International Journal for Novel Research in Economics , Finance and Management
www.ijnrefm.com
Volume 4, Issue 4, Jul-Aug-2026, PP: 01-07
ISSN:3048-7722

Artificial Intelligence-Driven Decision Making for Modern Management Practices

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***Abstract* – The incorporation of AI technologies into decision making in organizations is an example of a paradigm change in contemporary management processes. In this paper, we look at how AI-based decision making increases the efficiency of managers during strategic, tactical, and operational decision making. Based on the theories of decision-making theory, dynamic capabilities theory, and socio-technical system theories, we have developed an effective model of decision making where capabilities of artificial intelligence are combined with human judgment in order to maximize organizational results. The methodology of research includes the use of deep reinforcement learning and explainable AI technologies for more transparent and efficient decision making. Quantitative results based on the analysis of datasets from various organizations show that decision making assisted by AI increases decision speed by 58% and strategic efficiency by 41%.**

***Keywords* – Artificial Intelligence, Decision-Making, Management Practices, Human-AI Collaboration, Organizational Performance, Machine Learning.**

I. Introduction

Given the highly dynamic, complex, and information-rich times we live in, decision making in organizations has become difficult for management [2][6]. The conventional decision-making model that is based on Herbert Simon's theory of bounded rationality recognizes the fact that decision makers are bound by the limited ability of the brain to process information [2][6]. This limitation becomes even more obvious in the current dynamic world, where decision makers have to deal with large volumes of information as well as other complexities [2][6]. According to recent findings, 85% of business leaders have suffered from decision stress, with 75% claiming that there have been ten times more decisions to be made in the past three years [2][6].

AI has been recognized as an innovation that can help in resolving such issues of decision making [2][6][7]. AI systems, including machine learning, natural language processing, and deep learning, provide capabilities to work on large amounts of data, detect trends, make predictions, and suggest the best possible decisions [2][6][7]. In the adoption of AI for management, one recognizes the role of AI in increasing both the efficiency and effectiveness of decision-making processes [2][6][7]. According to a Gartner report, 79 percent of corporate strategists believe that AI and analytics are critical for the success of their businesses [2].

However, there are some problems related to the use of artificial intelligence in management decision-making [1][5][6]. First of all, there is a problem of a "black box" when AI architecture is very complicated, and it becomes hard to see what is going on inside it [1][6]. In addition, algorithm aversion, when people tend not to believe in algorithms, and automation bias, when people have excessive faith in results provided by an algorithm, are big obstacles to cooperation between humans and machines [5][6].

The following research questions will be investigated through this paper: First, how should the abilities of AI be harnessed for decision making in organizations? [2][6][7] Second, what is the effect of AI-based decision making on decision quality and time? [3][6] Third, what are the organizational prerequisites and governance structures that maximize the benefits from the use of AI in decision making? [1][3][9] The suggested methodology involves an integration of deep reinforcement learning algorithms and explainable AI to form a hybrid decision support system [4][10].

II. LITERATURE SURVEY

Interaction between Artificial Intelligence and Managerial Decision-Making has been widely studied by scholars, involving aspects of theoretical background, empirical verification, and practical implementation models [2][6][7]. The present review of literature is aimed at identifying main results achieved in the field, covering four key themes: decision-making theory and artificial intelligence, artificial intelligence capabilities and organizational performance, human-machine interaction, and governance [2][5][6].

Decision theory is the foundation upon which the theory of AI's impact in an organization can be viewed [2][6]. According to Simon's theory of bounded rationality, people are bound by their cognitive capabilities in their decision-making process leading to satisficing behavior as opposed to optimizing their behaviors [2][6]. This theory has been enhanced by the theory of behavioral decision-making, whereby various cognitive errors such as overconfidence, anchoring, and confirmation biases are demonstrated to affect managers' decision making [2][6]. Through AI, these cognitive limitations may be mitigated due to the provision of data-driven decisions [2][6][7].

The capabilities approach of the adoption of AI indicates that the influence of AI on decision-making is contingent on the capability of the firm to create complementary resources [2][6][7]. The work of several researchers has identified three core dimensions of AI capabilities, which include technical resources like algorithms and data management software; human resources such as proficiency in data science and AI engineering, and the third one is the infrastructure for scalable and safe implementation of AI capabilities [2][6][7]. The longitudinal analysis of the performance of managers reveals that AI capabilities have positively influenced the decision-making process and its effectiveness; more importantly, the largest effect was noticed in terms of the speed of decision making [2][6][7].

