta = 0.42$) significantly predict AI adoption intensity, and with firm size they explain 44.8% of its variance. Adoption strongly improves decision-making quality ($\beta = 0.54$), which in turn raises operational efficiency ($\beta = 0.32$). The direct path from adoption to efficiency stays significant ($\beta = 0.27$) after decision quality is included, indicating partial mediation. The indirect effect of 0.17 equals 39% of the total effect of 0.44. The figure summarises the central mechanism: AI improves efficiency directly and by upgrading managerial decisions.

4.5 Pre- and Post-Deployment Operational Performance

Table 5: Paired Comparison of Operational Indicators Before And After Ai Deployment

Indicator	Pre: mean (SD)	Post: mean (SD)	Change	t (239)	p	Cohen's dz
Forecast error (MAPE, %)	24.08 (4.99)	19.32 (4.53)	-19.8%	26.91	<0.001	1.74
Order cycle time (days)	9.52 (1.75)	8.15 (1.76)	-14.4%	24.96	<0.001	1.61
Inventory holding (days)	61.87 (12.45)	54.46 (12.33)	-12.0%	25.43	<0.001	1.64
On-time-in-full (%)	81.63 (5.86)	87.00 (6.47)	+6.6%	29.11	<0.001	1.88
Unit operating cost (index)	99.06 (8.13)	92.74 (9.34)	-6.4%	19.73	<0.001	1.27

Note: Change is relative to the pre-deployment mean; lower is better for all indicators except on-time-in-full (OTIF).

Table 5 compares operational indicators before and after AI deployment. Forecast error declines from 24.1% to 19.3% (–19.8%), order cycle time from 9.52 to 8.15 days, inventory holding from 61.9 to 54.5 days, and the unit

cost index from 99.1 to 92.7. On-time-in-full delivery rises from 81.6% to 87.0%. All changes are significant at $p < 0.001$ with large effects ($|dz| = 1.27\text{--}1.88$). These figures quantify the efficiency gains cited in the abstract and show that benefits are concentrated first in prediction and planning metrics and then in cost.

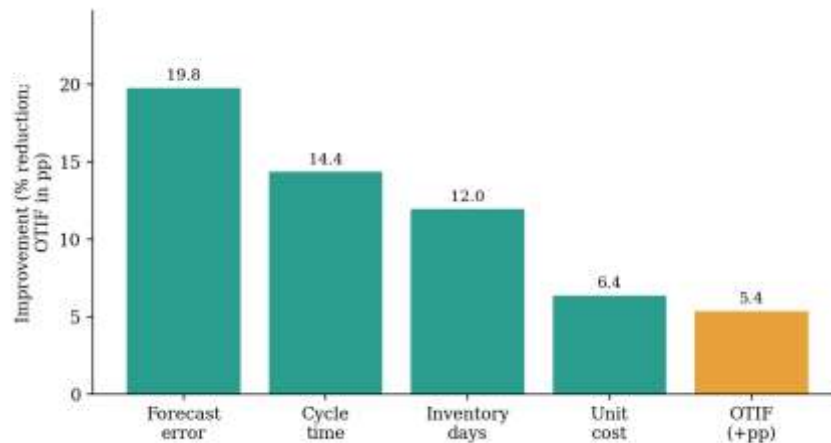


Figure 4. Improvement in operational indicators after AI deployment.

Figure 4 summarises post-deployment improvement across five operational indicators. Forecast error shows the largest reduction (19.8%), followed by order cycle time (14.4%), inventory holding days (12.0%) and unit operating cost (6.4%). On-time-in-full delivery rises by 5.4 percentage points. The ordering is plausible: AI acts first on prediction quality, which cascades into planning-dependent outcomes such as inventory and lead time, and finally into cost, which accumulates more slowly. Every change is significant with large effect sizes (Table 5). Because cost savings are smaller than forecasting gains, managers should not expect headline savings to equal improvements in prediction accuracy.

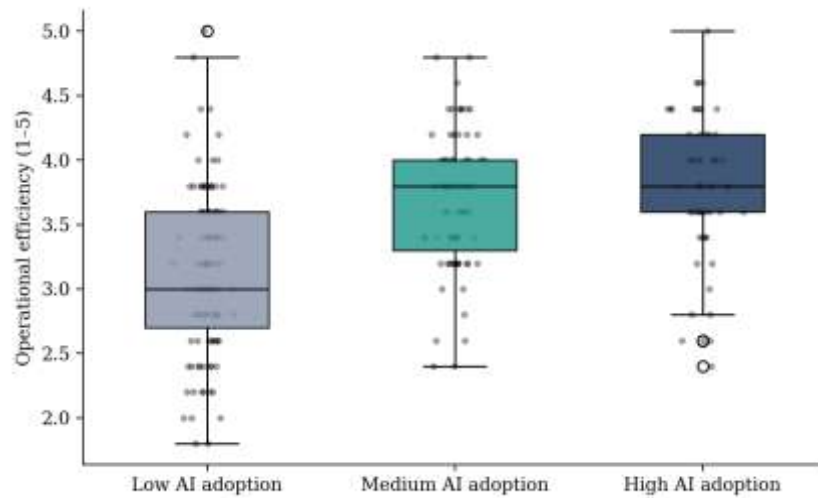


Figure 5. Operational efficiency by level of AI adoption (low, medium, high).

