International Journal of Engineering, Science and Humanities
An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552

Impact of Artificial Intelligence on Organisational Performance and Managerial Decision-Making

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Abstract
Artificial intelligence (AI) is now becoming a part of the working life of organisations, but the data on its impact on management decisions and organisational outcomes is yet scarce and varied, and on the conditions that enable it to succeed are even less so. The study investigates how the use of AI and organizational preparedness affect managerial decision-making quality and organizational performance. Managers and professionals were presented with a structured questionnaire with five-point Likert scale items and the data were analysed by SPSS-based procedures such as descriptive statistics, Cronbach's alpha, Pearson correlation, multiple regression, bootstrapped indirect effects, independent-samples t-test and one-way ANOVA. Good reliability was obtained for the measurement scales. Organisational readiness and AI use proved to be important positive factors in explaining the variance in decision-making quality, both individually and together, accounting for a significant amount of the variance in the actual quality of decision-making. In the same way, the quality of decisions and the readiness of organisations for AI had positive strong effects on the performance of organisations. The process of quality decision-making, further, partially mediated the relation between AI adoption, OR and OP. All the hypotheses were confirmed. The study reveals that the usefulness of AI depends on its ability to be incorporated into organisational processes for decision making, and supported by good and accurate data, employee skills, and management support and commitment.
Keywords*: artificial intelligence, organisational performance, managerial decision-making, AI adoption, organisational readiness*

1. Introduction

Few technologies have attracted as much managerial attention in recent years as artificial intelligence. Advances in machine learning, the availability of large data sets, and cheaper computing power have made it possible for organisations to automate routine tasks, predict customer behaviour, and support complex judgements. Whether these capabilities translate into better decisions and stronger performance is the central question of this paper, which examines the relationship empirically using a survey of managers.

Artificial intelligence refers to computer systems that perform tasks normally associated with human intelligence, such as learning from data, recognising patterns, and making predictions. Haenlein and Kaplan (2019) trace the history of the field and distinguish between systems built for narrow tasks and the more general intelligence that remains largely a goal for the future. Present-day organisational applications fall almost entirely in the first category.

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Brynjolfsson and McAfee (2017) argue that machine learning is a general-purpose technology whose business impact will depend on the complementary changes that organisations make in processes and skills.

Practical applications are already wide. Davenport and Ronanki (2018) describe three broad uses in business: automating structured processes, gaining insight through data analysis, and engaging customers and employees through intelligent interfaces. They also note that the most successful projects tend to be modest and well targeted, not ambitious transformations. This observation is important for the present study, because it suggests that the benefits of AI depend on how it is applied and not merely on whether it is adopted.

The pace of adoption varies widely between organisations. Ransbotham, Kiron, Gerbert, and Reeves (2017) found a gap between ambition and action: many executives believe that AI will change their business, but fewer have taken the steps needed to realise the benefits. Understanding what separates organisations that benefit from those that do not is therefore an important practical and research question.

The risks of AI are also part of the picture. Mikalef, Conboy, Lundström, and Popovič (2022) draw attention to the dark side of AI, including bias, privacy intrusion, and lack of accountability, and argue that organisations need to think responsibly about how they deploy it. Benefits and risks therefore have to be considered together when judging the impact of AI on organisations.

Organisational performance describes how well an organisation achieves its goals, including efficiency, service quality, financial results, and the ability to innovate. In digital markets, where competitors can copy products quickly and customers can switch easily, performance increasingly depends on speed of response, quality of information, and the capacity to learn. Wamba-Taguimdje, Wamba, Kamdjoug, and Wanko (2020) studied AI-based transformation projects and found that they influence firm performance through process automation, cost reduction, and innovation.

Mikalef and Gupta (2021) conceptualise AI capability as a combination of tangible resources, human skills, and intangible resources, and show that it is associated with organisational creativity and firm performance. These findings suggest that performance gains come from capabilities built around AI and not from the technology in isolation. Performance is measured in this study through perceptions of efficiency, service quality, financial results, and responsiveness, which allows comparison across organisations of different sectors.

Performance is also a lagging indicator. Improvements in decisions and processes may take time to show up in financial figures, so perceived measures that include operational and strategic dimensions are useful in capturing early effects. The study therefore uses a multi-dimensional perceived measure and treats decision quality as a link between AI and performance.

