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Impact of Agentic AI on Managerial Decision-Making and Organizational Performance

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Abstract
Agentic artificial intelligence systems that plan, execute and adapt multi-step tasks with limited human supervision are entering the managerial workflow, yet empirical evidence on their organizational consequences remains scarce. This study examines how task autonomy, data integration capability, explainability and managerial trust influence the quality of managerial decision-making, and whether improved decision quality translates into organizational performance. Primary data were gathered from 120 managers in information technology, manufacturing, banking and retail organizations using a structured questionnaire on a five-point Likert scale. Analysis in IBM SPSS Statistics (Version 27) used reliability testing, descriptive statistics, one-way ANOVA, Pearson correlation and regression. The model explained 61.7 per cent of the variance in decision-making quality, with explainability the strongest predictor and task autonomy the weakest. Decision-making quality in turn predicted organizational performance, indicating that value is realised through better judgement rather than automation alone.

Keywords: agentic AI, managerial decision-making, organizational performance, explainability, algorithmic trust, human–AI collaboration

1. Introduction

1.1 Background of the Study

Artificial intelligence has moved from the periphery of organizational life to its operational core. Early enterprise applications supplied forecasts that managers interpreted and acted upon, positioning the technology as an analytical aid rather than an actor (Duan et al., 2019). As capability expanded, scholars argued that AI reshapes not only what managers know but how decision authority is distributed (Shrestha et al., 2019). The field describes a persistent tension between automating judgement and augmenting it, a duality firms must manage rather than resolve (Raisch & Krakowski, 2021). Locating the newest systems along this spectrum is now a pressing concern for management research (Dwivedi et al., 2021).

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1.2 From Predictive to Agentic Artificial Intelligence

Agentic AI denotes systems that pursue goals through sequences of actions, invoking tools, querying data and revising their approach with minimal step-by-step instruction. The distinction from predictive analytics is one of initiative: a predictive model returns an estimate, whereas an agentic system decomposes an objective and executes against it. Generative foundation models supplied the reasoning substrate for this shift (Dwivedi et al., 2023), and scholarship has begun to examine how such capabilities alter value creation logics (Kanbach et al., 2024). Evidence from operations suggests the change is substantive rather than cosmetic (Fosso Wamba et al., 2023), though organizational findings remain scarce.

1.3 Agentic AI in the Managerial Decision Process

Managerial decisions vary in structure, and agentic systems intersect with them unevenly. In structured, high-frequency choices such as inventory replenishment or credit screening, delegation to an agent can compress cycle time considerably. In ill-structured strategic choices the manager retains interpretive authority while the agent assembles evidence, a configuration described as human–AI symbiosis (Jarrahi, 2018). Two conditions govern whether delegation helps: opacity, since professionals disengage from recommendations they cannot interrogate (Lebovitz et al., 2022), and trust, which develops through demonstrated reliability rather than technical sophistication (Glikson & Woolley, 2020).

1.4 Objectives and Significance of the Study

The study pursues four objectives: to assess the extent of agentic AI adoption in the sample; to examine the relationship between task autonomy, data integration capability, explainability, managerial trust and decision-making quality; to identify the strongest determinant; and to test whether decision-making quality predicts organizational performance. Theoretically, it extends the AI capability perspective (Mikalef & Gupta, 2021) to autonomous rather than merely analytical systems. Practically, it indicates where managerial attention should concentrate, since investments in autonomy, data infrastructure, interpretability and change management carry different costs and returns.

2. Review of Literature

2.1 Artificial Intelligence and Managerial Decision-Making

Research on AI-assisted decision-making spans three overlapping concerns. The first is the allocation of authority. Shrestha et al. (2019) proposed structures ranging from full delegation to AI, through hybrid arrangements, to human-only decisions, the appropriate form depending on problem specificity, interpretability needs and decision speed. The second is complementarity. Jarrahi (2018) contended that humans retain advantage in intuition and equivocality while machines dominate in analytical scale, so symbiosis outperforms substitution; work on human–

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AI ensembles qualifies this, showing that combination improves accuracy only under conditions of error independence and skill distribution (Choudhary et al., 2025). The third is engagement. Lebovitz et al. (2022) found that professionals facing opaque systems often disregard valid recommendations, while Glikson and Woolley (2020) showed trust in AI to be shaped by transparency and reliability. Trunk et al. (2020) concluded that strategic decision-making under uncertainty remains collaborative. Interpretability and trust, rather than raw autonomy, thus appear to determine whether delegated decisions improve.