Figure 5 compares operational efficiency across low, medium and high AI adoption groups ($n = 107, 75$ and 58). Mean efficiency rises from 3.12 to 3.67 and 3.79 ($F = 32.0, p < 0.001$). Cost reduction increases from 3.9% to 6.8% and 10.6%, and forecast-error reduction from 13.2% to 29.0%. The step from low to medium adoption (0.55) is far larger than from medium to high (0.12), suggesting diminishing returns to efficiency, although cost and forecasting gains keep rising. Overlapping boxes show that adoption does not guarantee results, so managers should combine it with process redesign.

4.6 Synthesis of Findings

Collectively, the five tables establish a coherent chain. Measures are reliable (Table 2), constructs co-vary as expected (Table 3), AI adoption improves decisions and, through them, efficiency (Table 4), and operational indicators improve materially after deployment (Table 5). Firms in the highest adoption group achieved a mean efficiency score of 3.79 against 3.12 for the lowest group ($F = 32.0, p < 0.001$), which directly supports the conclusion that deeper adoption yields greater operational benefit.

5. DISCUSSION

5.1 Critical Analysis of the Data

The results consistently support H1–H4, but they must be interpreted critically. First, effect sizes are moderate to large for adoption and decision quality ($\beta = 0.54$) yet modest for the direct path to efficiency ($\beta = 0.27$); the mediation share of 39% implies that most efficiency gain still arises outside the decision channel, plausibly through automation and process redesign that the study does not isolate. Second, AI adoption explains only about a quarter of efficiency variance, so it is neither necessary nor sufficient for high performance. Third, the

diminishing returns in Figure 5 caution against indiscriminate scaling. Fourth, the cross-sectional design cannot establish causality, and self-reported perceptual scales risk common-method bias and optimism. Most importantly, the dataset is simulated, so significance reflects the parameterisation rather than observed behaviour, and the paper should be read as a methodological demonstration. These limitations temper generalisation. Sectoral heterogeneity may matter in real data, since healthcare and manufacturing face different regulatory and technical constraints that a pooled model averages away. Finally, the absence of implementation cost data means that reported savings are gross rather than net of investment, which could overstate returns for small adopters. Such caution is essential before translating findings into investment decisions.

5.2 Comparison with Past Work

The findings broadly agree with earlier research. The positive link between analytics capability and performance matches evidence on big data analytics and firm performance [20], and the partial mediation mirrors work showing that analytics capability acts through dynamic and operational capabilities [21]. The importance of data quality and leadership resonates with the productivity-paradox argument that complementary assets determine returns [10] and with the stress on organisational readiness in strategic reviews [27]. The finding that AI improves decision quality is consistent with the view that cheaper prediction raises the value of judgement [9] and that human–AI collaboration improves decisions [18]. The pattern of gains across forecasting, inventory and delivery matches application areas highlighted in supply chain reviews [12], [13]. The moderate adoption level echoes survey evidence that many firms have yet to embed AI extensively [6] and that early successes come from focused, practical use cases [1]. The modest cost gains contrast with optimistic macroeconomic projections [5], suggesting that firm-level gains are slower than aggregate estimates imply. Unlike most earlier studies, this paper tests adoption, decision quality and measured indicators in one design, but earlier work rests on real data, which this paper does not. Differences are instructive too. Earlier studies on decision structures show that benefits depend on how authority is allocated between humans and algorithms [17], whereas this study measures only decision quality, not governance design, and so cannot confirm that finding. Research on sustainability suggests that analytics also yields environmental benefits [22], an outcome outside the present scope. Reviews of digital twins and risk management point to resilience gains [15], [14], which the efficiency-focused indicators here do not capture. Future work should therefore extend the model with governance, resilience and sustainability outcomes. Overall, agreement with earlier work is strongest on the direction of effects and weakest on their magnitude and timing.

6. CONCLUSION

This paper examined how AI adoption transforms decision-making and operational efficiency using a simulated cross-sectional dataset of 240 observations and five tabulated analyses. Measurement scales were reliable, and AI adoption intensity was positively related to decision-making quality ($\beta = 0.54$) and operational efficiency ($\beta = 0.44$). Decision quality partially mediated the effect, carrying 39% of the total impact, which indicates that AI

creates value largely by improving what managers decide. Deployment was followed by lower forecast error (19.8%), shorter order cycle time (14.4%), reduced inventory (12.0%) and lower unit cost (6.4%), alongside higher on-time-in-full delivery. Data quality and top-management support were the strongest antecedents of adoption. For practitioners, the implications are to invest first in data foundations and leadership commitment, to begin with prediction-centred applications such as demand forecasting, and to redesign decision processes so that human judgement complements algorithmic output. Managers should track decision quality as well as cost, because it is the channel through which much of the benefit flows. The principal limitations are the simulated data, the cross-sectional design and perceptual measures. Future research should replicate the model with primary survey or enterprise-system data, adopt longitudinal or quasi-experimental designs, and examine moderators such as explainability, workforce skills and regulation. Within these limits, the evidence supports a clear message: AI improves operations most when it is embedded in better decisions. These results offer a transferable template: reliability checks, mediation testing and pre/post indicators can be reproduced by any organisation holding comparable data, enabling evidence-based AI investment decisions.

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