2. Literature Review

There are some theoretical frameworks that can give insight into how AI may impact decision-making and performance.Several theories can provide a perspective on potentially how AI can influence decisions and outcomes. According to the resource-based view, firms can

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leverage their resources and capabilities to achieve competitive advantage when they are valuable and hard to imitate, as proposed by Mikalef and Gupta (2021) for applying the resource-based view to AI. AI capability is so chock full of data, technology, human skills and systems and processes. According to this perspective, human investment in complementary technologies is needed to benefit from AI, and this agrees with Brynjolfsson and McAfee (2017), who state that the gains from generalpurpose technologies rely on complementary investments.

Theories of decision making offer a second basis. Jarrahi (2018) differentiates uncertainty, complexity and equivocality as the predominant challenges of decisions within organisations, and posits that AI can address the first two challenges but humans are still the best option for the latter. Shrestha et al. (2019) go further: they demonstrate that organisational decision making processes must be reshaped to leverage the use of AI. Raisch and Krakowski (2021) further outlay that organisations must grapple with an automation/augmentation paradox – both approaches require different things at different times and a combination of the two is necessary.

Another economic lens is provided by Agrawal et. al (2018) who argue that AI reduces the value of an economic input – prediction – and consequently increases the value of other inputs – in this case data and judgement. The impact of AI on decisions' hinges on having good data and the capacity of managers to act on what AI can predict, this outlook showing the impact of AI relating directly to organisational readiness.

However, as Haenlein and Kaplan (2019) have already reminded us, the current AI is still specialised, so that only certain decisions can be made by AI alone. The researchers Trunk, Birkel & Hartmann (2020) review the fusion of human and AI in the decision making process and find that AI is most suitable for structured problems, while complex and ambiguous strategic problems still demand humans' judgement. Combined, these studies suggest that the adoption of AI enhances decision quality in conjunction with human skills and context and that decision quality, in its turn, enhances the performance.

The level of technology adoption is an additional layer. To examine AI adoption in manufacturing and production companies Chatterjee et al (2021) combine perspectives of technology acceptance and technology–organisation–environment. They demonstrate that all three factors relate to technology adoption. This underlines the need to include organisational readiness as a separate construct in the present model.

There is evidence about performance that overall it is positive and beneficial under the right conditions. According to Wamba-Taguimdje et al. (2020) AI transformation projects have the ability to enhance performance by providing automation, reducing cost, and introducing new innovations. Building on the previous research, Enholm et al. (2022) summarize the literature on the value creation potential of AI in business and find that AI can contribute to value creation through performance, decision and innovation, but that it is organisational-centered. Strategic use of AI was the subject of a review of its growing number of applications in business functions and gaps in knowledge about the conditions of success by Borges, Laurindo, Spinola, Gonçalves and Mattos (2021).

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There is also some evidence that supports the quality of decisions. Ghasemaghaei and Calic (2019) identified the data quality and diversity as important and concluded that big data analytics could enhance quality of decisions made by firms. But the results of Duan et al. (2019) and Trunk et al. (2020) indicate that AI may assist in making managerial decisions, but it is not necessarily robust enough on its own – and conversely, its utility is reliant on the nature of the decision and on the involvement of humans. Kellogg, Valentine and Christin (2020) demonstrate that algorithms also guide, assess and coordinate work, suggesting that AI is transforming not merely the information that managers receive, but also how they exert control.

3. Research Methodology

3.1 Research Design

The study uses a quantitative, explanatory, cross-sectional design based on a structured survey. The design permits standardised measurement of AI adoption, readiness, decision quality, and performance in a reasonably large sample and statistical testing of the five hypotheses (Hair, Black, Babin, & Anderson, 2019). Secondary sources, mainly peer-reviewed articles and books published between 2015 and 2023, were used to define constructs and develop hypotheses, while primary data were collected through the questionnaire.

The conceptual model has four variables. AI adoption and organisational readiness are the independent variables, decision-making quality is both an outcome of these resources and a predictor of performance, and organisational performance is the final dependent variable. This structure allows the study to examine direct paths from adoption and readiness to performance as well as indirect paths through decision quality.

3.2 Population, Sample Size, and Sampling Technique

The population consists of managers and professionals who take or support decisions in organisations that use or are considering AI. The final sample comprises 220 valid responses. This size exceeds the guideline of at least ten observations per questionnaire item, which implies a minimum of 140 for 14 items (Hair et al., 2019), and satisfies the rules of thumb for multiple regression with three predictors discussed by Field (2018). Respondents were selected by convenience sampling through an online questionnaire distributed through professional networks. Participation was voluntary and anonymous, and only fully completed questionnaires were retained, so the final data contain no missing values.

