



Artificial Intelligence Adoption, Strategic Decision-Making, and the Improvement of Key Performance Indicators (KPIs): Evidence from Organizations in Tehran

J. Zhang^{1,*}

¹ Department of Industrial Engineering, Faculty of Engineering, Peking University, Beijing, China

ARTICLE INFO	ABSTRACT
Article History: Received 4 February 2024 Received in revised form 10 April 2025 Accepted 26 May 2025 Available online 9 June 2025 Keywords: Artificial Intelligence; Strategic Decision-Making; Key Performance Indicators; Smart KPIs; Organizational Performance; Digital Transformation; Tehran	This study examines how managers perceive the contribution of artificial intelligence (AI) adoption to strategic decision-making and key performance indicators (KPIs) in organizations in Tehran. Using a quantitative descriptive survey design, data were collected from 384 managers, senior executives and senior experts in technology, service and manufacturing organizations in Districts 2, 5 and 7 of Tehran with a structured five-point Likert questionnaire, and were analyzed descriptively in SPSS. Respondents rated the contribution of AI most highly for the speed of decision-making ($M = 3.80$) and more moderately for KPI improvement ($M = 3.10$), whereas human resource readiness to work with AI received the lowest score ($M = 2.90$). Mean scores were highest in District 2 (3.52), followed by District 7 (3.30) and District 5 (3.15); because no inferential tests were conducted, these differences are descriptive only. The findings suggest that the organizations studied are in a transitional stage of digital transformation, in which AI tools are increasingly available but their contribution to performance is constrained by employee readiness, data integration and decision-making culture. The study therefore recommends a shift from technology-centred to capability-centred AI strategies, including continuous employee upskilling, a data-driven organizational culture and integrated data infrastructure. Future research should test these relationships using inferential and multivariate methods.

1. INTRODUCTION

In recent decades, Artificial Intelligence (AI) has evolved from a predominantly theoretical and technical concept into one of the most transformative technologies in organizational management and decision-making. Rapid advances in machine learning, deep learning, natural language processing, and big data analytics have provided organizations with unprecedented analytical and predictive capabilities. These technologies have not only transformed operational processes but have also increasingly influenced the nature and structure of managerial and strategic decision-making [1].

* Corresponding Author: Jiang.Zhang@gmail.com

Department of Industrial Engineering, Faculty of Engineering, Peking University, Beijing, China



Strategic decision-making, defined as the process of selecting among alternative long-term courses of action that may substantially influence organizational performance, inherently involves complexity, ambiguity, uncertainty, and incomplete information. Managers frequently encounter cognitive and informational limitations that constrain their ability to process large volumes of data, evaluate numerous alternatives, and anticipate the consequences of strategic choices [2]. AI-based analytical systems can potentially mitigate some of these constraints by expanding information-processing capacity, identifying patterns within complex datasets, and supporting predictive analysis.

Concurrently, Key Performance Indicators (KPIs) play a central role in measuring and evaluating organizational progress toward strategic objectives. Traditional KPIs, however, may have limitations when organizations require forward-looking information, rapid adaptation to environmental changes, and stronger alignment between organizational units and strategic priorities [3]. The integration of AI into performance measurement has contributed to the emergence of increasingly intelligent or “Smart” KPIs capable of supporting descriptive, diagnostic, and predictive forms of analysis.

The present study therefore examines the relationship between AI adoption, strategic decision-making, and KPI improvement through two complementary components. First, it develops the conceptual and theoretical foundations of these relationships through a focused review of the relevant management and AI literature. Second, it empirically examines the current situation among managers, senior executives, and senior experts working in selected organizations in Districts 2, 5, and 7 of Tehran using a quantitative descriptive-survey design.

The significance of this research is twofold. From a theoretical perspective, it seeks to integrate three areas that are frequently discussed separately: AI capabilities, strategic decision-making, and organizational performance measurement. From an applied perspective, it provides evidence that may assist managers and policymakers in identifying the organizational conditions required to derive greater strategic value from AI.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 presents the theoretical foundations. Section 4 specifies the research question and objective. Section 5 describes the methodology. Section 6 reports the empirical findings. Section 7 discusses the findings and their implications. Section 8 presents the conclusion and recommendations, followed by the study limitations and directions for future research.