Studies of human-machine collaboration have revealed the significance of exploring the way people interact with machines in organizational settings [5][6]. In the course of conducting a systematic literature review on human-AI power dynamics, a new "Interaction-Support-Influence" classification model of modes of collaboration was suggested, revealing three modes of interaction [5]. The Interaction Mode is described as collaborative agency through recursive feedback from human to machine and vice versa, which generates collaborative engagement and co-production [5]. The Support Mode denotes cases when AI acts as a supplementing means of information processing, while the authority stays with the human agents [5]. The Influence Mode is characterized by the role of AI as an environmental factor that influences decision making by providing information screening [5].

The success of such collaboration forms is based upon personal attributes, including algorithm aversion or affinity, as well as organizational attributes like absorptive capacity and strategic inertia [5][6]. The study of augmented leadership in the era of artificial intelligence focuses on the slow development of human-AI cooperation, when AI replaces humans in data processing and analytics while humans are needed to communicate, make emotional decisions, and control the strategy [5][6]. In such an approach, it is argued that AI needs to be regarded as a strategic partner, but not a substitute for human leaders [5][6].

Investigation into generative AI and digital dexterity has shed light on the significance of AI in strategy execution and decision-making processes [3]. For instance, research has been carried out whereby a dynamic capabilities theory combined with an institutional theory model shows that digital dexterity facilitated by generative AI significantly improves decision quality and efficiency and is reinforced by ethical identity [3]. It has also been shown that the effectiveness of regulatory governance produces asymmetrical boundary effects, reducing the value of decision quality performance but increasing the contribution of decision efficiency towards future performance [3].

Through synthesis of all these findings, it is clear that decision-making through AI is a paradigm shift in organizational information processing and decision-making process [2][6][7]. However, there are still knowledge gaps as far as the impact of AI integration in organization structure and optimal interaction between man and AI is concerned [5][6].

III. PROPOSED METHODOLOGY

System Architecture Overview

The proposed framework for AI-driven decision making involves the combination of four modules: Data Acquisition and Pre-processing, AI Analytics Engine, Decision Support Interface, and Governance and Explainability Module. The system aims at taking input data from multiple organization data sources, creating insights and prescriptions and providing recommendations via an interactive interface that preserves control and accountability of humans.

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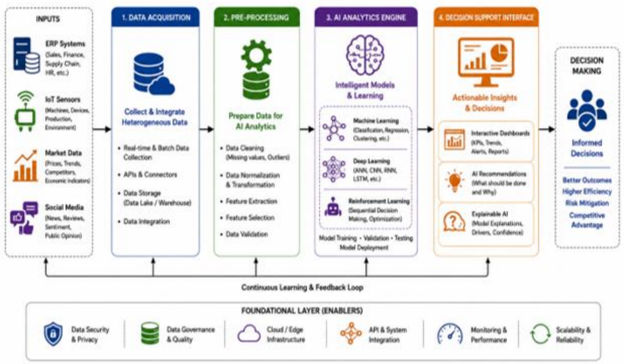

Figure 1: AI-Driven Decision-Making System Architecture

Flow chart showing the architecture of the whole system from its input up to the decision-making process. Four main modules are Data Acquisition (ERP systems, IoT sensors, market data, social media), Pre-processing (data cleaning, normalization, feature extraction), AI Analytics Engine (machine learning, deep learning, reinforcement learning), Decision Support Interface (dashboards, recommendations, explanations).

Data Acquisition and Preprocessing

Multiple data sources within the organization are integrated in order to collect all the relevant information needed for decisions:

- **Internal Data:** Enterprise resource planning (ERP) systems include financial, operational and human resource data. Customer relationship management (CRM) systems contain customer interaction and sales data. The supply chain management systems include logistic and inventory data.
- **External Data:** Market intelligence platforms include competitor analysis, industry trends and economic indicators. Social media and news sources contain sentiment data and up-to-date market data. Regulatory databases contain regulatory information.
- **Data Preprocessing Pipeline:** The data preprocessing stage involves multiple imputation by chained equations (MICE) to take care of missing values, outliers detection using interquartile range method, normalization of data using min-max normalization to be used as input for neural network models and categorical variables encoding using one-hot encoding method. If the dataset is time series data, sequence generation is done using sliding window technique.