Convenience sampling was used because it allows access to managers across sectors within a reasonable time and cost, and because a list of all managers in the target population was not available. The weakness of this approach is that respondents may differ from non-respondents, for example by being more interested in technology. The sample is therefore best seen as an illustrative cross-section of managers and not as a statistically representative one, and the interpretation of the findings reflects this limit.

4. Results and Discussion

This section presents the profile of respondents, descriptive results, reliability, correlations, regression and mediation results, group comparisons, hypothesis testing, and a discussion. Six tables and five figures are used.

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4.1 Demographic Profile of Respondents

Table 1 shows the profile of the 220 respondents. Male respondents accounted for 54.5 per cent and female respondents for 45.5 per cent. The largest age group was 25–34 years (34.5 per cent), followed by 35–44 years (29.5 per cent), so the sample is dominated by managers and professionals in early and mid-career. Most respondents held a graduate or postgraduate qualification, and the largest sector was IT and services (29.1 per cent). Figure 1 shows the distribution by sector and Figure 2 shows the distribution of managerial experience.

Education and experience show a balanced spread. Respondents with a graduate qualification or below accounted for 48.2 per cent, postgraduates for 41.4 per cent, and those with professional or doctoral qualifications for 10.5 per cent. In terms of experience, 31.4 per cent had three to six years of managerial experience and 19.5 per cent had more than ten years, so the sample combines recent entrants to management with long-serving managers whose views of AI may differ.

Table 1

Demographic Profile of Respondents (N = 220)

Characteristic	Frequency	Percentage (%)
Gender		
Male	120	54.5
Female	100	45.5
Age (years)		
Below 25	30	13.6
25–34	76	34.5
35–44	65	29.5
45 and above	49	22.3
Education		
Graduate or below	106	48.2
Postgraduate	91	41.4
Professional / doctoral	23	10.5
Managerial experience		
Less than 3 years	48	21.8
3–6 years	69	31.4
7–10 years	60	27.3
More than 10 years	43	19.5
Sector		
Manufacturing	46	20.9
IT and services	64	29.1
Banking and finance	61	27.7
Retail and others	49	22.3

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4.2 Questionnaire Items and Descriptive Results

Table 2 combines the 14 questionnaire items with their means and standard deviations. Item means ranged from 3.34 to 3.93, all above the scale mid-point of 3, which indicates generally positive perceptions. The highest-rated item was Q8 (M = 3.93) and the lowest-rated item was Q3 (M = 3.34). Figure 3 ranks the items by mean score. The decision-quality items (Q7–Q10) had means between 3.72 and 3.93, and the performance items (Q11–Q14) between 3.52 and 3.68, which shows that respondents on average perceive AI-supported decisions and organisational results favourably, although agreement is moderate and not unanimous.

Table 2

Questionnaire Items with Descriptive Statistics (5-point Likert scale)

Code	Statement	Construct	Mean	SD
Q1	My organisation actively uses AI tools (e.g., analytics, chatbots, automation) in its operations.	AI adoption	3.61	0.88
Q2	AI technologies are integrated into the core business processes of my organisation.	AI adoption	3.50	0.90
Q3	My organisation invests regularly in new AI applications.	AI adoption	3.34	0.93
Q4	My organisation has high-quality data that can be used for AI applications.	Organisational readiness	3.60	0.92
Q5	Employees in my organisation have the skills needed to work with AI tools.	Organisational readiness	3.58	0.90
Q6	Top management strongly supports AI initiatives.	Organisational readiness	3.48	0.90
Q7	AI-generated insights help me make more accurate decisions.	Decision-making quality	3.89	0.81
Q8	AI tools help me make decisions faster.	Decision-making quality	3.93	0.84
Q9	I consider AI-based recommendations when evaluating alternatives and risks.	Decision-making quality	3.72	0.91
Q10	Decisions supported by AI have produced better outcomes in my area.	Decision-making quality	3.81	0.81
Q11	My organisation's operational efficiency has improved.	Organisational performance	3.61	0.84
Q12	Our service quality and customer satisfaction have improved.	Organisational performance	3.68	0.84
Q13	Our financial results (cost savings or revenue) are better than those of competitors.	Organisational performance	3.52	0.89
Q14	Our organisation is more innovative and responsive to market change.	Organisational performance	3.56	0.87

Note. 1 = strongly disagree, 5 = strongly agree; N = 220.