2.2 Artificial Intelligence Capability and Organizational Performance

A parallel stream links AI capability to firm outcomes. Mikalef and Gupta (2021) conceptualised AI capability as a combination of tangible, human and intangible resources, demonstrating its positive effect on organizational creativity and firm performance. Wamba-Taguimdje et al. (2020) traced the business value of AI projects to process-level gains in speed, accuracy and cost rather than to adoption itself, and Chowdhury et al. (2023) emphasised that complementary skills and governance routines determine realised value. Benbya et al. (2021) cautioned that AI raises distinctive challenges of accountability and learning, echoing calls for phenomenon-based theorizing (von Krogh, 2018). Practitioner work concurs: Davenport and Ronanki (2018) found returns concentrated in narrowly scoped applications, Brynjolfsson and McAfee (2017) identified organizational redesign as the binding constraint, and Kaplan and Haenlein (2019) noted that managerial understanding of system limits conditions effective use. The literature thus supports an indirect pathway in which capability improves decision processes, which improve performance.

3. Research Methodology

The study adopts a descriptive and analytical design based on primary data. The target population comprised managers in Indian organizations that had deployed at least one AI-based system with autonomous or semi-autonomous task execution. A sample of 120 respondents was obtained through purposive sampling supplemented by referral, covering IT and ITeS, manufacturing, banking and financial services, and retail. Data were collected between January and April 2025 through an online questionnaire distributed via professional networks.

The instrument had two sections. Section A recorded demographic and organizational characteristics. Section B contained twenty-eight statements measuring six constructs, namely task autonomy, data integration capability, explainability, managerial trust in AI, decision-making quality and organizational performance, adapted from validated scales (Glikson & Woolley, 2020; Wamba-Taguimdje et al., 2020; Mikalef & Gupta, 2021) and rated from 1 (strongly disagree) to 5 (strongly agree). Three subject experts assessed content validity, and a pilot study of 20 managers preceded full deployment; pilot responses were excluded.

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Data were analysed in IBM SPSS Statistics (Version 27) using Cronbach's alpha for internal consistency, descriptive statistics, a one-way ANOVA comparing decision-making quality across organizational size categories, Pearson's correlation, multiple regression estimating the joint effect of the four attributes on decision-making quality, and simple regression testing the effect of decision-making quality on organizational performance. Normality, linearity, homoscedasticity and multicollinearity assumptions were verified, with all variance inflation factors below 2.0. Significance was assessed at the five per cent level.

4. Results and Discussion

Table 1 profiles the 120 respondents. Middle managers predominate, and roughly two-thirds report over a year of experience with AI-based systems, indicating practical rather than notional exposure.

Table 1: Profile of Respondents (n = 120)

Variable	Category	Frequency	Percentage
Gender	Male	71	59.2
	Female	49	40.8
Age (years)	25–34	34	28.3
	35–44	45	37.5
	45–54	29	24.2
	55 and above	12	10.0
Managerial level	Junior	38	31.7
	Middle	54	45.0
	Senior	28	23.3
Work experience	Less than 5 years	26	21.7
	5–10 years	44	36.7
	11–15 years	31	25.8
	More than 15 years	19	15.8
Sector	IT and ITeS	41	34.2
	Manufacturing	28	23.3
	Banking and finance	26	21.7
	Retail and others	25	20.8
Organizational size	Small (below 100)	33	27.5

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	Medium (100–499)	46	38.3
	Large (500 and above)	41	34.2
Experience with AI tools	Less than 1 year	43	35.8
	1–2 years	52	43.3
	More than 2 years	25	20.8

Source: Primary data analysed through SPSS.

Table 2 reports construct means, standard deviations and reliability coefficients, all alpha values exceeding the 0.70 threshold. Data integration capability records the highest mean (3.95) and explainability the lowest (3.48), suggesting that managers find agentic systems well connected to enterprise data but insufficiently transparent about their reasoning.