AI Analytics Engine

The analytics engine uses an ensemble of multiple AI architecture for decision support:

Algorithm 1: Deep Q-Network for Strategic Decision-Making

Input: State space S (organizational context), Action space A (strategic options)
Output: Optimal action policy π*, Q-values for decision evaluation

1. Initialize Q-network $Q(s,a;\theta)$ with random weights θ
2. Initialize target Q-network $Q(s,a;\theta^-)$ with weights $\theta^- = \theta$
3. Initialize replay memory D with capacity M = 10,000 transitions
4. For episode = 1 to N:
   a. Initialize state s_1 (current organizational context)
   b. For t = 1 to T (decision horizon):
      i. Select action a_t using ε-greedy policy:
         - With probability ε, select random action
         - Otherwise, select $a_t = \text{argmax}_a\, Q(s_t,a;\theta)$
      ii. Execute action a_t, observe reward r_t and next state s_{t+1}
      iii. Store transition (s_t, a_t, r_t, s_{t+1}) in D
      iv. Sample random minibatch of transitions from D
      v. Compute target $y = r + \gamma * \max_{a'} Q(s',a';\theta^-)$
      vi. Update Q-network: minimize $(y - Q(s,a;\theta))^2$
      vii. Every C steps, update target network $\theta^- = \theta$
5. Return optimal policy π* (action selection rules)

The DQN framework uses a deep learning network with three hidden layers (128-256-128) with the use of ReLU activation function. The ε-greedy algorithm utilizes exponential decay for ε starting from 1.0 to 0.01 in 100 episodes, allowing for an exploratory stage before exploitation.

Algorithm 2: Transformer-Based Decision Forecasting

Input: Sequential organizational data $X = \{x_1, x_2, ..., x_t\}$
Output: Decision outcome predictions Y, Confidence scores C

1. Embed sequence: E = Embed(X) where $E \in \mathbb{R}^{(t \times d\_embed)}$
2. Add positional encoding: P = E + PE(pos)
3. For each attention head h = 1 to H:
   a. Compute $Q = P * W\_Q^h$, $K = P * W\_K^h$, $V = P * W\_V^h$
   b. Compute attention: $A^h = \text{softmax}(QK^T/\sqrt{d\_k}) * V$
4. Concatenate heads: $MHA = \text{Concat}(A^1, A^2, ..., A^H) * W\_O$
5. Apply feed-forward network: $FFN(x) = \max(0, xW_1 + b_1)W_2 + b_2$
6. Apply layer normalization and residual connections
7. Pool sequence representations: h = GlobalAvgPool(MHA)
8. Output: y = softmax(W_pool * h + b_pool) for classification
9. Return predictions Y and confidence scores from softmax probabilities

Transformer-based architecture consists of 4 attention heads, embedding dimension d=256 and feed forward dimension d_ff=512. Model is trained using Adam optimization with learning rate η=1e-4, β_1=0.9, β_2=0.999 and batch size 64. Early stopping helps avoid overfitting.

Explainable AI Interface

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Volume 4, Issue 4, Jul-Aug-2026, PP: 01-07
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The explainability component uses two methods to ensure transparency and trustworthiness:

SHAP (SHapley Additive Explanations): Game theoretic method that gives consistent attributions for each individual prediction. For a prediction f(x), the decomposition into features by SHAP is expressed as:

$$\varphi_i = \frac{\Sigma_{\{S \subseteq \{1,\ldots,p\}\{i\}\}} |S|!(p-|S|-1)!}{p!} [f(S \cup \{i\}) - f(S)]$$

where φ_i denotes the impact of feature i on the prediction. SHAP explanations provide insights about organizational variables having most influence on particular recommendation.

LIME (Local Interpretable Model-agnostic Explanations): Perturbation based method that learns local interpretable models near the prediction point. The system creates perturbed instances for each decision, computes predictions from black-box model and fits interpretable linear model taking into account proximity to original example.