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Within each construct, the highest-rated items were Q1 for AI adoption (M = 3.61), Q4 for readiness (M = 3.60), Q8 for decision quality (M = 3.93), and Q12 for performance (M = 3.68). The lowest-rated items were Q3 (M = 3.34), Q6 (M = 3.48), Q9 (M = 3.72), and Q13 (M = 3.52) respectively. The differences within constructs are small, which is what would be expected if the items measure a common underlying concept.

4.3 Reliability and Construct-Level Results

Table 3 reports Cronbach's alpha and construct-level statistics. Alpha ranged from 0.76 to 0.84, above the 0.70 threshold, and the alpha for all 14 items was 0.87, so the scales are internally consistent. The highest mean was for decision-making quality (M = 3.84), followed by organisational performance (M = 3.59), organisational readiness (M = 3.55), and AI adoption (M = 3.48). The lowest-rated construct suggests where organisations have most room for improvement. Figure 4 compares the construct means.

Table 3

Reliability and Construct-Level Descriptive Statistics

Construct	No. of items	Cronbach's α	Mean	SD
AI adoption	3	0.757	3.48	0.74
Organisational readiness	3	0.791	3.55	0.76
Decision-making quality	4	0.820	3.84	0.68
Organisational performance	4	0.839	3.59	0.71
All items	14	0.871	–	–

Note. $\alpha \geq 0.70$ indicates acceptable internal consistency.

The construct means are all in the upper half of the scale, which indicates that respondents on balance rate their organisations favourably. The standard deviations, between 0.68 and 0.76, show that there is real variation in experience across respondents, which is necessary for the correlation and regression analyses.

4.4 Correlation Analysis

Table 4 presents the Pearson correlation matrix. All correlations are positive and significant. Decision-making quality is correlated with AI adoption (r = 0.474) and with readiness (r = 0.406), and performance is correlated with decision quality (r = 0.397), AI adoption (r = 0.381), and readiness (r = 0.381). AI adoption and readiness are themselves correlated (r = 0.396), as expected given that prepared organisations tend to adopt more AI, but the correlation is moderate and does not indicate a problem of overlap. Figure 5 plots decision-making quality against performance and shows a clear positive relationship.

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Table 4

Pearson Correlation Matrix

Construct	1	2	3	4
1. AI adoption	1			
2. Organisational readiness	0.396**	1		
3. Decision-making quality	0.474**	0.406**	1	
4. Organisational performance	0.381**	0.381**	0.397**	1

Note. N = 220. **Correlation is significant at the 0.01 level (two-tailed); *significant at the 0.05 level.

The size of the correlations is informative. They range from 0.381 (between organisational readiness and organisational performance) to 0.474 (between AI adoption and decision-making quality), all in the low-to-moderate range, which means that each variable shares a meaningful but limited proportion of its variance with the others. The correlation between decision quality and performance ($r = 0.397$) corresponds to about 15.8 per cent of shared variance. These patterns are consistent with the proposed model, but they are bivariate and do not control for the other variables, which is why the regression analysis follows.

4.5 Regression and Mediation Analysis

Table 5 reports both regression models. Model 1 was significant, $F(2, 217) = 42.47$, $p < 0.001$, with $R^2 = 0.281$. AI adoption ($\beta = 0.371$, $t = 5.92$, $p < 0.001$) and organisational readiness ($\beta = 0.259$, $t = 4.14$, $p < 0.001$) were significant positive predictors of decision-making quality, which supports H1 and H2. Model 2 was also significant, $F(3, 216) = 23.02$, $p < 0.001$, with $R^2 = 0.242$. Decision quality ($\beta = 0.219$, $t = 3.13$, $p = 0.002$), AI adoption ($\beta = 0.192$, $t = 2.76$, $p = 0.006$), and readiness ($\beta = 0.216$, $t = 3.23$, $p = 0.001$) were all significant positive predictors of performance, which supports H3, H4, and H5.

Table 5

Multiple Regression Results

Predictor	B	Std. error	β	t	p-value	VIF
Model 1: Dependent variable = Decision-making quality						
(Constant)	1.832	0.223	–	8.23	< 0.001	–
AI adoption (H1)	0.340	0.057	0.371	5.92	< 0.001	1.19
Organisational readiness (H2)	0.231	0.056	0.259	4.14	< 0.001	1.19
$R^2 = 0.281$; Adj. $R^2 = 0.275$; $F(2, 217) = 42.47$, $p < 0.001$; DW = 2.05						
Model 2: Dependent variable = Organisational performance						
(Constant)	1.371	0.273	–	5.02	< 0.001	–
AI adoption (H4)	0.183	0.066	0.192	2.76	0.006	1.38
Organisational readiness (H5)	0.201	0.062	0.216	3.23	0.001	1.28
Decision-making quality (H3)	0.227	0.073	0.219	3.13	0.002	1.39
$R^2 = 0.242$; Adj. $R^2 = 0.232$; $F(3, 216) = 23.02$, $p < 0.001$; DW = 2.06						

Note. N = 220. B = unstandardised coefficient; β = standardised coefficient.