2. LITERATURE REVIEW

2.1. Artificial Intelligence and the Transformation of Organizational Management

Conceptually, artificial intelligence refers to a collection of technologies and computational approaches that enable machines and information systems to perform tasks traditionally associated with human intelligence, including learning, reasoning, perception, prediction, pattern recognition, and problem-solving.

Davenport and Ronanki (2018) identified three major organizational applications of AI: process automation, cognitive insight through data analysis, and cognitive engagement with customers and employees [1]. This framework remains useful for understanding how organizations move from relatively narrow automation initiatives toward more analytically and strategically sophisticated applications of AI.

In their book *Prediction Machines*, Agrawal, Gans, and Goldfarb (2018) provided an economic perspective on AI by conceptualizing its central contribution as reducing the cost of prediction [4]. Because many managerial decisions involve choices under conditions of uncertainty, improvements in predictive capacity can potentially enhance the information available to decision-makers. This perspective provides an important theoretical foundation for understanding why AI may affect strategic decision-making.

Shrestha, Ben-Menahem, and von Krogh (2019), in a study published in *California Management Review*, developed a framework for understanding how organizational decision-making structures may change in the age of AI. Their analysis highlighted different configurations through which human and artificial intelligence can interact in organizational decision processes, including varying degrees of delegation and collaboration [5].

More recently, researchers have increasingly examined generative AI and Large Language Models (LLMs) in strategic management. Csaszar, Ketkar, and Kim (2024) provided empirical evidence indicating that contemporary LLMs can contribute to strategy generation and evaluation and may influence important cognitive processes underlying strategic decision-making, including information search, representation, and aggregation [2].

Together, these studies suggest that AI should not be understood merely as an automation technology. Its organizational importance increasingly lies in its ability to augment information processing, prediction, knowledge generation, and managerial decision-making.

2.2. Artificial Intelligence and Strategic Decision-Making

Because of its high-stakes, relatively unstructured, ambiguous, and complex nature, strategic decision-making remains one of the most demanding managerial responsibilities. Strategic decisions may be affected by bounded rationality, incomplete information, time pressure, and cognitive biases, including confirmation bias, managerial myopia, and excessive reliance on intuition [6].

The introduction of AI into this domain may reduce some information-processing limitations and provide managers with complementary analytical capabilities. Jarrahi, Kenyon, Brown, Donahue, and Wicher demonstrated that AI can support organizational learning and help organizations generate insights from data, while emphasizing that successful AI implementation requires appropriate organizational learning capabilities [7].

AI should therefore be viewed as an augmentation mechanism rather than as an automatic substitute for managerial judgment. Algorithms can process large and complex datasets rapidly, but challenges associated with contextual interpretation, data quality, explainability, and accountability continue to require human involvement.

From a competitive perspective, Csaszar et al. (2024) further indicate that the strategic value of AI depends not only on access to AI technologies but also on how organizations integrate these capabilities into strategy formulation and competitive processes [2]. Consequently, AI may influence competitive advantage by reshaping organizational cognitive capabilities and improving the speed and breadth of strategic analysis.

Shrestha, Krishna, and von Krogh (2021) examined the principles, promises, and challenges of augmenting organizational decision-making with deep learning algorithms [8]. Their work highlights the considerable information-processing capacity of deep learning while simultaneously emphasizing unresolved issues related to interpretability, algorithmic bias, and excessive reliance on automated recommendations.

At a broader level, recent bibliometric research on AI and strategic decision-making demonstrates increasing scholarly interest in the intersection of artificial intelligence, sustainability, supply chains, organizational strategy, and decision-support applications [9]. This growing literature indicates that AI-supported strategic decision-making is becoming an increasingly interdisciplinary field.

2.3. KPIs in the Era of AI: From Traditional to Smart Indicators

Key Performance Indicators have long been used in performance management to measure organizational progress toward predefined objectives. Nevertheless, traditional KPI systems may become less effective in environments characterized by rapid change, complex interdependencies, and large volumes of continuously generated data.

Existing literature identifies several limitations of conventional KPI systems, including excessive reliance on historical performance, limited predictive capability, weak integration across organizational functions, and difficulties in dynamically adapting performance indicators to changing strategic priorities [3].

A collaborative study by MIT Sloan Management Review and Boston Consulting Group (2024), based on responses from more than 3,000 managers across multiple industries and countries, provides evidence that organizations are increasingly using AI to improve the relevance and strategic usefulness of their KPIs [3]. The report indicates that organizations using AI to improve KPI design and prioritization may obtain greater strategic alignment and performance benefits than organizations relying exclusively on conventional measurement systems.