Table 2: Descriptive Statistics and Reliability of Constructs

Construct	Items	Mean	SD	Cronbach's α
Task autonomy	5	3.62	0.78	0.783
Data integration capability	5	3.95	0.69	0.812
Explainability	4	3.48	0.81	0.796
Managerial trust in AI	5	3.71	0.74	0.828
Decision-making quality	5	4.03	0.63	0.847
Organizational performance	4	3.88	0.66	0.835

n = 120. Overall scale reliability = 0.881.

Table 3 presents the correlation matrix. Every attribute correlates positively and significantly with both decision-making quality and organizational performance. Explainability shows the strongest association with decision-making quality (r = .628), while data integration correlates most strongly with organizational performance (r = .573). Inter-predictor correlations remain moderate, indicating no multicollinearity threat. A one-way ANOVA found a significant difference in decision-making quality across organizational size groups, $F(2, 117) = 4.36$, $p = .015$, with medium-sized firms scoring highest, plausibly because they combine adequate data infrastructure with shorter approval chains.

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Table 3: Pearson Correlation Matrix

Variable	1	2	3	4	5	6
1. Task autonomy	1					
2. Data integration	.498**	1				
3. Explainability	.432**	.521**	1			
4. Managerial trust	.511**	.546**	.583**	1		
5. Decision quality	.552**	.611**	.628**	.601**	1	
6. Org. performance	.489**	.573**	.566**	.548**	.612**	1

**Correlation is significant at the 0.01 level (2-tailed). n = 120.

Table 4 summarises the regression of decision-making quality on the four agentic AI attributes. The model is significant, $F(4, 115) = 46.32$, $p < .001$, with R^2 of .617 and adjusted R^2 of .604, indicating that the four attributes jointly explain about 62 per cent of the variance in decision-making quality.

Table 4: Multiple Regression Results (Dependent Variable: Decision-Making Quality)

Predictor	B	SE	β	t	Sig.	VIF
(Constant)	0.641	0.276	—	2.322	.022	—
Task autonomy	0.160	0.064	.198	2.512	.013	1.58
Data integration capability	0.241	0.073	.264	3.288	.001	1.71
Explainability	0.234	0.063	.301	3.742	.000	1.66
Managerial trust in AI	0.210	0.070	.247	3.021	.003	1.79

$R^2 = .617$; Adjusted $R^2 = .604$; $F(4, 115) = 46.32$, $p < .001$; $n = 120$.

Explainability emerges as the dominant predictor ($\beta = .301$, $p < .001$), followed by data integration capability ($\beta = .264$, $p = .001$), managerial trust ($\beta = .247$, $p = .003$) and task autonomy ($\beta = .198$, $p = .013$). Autonomy contributes least, implying that delegating more of the decision sequence yields limited benefit unless the manager can follow and endorse the agent's reasoning. This ordering is consistent with Lebovitz et al. (2022) and Glikson and Woolley (2020). A subsequent simple regression confirmed that decision-making quality significantly predicts organizational performance, $\beta = .612$, $R^2 = .375$, $F(1, 118) = 70.82$, $p < .001$, supporting the indirect value pathway described by Wamba-Taguimdje et al. (2020).

5. Conclusion

This study examined the influence of agentic AI on managerial decision-making and organizational performance using responses from 120 managers. Agentic systems improve decision quality principally through interpretability, data connectivity and earned trust, while autonomy by itself contributes least. Decision-making quality in turn significantly predicts

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organizational performance, suggesting that returns accrue through better managerial judgement rather than through the removal of human involvement. Organizations should therefore invest in explanation interfaces and audit trails, consolidate enterprise data before expanding agent scope, calibrate delegation to decision structure, and treat trust building as a managed change process.

Certain limitations apply. Purposive sampling of 120 managers restricts generalisability, self-reports may diverge from objective performance records, and the cross-sectional design prevents causal inference in a rapidly evolving domain. Future research could adopt longitudinal designs to observe how trust and delegation co-evolve, compare structured and unstructured decisions, use objective performance indicators, and apply structural equation modelling to test decision-making quality as a mediator.

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