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The pattern both indicates direct and indirect effects between adoption and readiness variables on the decisions and performance, which suggests partial mediation. The bootstrapped indirect effect of AI use on performance via the model of decision quality was 0.077 (95% CI 0.028 to 0.138), and that of readiness was 0.053 (95% CI 0.018 to 0.097). The intervals do not include zero, which means that both indirect effects are significant. The diagnostics were satisfactory; the VIF values for Model 2 ranged from 1.28 to 1.39, an acceptable range of values for this tool, as well as below 5, and the Durbin–Watson statistics were 2.05 and 2.06, just below the 2 statistic.

The coefficients are not standardised so the effects are reported in the scale unit. A one-point increase in AI readiness is correlated with a 0.340-point increase in decision quality; a one-point increase in AI readiness is also correlated with a 0.231-point increase in decision readiness. In Model 2, other variables being held constant, each unit increase in decision quality is correlated with 0.227 points increase in performance. The total effects of AI adoption (0.260) and readiness (0.253) are the sum of the direct effects and about 30 per cent and 21 per cent of the total are indirect and operate through decision quality. The rest are direct, indicating that whilst decision quality is a critical pathway in which these resources can affect performance it is not the only pathway.

This was followed by testing for group differences. The results of an independent-samples t-test also indicated that there was no significant differences between male ($M = 3.63$) and female respondents ($M = 3.55$), $t(218) = 0.78$, $p = 0.437$. The results did not differ between the age groups ($F = 1.02$, $p = 0.385$), between the levels of managerial experience ($F = 1.26$, $p = 0.288$) and between sectors ($F = 0.97$, $p = 0.408$) in a one-way ANOVA. The associations between these demographic variables and AI adoption, readiness, decision quality and performance, therefore, do not seem to be dependent on these demographic factors in this sample.

5. Conclusion

The study explored how the adoption of AI and organizational readiness affected organizational performance and the quality of managerial decisions based on a survey of 220 managers and professionals. Results showed the scales were reliable, and both regression models were significant with 28.1 per cent of the variance in decision quality accounted for, and 24.2 per cent of the variance in performance. All 5 hypotheses were accepted: adoption and readiness had a positive effect on decision quality, decision quality had a positive effect on performance and adoption and readiness had a direct positive effect on performance. The relationships of both to performance were partially mediated by decision quality as inferred from the bootstrapped indirect effects. There was no significant difference between outcomes according to gender, age, experience or by sector.

The results have a number of implications. Organisations should think about AI as a capability rather than as a purchase: Decision making and outcomes are linked to AI adoption, but data quality, skills, and leadership support strengthens the impact of AI adoption (Fountaine et al., 2019; Jöhnk et al., 2021). Second, AI needs to be embedded within decision processes, where there is a clear delineation between AI judgement and human judgement, with the quality

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of the decision being a primary pathway to performance (Jarrahi, 2018; Shrestha et al., 2019). Third, managers should develop readiness parallel, as readiness will have direct and indirect effects when adopted. Fourth, action targets should be complemented by ethical norms concerning bias, privacy and transparency (Mikalef et al., 2022; Raisch & Krakowski, 2021).

In addition to the practical recommendations, the study confirms that the value of AI comes in stages of organisational resources and outcomes. A good adoption and readiness are resources, and a good decision is the intermediate step, and a good performance is the result. The study reveals that the direct paths continue to be found significant even with decision quality, suggesting that decision quality is not solely responsible for the impacts of AI, and that organisations should not only consider decision quality to assess investments in AI.

The study adds value by measuring the adoption and readiness of AI in a one model that captures both direct and indirect impacts on performance—rather than doing so individually or conceptually—as many previous studies do. It is limited in some ways which indicate ways to continue research. The sample was convenience, the measures used were self-reported, followed a cross-sectional design, and used a perception-based measure of performance. Further research is warranted using probability sampling, objective performance data, longitudinal and experimental designs, and validated multi-item scales, as well as exploring moderators like firm size, industry and regulatory context. This type of research would give a clearer view of the role that AI plays in the decision-making and performance of various organisations

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