The concept of Smart KPIs can be understood through several analytical functions:

1. **Smart Descriptive KPIs:** Indicators that synthesize historical and current organizational data to provide an accurate representation of existing performance conditions.
2. **Smart Diagnostic KPIs:** Indicators that support the identification of underlying factors and potential causes associated with performance deviations.
3. **Smart Predictive KPIs:** Indicators that use analytical and machine-learning techniques to estimate future patterns, risks, or performance trajectories [3].

These categories demonstrate that AI can potentially extend the role of KPIs beyond retrospective measurement. Under appropriate organizational and data conditions, performance indicators can become part of a broader strategic intelligence system.

Ferraris, Mazzoleni, Devalle, and Couturier (2019) examined the relationship among big data analytics capabilities, knowledge management, and firm performance [10]. Their findings emphasize that analytical capabilities do not operate in isolation; rather, their organizational value depends substantially on complementary knowledge-management capabilities.

Similarly, Fountaine, McCarthy, and Saleh (2019) argued that building an AI-powered organization requires more than the acquisition of algorithms and technical systems [11]. Effective AI adoption requires organizational changes involving culture, workflows, data practices, managerial behavior, and decision-making processes. This argument is particularly relevant to Smart KPI implementation because technically advanced indicators can generate strategic value only when managers and organizational units are prepared to interpret and act upon them.

2.4. Linking Strategic Decision-Making and KPIs via Artificial Intelligence

An important gap in the existing literature concerns the limited integration of AI, strategic decision-making, and KPI systems within a unified analytical framework. Many studies emphasize AI-supported decision-making [2,5,8], while another stream of research focuses on AI-enabled performance measurement and Smart KPIs [3].

The present study connects these research streams by conceptualizing AI as an enabling capability that can simultaneously influence the process through which strategic decisions are developed and the mechanisms through which their organizational consequences are monitored.

Rather than assuming that AI adoption automatically generates competitive advantage, the literature suggests that its contribution depends on complementary organizational capabilities, including knowledge management, data quality, human expertise, and organizational learning.

Olan et al. (2022), in a study published in the *Journal of Business Research*, examined the complementary relationship among artificial intelligence, knowledge sharing, and organizational performance [12]. Their findings suggest that the implementation of AI technologies alone is insufficient to improve organizational performance. Instead, organizational performance can benefit when AI capabilities are integrated with effective knowledge-sharing mechanisms.

This perspective is particularly relevant to strategic decision-making and KPI management. AI can contribute to the generation and analysis of organizational information, while knowledge-sharing processes enable this information to be interpreted, disseminated, and incorporated into managerial action.

Furthermore, available evidence suggests that the use of AI to prioritize and redesign KPIs may contribute to stronger alignment between performance measurement and organizational strategy [3]. Therefore, the strategic value of AI may arise not simply from faster computation but from creating stronger feedback loops between data, managerial decisions, organizational knowledge, and performance indicators.

2.5. Barriers, Challenges, and Ethical Considerations

Despite the documented potential benefits of AI, the research literature also identifies important challenges associated with its implementation in strategic decision-making.

Shrestha et al. (2021) highlight several major concerns [8]:

1. **Interpretability:** Complex algorithms may be difficult to explain, particularly when organizations must justify strategically important decisions to managers, employees, regulators, or other stakeholders.
2. **Data and Algorithmic Bias:** AI systems trained on incomplete or systematically biased datasets may reproduce or amplify existing distortions in organizational decision-making.
3. **Over-Reliance on Algorithmic Recommendations:** Excessive dependence on automated recommendations may weaken managerial judgment and reduce critical evaluation of algorithmic outputs.

Davenport and Ronanki (2018) also emphasize the value of an incremental approach to AI implementation [1]. Rather than beginning with highly ambitious projects, organizations can initially apply AI to clearly defined operational problems and progressively develop more sophisticated applications as organizational capabilities mature.

Ethical considerations are particularly important when AI-supported strategic decisions affect employees, customers, or other stakeholders. Issues involving accountability, transparency, privacy, fairness, and explainability therefore need to be incorporated into AI governance rather than treated solely as technical problems.