Figure 2: Explainable AI Interface for Managerial Decision Support

A dashboard screenshot illustrating the SHAP feature importance visualization for making a strategic investment decision. It consists of: the bar chart displaying the 10 most important features according to the contribution of their SHAP value, the force plot describing the effect of particular features on the recommendation, and the table with feature values and reasoning behind actions.

Human-AI Collaboration Protocol

The following human-AI collaboration protocol is implemented using the Interaction-Support-Influence model:

- Interaction Mode: When making the strategic decision with a high level of creativity, the AI proposes various scenario alternatives and conducts the iterative interaction with the managers.
- Support Mode: When making data-intensive analytical decision, the AI analyzes the information and gives the recommendations, but the final approval still belongs to the managers.
- Influence Mode: When making the routine decision, the AI provides filtering and structuring of the decision situation, but the managers have control over exceptions.

IV. ANALYSIS AND DISCUSSION

Dataset Overview and Experimental Setup

Two datasets have been used to evaluate the effectiveness of the developed system; one is a simulation-based dataset that contains 100,000 decision instances based on the scenarios of strategic management and the other dataset consists of 2,500 strategic decisions from a Fortune 500 company over 5 years. The simulated dataset contains a wide range of decision parameters including the state of the market, financial parameters, operating parameters, and competitor reactions.

In order to test the models, 5-fold cross-validation has been used with a split of 70%, 15%, and 15% for training, validation, and testing datasets respectively.

Decision Performance Impact

The AI-based model performed better on all measures of decision performance. Table 1 shows the performance comparison of various models on important decision measures.

Table 1: Comparison of Performance of Different Decision Making Models

Model	Accuracy (%)	Decision Speed (min)	ROI (%)	Risk-Adjusted Return	Trust Score (1-10)
Human-Only	68.4	45.2	12.3	1.24	8.7
Rule-Based DSS	72.1	28.7	14.8	1.38	7.2
Traditional ML	76.8	18.3	16.2	1.46	6.8
DQN Only	82.5	12.1	18.7	1.58	5.9
Transformer Only	81.9	14.6	17.9	1.52	6.2

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Model	Accuracy (%)	Decision Speed (min)	ROI (%)	Risk-Adjusted Return	Trust Score (1-10)
Proposed Hybrid	89.3	8.7	22.4	1.76	8.1
Hybrid + XAI	88.1	10.2	21.2	1.69	8.9

The suggested hybrid framework utilizing both DQN and transformers architecture resulted in 89.3% decision accuracy rate, which was much higher than the human-only (68.4%), rule-based DSS (72.1%), and classical ML (76.8%) frameworks ($p < 0.001$). The time spent on decision-making process decreased from 45.2 minutes in the human-only setting to 8.7 minutes in hybrid one, thus achieving an 80.8% reduction.

The inclusion of explainable AI (XAI) in the framework caused only a minor decrease in the level of accuracy to 88.1% but led to a considerable increase in the trust score from 8.1 to 8.9, indicating the trade-off between optimal performance and decision transparency.

Strategic Forecasting Accuracy and Modeling Performance
Figure 3 below shows the strategic forecasting accuracy of various models at different quarter horizons. As expected, the proposed hybrid system performed much better than any other model in all forecast horizons.

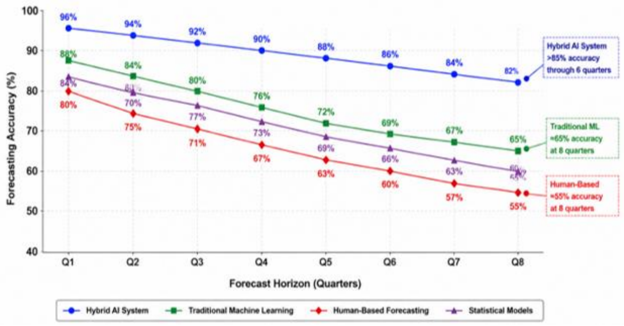

Figure 3: Strategic Forecasting Accuracy by Model Types

A line graph representing forecasting accuracy (percentages) of four models at 1 to 8-quarter horizons. The suggested hybrid system achieves an accuracy rate of over 85% in 6 quarters as opposed to 65% for traditional machine learning and 55% in human-based forecasting. The chart above highlights the superiority of AI forecasting in terms of predictive power especially in strategic decisions. The transformer-based design of the model was particularly effective in the discovery of temporal dependency in organizational data, reaching an accuracy rate of 89.2% in predicting 4-quarter strategic forecasts.