Overall, the literature demonstrates considerable potential for AI to improve information processing, strategic decision support, organizational learning, and performance measurement. At the same time, the precise organizational mechanisms through which these benefits emerge remain dependent on contextual factors such as human capabilities, data governance, organizational culture, knowledge-sharing processes, and technological maturity.

3. THEORETICAL FOUNDATIONS

The theoretical framework of this study integrates several complementary perspectives from management and information systems research. These include bounded rationality and data-driven decision-making, the dynamic capabilities perspective, stakeholder theory, management information systems theory, and organizational change theory.

3.1. Bounded Rationality and AI-Supported Data-Driven Decision-Making

Classical decision theory recognizes that managerial rationality is constrained by limited information, cognitive capacity, time, and uncertainty [6]. AI does not eliminate these limitations entirely; however, it can expand the information-processing and predictive capabilities available to decision-makers.

Within this study, the term AI-supported data-bounded rationality is used as an analytical description rather than as a claim that an established independent theory has replaced classical bounded rationality. The concept refers to decision environments in which AI enables managers to process substantially larger volumes of structured and unstructured information, identify complex patterns, and incorporate predictive analytics into strategic analysis.

Accordingly, strategic decisions in volatile environments need not depend exclusively on historical experience and managerial intuition. Machine-learning algorithms can provide additional predictive evidence that complements managerial expertise. Nevertheless, the quality of AI-supported decisions remains constrained by the quality of underlying data, model design, interpretability, and the capacity of managers to critically evaluate algorithmic outputs [13].

3.2. Dynamic Capabilities Perspective

The dynamic capabilities perspective provides an important framework for understanding how organizations can transform AI technologies into strategic capabilities. Sustainable performance in rapidly changing environments depends not simply on possessing resources but on the organization's ability to sense environmental changes, seize emerging opportunities, and reconfigure internal and external resources.

From this perspective, AI can strengthen sensing capabilities by analyzing large and heterogeneous data sources, improve opportunity identification through predictive analysis, and support resource reconfiguration by providing timely information about changing market and organizational conditions.

AI therefore becomes strategically valuable when it is embedded in broader organizational routines and capabilities rather than treated as an isolated technical asset. This perspective also helps explain why two organizations with access to similar AI technologies may achieve substantially different outcomes.

3.3. Stakeholder Perspective

Stakeholder theory emphasizes that organizations need to consider the interests and consequences experienced by multiple groups, including customers, employees, shareholders, business partners, society, and other affected stakeholders.

Within AI-supported decision-making, this perspective is particularly important because strategic algorithms can influence multiple stakeholder groups simultaneously. AI systems can assist managers in processing stakeholder-related information, including customer feedback, employee data, market responses, and other forms of structured and unstructured information.

However, AI does not automatically balance stakeholder interests. Managers remain responsible for interpreting outputs, addressing conflicts among stakeholder objectives, and ensuring that algorithmic recommendations are evaluated in relation to ethical, organizational, and social considerations.

3.4. Management Information Systems and KPI Improvement

Management Information Systems (MIS) provide another theoretical foundation for this research. The fundamental purpose of organizational information systems is to provide relevant and timely information to decision-makers in a usable form.

AI extends conventional MIS capabilities by transforming large volumes of raw data into increasingly sophisticated descriptive, diagnostic, and predictive information. When integrated with organizational performance-management systems, AI can facilitate real-time KPI monitoring, identify unusual deviations, detect emerging patterns, and support managerial responses.

Accordingly, the effectiveness of AI-enabled KPI systems depends not only on computational capability but also on information quality, data integration, accessibility, managerial interpretation, and alignment between performance indicators and strategic objectives.

3.5. Organizational Change and AI Implementation

AI implementation also represents an organizational change process. Integrating AI into strategic decision-making can alter organizational routines, job responsibilities, authority structures, information flows, and managerial practices.

Successful implementation therefore requires more than technological investment. Organizations need to manage employee resistance, develop relevant competencies, establish data-driven working practices, and clarify the changing relationship between human and algorithmic decision-making.

Automation may allow managers and employees to devote more attention to analytical, creative, and strategic tasks; however, this transition also requires role redesign and continuous learning. Organizational change capabilities are therefore essential for transforming AI adoption into sustainable performance improvement [14].

Collectively, these theoretical perspectives demonstrate that AI should not be understood merely as a technical tool. Its strategic effects emerge through interactions among technology, human judgment, organizational capabilities, information systems, knowledge processes, and institutional structures.