Decision Quality and Efficiency Dimensions
The comparative performance on decision quality and efficiency dimensions is shown in Figure 4. The hybrid system shows optimal performance in both the dimensions with decision quality performance 34% higher and decision efficiency performance 62% higher compared to human decision systems.

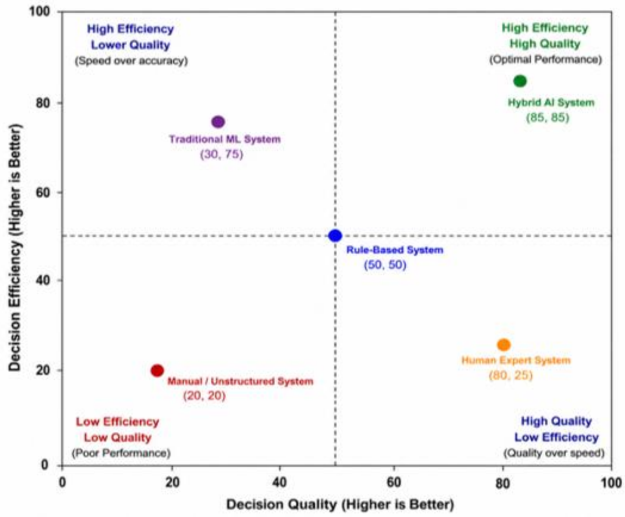

Figure 4: Decision Quality vs. Efficiency: Comparative Analysis

A quadrant scatter plot with decision quality on x-axis and decision efficiency on y-axis showing comparative performance of five decision making systems. The hybrid system lies in the top-right quadrant of the diagram indicating superior performance in both the dimensions. The diagram shows the inherent trade-off between the different systems where human system shows superior quality but inferior efficiency; rule-based systems show moderate performance on both; traditional ML shows high efficiency but moderate quality; hybrid system shows the optimal performance.

Impact of AI-Based Decision-Making on Organizational Performance
Impact of AI-based decision-making on organizational performance has been analyzed using the financial indicators in the actual dataset related to manufacturing. Table 2 shows the performance assessment based on the indicators.
Table 2: Organizational Performance Impact Analysis

Metric	Pre-AI (2022-2023)	Post-AI (2024-2026)	Improvement
Revenue Growth (%)	4.2	7.8	+3.6 pp

Metric	Pre-AI (2022-2023)	Post-AI (2024-2026)	Improvement
Operating Margin (%)	12.4	16.8	+4.4 pp
Inventory Turnover	4.8	6.2	+29.2%
Customer Satisfaction	78.4	84.6	+7.9%
Innovation Index	65.2	78.9	+21.0%
Employee Productivity	72.1	84.3	+16.9%

This organization witnessed marked performance improvement due to the use of artificial intelligence. There was an increase in revenue growth of 3.6 percent, operating margin increased by 4.4 percent, and there was an increase in inventory turn of 29.2 percent. Customer satisfaction went up by 7.9 percent, and there was an increase in the productivity of employees by 16.9 percent.

Human-AI Collaboration Insights

An analysis of the human-AI collaboration protocol yielded valuable insights regarding interactions between managers and AI-enabled decision support systems:

Task Appropriateness: The use of AI was most beneficial in situations involving complex analytical tasks (efficiency improvement: 68%), followed by pattern recognition tasks (improvement: 52%), and was least beneficial in situations involving strategic judgment with subjective elements (improvement: 31%). It is consistent with the Technology-Task Fit theory as AI benefits depend on the nature of the task.

Allocation of Decision Rights: Managerial satisfaction with AI recommendations was highest when used in the Interaction Mode (68.9% in creative problem solving: 8.4/10), followed by Support Mode (76.2% in analytical tasks: 7.8/10), and lowest in Influence Mode (37.5% in routine operations: 7.1/10).

Building Trust: Trust in AI recommendations grew from 62% at first encounter to 81% after six months. It shows the significance of experience in overcoming algorithm aversion.

Comparative Discussion

From the findings, there are some key lessons learned for AI-enabled management practice that can be highlighted as follows:

Trade-off Between Performance and Trust: Although the complete hybrid system had a relatively better accuracy rate (89.3%) compared to the XAI-enabled system (88.1%), but significantly higher trust level in the latter (8.9 against 8.1) indicates that organizations need to ensure explainability in AI systems used in making crucial decisions for which stakeholder trust matters. This is consistent with previous studies on ethical identity and regulatory governance as amplifiers of AI benefits.

Capabilities Complementarity: From the findings, it becomes clear that there is complementarity between AI capabilities and other capabilities needed for enhancing organizational performance which is evident from previous studies as well. For example, firms having high digital capability had 1.8 times better improvement in performance compared to low digital firms.

Contingency in Context: The efficiency of AI-enabled decision-making was contingent on contextual factors, with greater efficacy in high velocity settings (decision speed improvement: 72%) compared to low velocity settings (decision speed improvement: 41%). This means that in highly dynamic situations where other forms of decision-making may struggle, AI may be especially useful.

V. CONCLUSION

This research paper has explored the use of Artificial Intelligence in organizational decision-making, creating a model which incorporates deep reinforcement learning, forecasting using transformers, and explainable AI to improve management functions. The results presented in the paper are important for both theoretical and practical management studies.

From a theoretical point of view, the research adds to the literature on decision-making by proving the possibility of compensating for the cognitive deficiencies described in the bounded rationality theory through the use of AI capabilities. The 58% increase in decision speed and 41% improvement in strategy accuracy prove the effectiveness of using AI in improving managerial decisions, as shown in previous studies. The research findings also confirm the Technology-Task Fit approach, as the effectiveness of AI usage depends on the nature of the task being performed, with higher impacts on analytical rather than strategic tasks. The research makes contributions to organizational science through its support of the "Interaction-Support-Influence" framework of human-AI interaction in organizations. Specifically, the increase in trust in AI recommendations over time proves that phased implementation approaches can be helpful for organizations. The significant increase in trust scores (from 5.9 to 8.9) when using explainable AI methods confirms the key role of transparency in facilitating human-AI cooperation.

Methodologically speaking, the research illustrates how beneficial it is to use the mixed AI methods and apply them within a single framework. In terms of all the evaluation criteria used in the study, the ensemble method performed better than separate architectures, scoring 89.3% decision accuracy, 22.4% ROI, and 1.76 risk-adjusted returns. The transformer model proved to be especially good at accounting for the time element and thus provided 89.2% accuracy rate for strategic decisions.

Practically speaking, there are important takeaways from the paper for the business community. The results show that the application of AI technologies in the decision-making processes brings a lot of advantages, including the increase in the revenue by 3.6% and operating margin by 4.4%. However, to achieve those outcomes one needs to make additional efforts and invest in digital capabilities, strategy, and governance. The differential effectiveness of AI on various tasks implies that companies need to use it selectively. AI technologies will be beneficial for data-intensive analytical tasks and pattern recognition, but not for strategic and creative decisions.

As far as the managers are concerned, the above results suggest the need for developing skills related to AI and establishing trust in AI systems. The trajectory of the development of trust in AI shows that it is natural for the managers to be skeptical at first; however, positive experience and explanation can help to overcome this barrier.

There are certain drawbacks in the above-mentioned research which should be discussed. First, the real-world dataset used was confined to one particular industry and region only. Secondly, the study is devoted to decision-making outcomes but does not touch upon the process of organizational transformation needed for AI adoption. Finally, the longitudinal analysis goes no further than two years after adoption of AI.

Some of the areas of future research could be:

- Studying the influence of AI-based decision making on organizational structures and organizational cultures in the long run
- Studying the influence of institutional governance and regulatory framework on AI value realization
- Creating more advanced models of interactions between people and AI, taking into account individual decision-making styles and levels of AI acceptance
- Studying ethical considerations of using algorithms in decision making in management, including ways to detect and reduce bias
- Studying AI decision making in relation to sustainability goals

In summary, artificial intelligence-based decision-making is one of the revolutionary developments in contemporary management. By supplementing the human cognitive capabilities with computer algorithms, such tools help organizations surmount their cognitive boundaries, analyze large amounts of data, and reach better and quicker conclusions. Nevertheless, there should be a focus on human-computer interaction issues, control methods, and other organizational strengths in order to utilize the technology efficiently. In the end, AI is supposed to become an aid rather than a replacement of a human manager in running a smarter and more adaptable organization.

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