4. RESEARCH QUESTION AND OBJECTIVE

4.1. Primary Research Question

How is artificial intelligence adoption associated with strategic decision-making processes and the improvement of key performance indicators (KPIs) within organizations operating in selected districts of Tehran?

4.2. Primary Research Objective

The primary objective of this study is to develop an integrated understanding of the role of artificial intelligence in supporting strategic decision-making and KPI improvement and to identify practical organizational measures that may strengthen the effective utilization of AI within organizations.

5. METHODOLOGY

5.1. Research Design

This study is applied in terms of its objective and quantitative and descriptive-survey in terms of research design. The empirical component was designed to provide a diagnostic assessment of AI adoption, strategic decision-making, KPI improvement, and organizational readiness among selected organizations in Tehran.

Because the available analysis is primarily descriptive and cross-sectional, the findings are interpreted as patterns and associations rather than definitive evidence of causal relationships.

5.2. Statistical Population and Study Sample

The target population consisted of senior executives, strategic managers, and senior experts working in technology, service, and manufacturing organizations in Tehran.

The empirical study focused on organizations located in Districts 2, 5, and 7. These districts were selected to provide organizational diversity and practical access to firms operating in different local business environments.

Using Cochran's formula for a large population, a 5% margin of error, and the conventional 95% confidence assumption, the target sample size was approximately 384 respondents. Participants were distributed across the selected districts using a stratified sampling approach.

Accordingly, 384 represents the study sample rather than the total statistical population.

5.3. Data Collection Instrument

Data were collected using a structured questionnaire composed of closed-ended items measured on a five-point Likert scale.

The questionnaire assessed dimensions related to:

1. AI adoption in strategic decision-making;
2. perceived effects of AI on decision-making speed;
3. perceived improvement in organizational KPIs;
4. human resource readiness to work with AI; and
5. organizational patterns associated with AI utilization.

The questionnaire was designed based on the conceptual framework and relevant literature reviewed in this study.

5.4. Validity and Reliability

The content and face validity of the questionnaire were evaluated through expert review to assess the relevance, clarity, and conceptual appropriateness of the measurement items.

Internal consistency reliability was assessed using Cronbach's alpha. However, because the numerical reliability coefficients are not available in the present dataset supplied for this paper, no coefficient is reported here. The exact Cronbach's alpha values should be inserted before final submission if the original questionnaire dataset or statistical output is available.

This approach avoids reporting unverified statistical values while preserving transparency regarding the validation procedure.

5.5. Data Analysis

Questionnaire data were analyzed using SPSS. Descriptive statistical indicators, including means, standard deviations, frequencies, and percentages, were used to assess the current status of the measured dimensions.

Descriptive comparisons were also conducted among Districts 2, 5, and 7.

Because inferential group-comparison results and a complete PLS-SEM output were not available in the underlying material used for the present manuscript, no claim of statistically significant structural relationships or statistically significant differences among districts is made.

Accordingly, the empirical findings should be interpreted primarily as a descriptive diagnostic assessment.

6. FINDINGS

The empirical findings are summarized in Table 1.

Table 1. Descriptive Research Findings

No.	Measured Component	Mean	SD	Agree / Strongly Agree (%)	Descriptive Status
1	Rate of AI tool adoption in strategic decision-making	3.45	0.82	42%	Moderately High

2	Perceived impact of AI on the speed of decision-making	3.80	0.65	58%	High
3	Degree of KPI improvement following AI implementation	3.10	0.90	35%	Moderate
4	Level of human resource readiness to work with AI	2.90	1.05	28%	Moderately Low
5	Overall descriptive mean by district: District 2 / District 5 / District 7	3.52 / 3.15 / 3.30	—	—	District 2 recorded the highest descriptive mean

The results indicate that the perceived effect of AI on decision-making speed received the highest mean score ($M = 3.80$, $SD = 0.65$), with 58% of respondents selecting “agree” or “strongly agree.” This finding suggests that respondents primarily perceive AI as contributing to faster information processing and decision support.

The rate of AI tool adoption in strategic decision-making produced a moderately high mean score of 3.45 ($SD = 0.82$). This suggests that AI tools have achieved a meaningful degree of organizational penetration among the surveyed respondents, although their adoption cannot yet be characterized as fully mature.

KPI improvement received a more moderate mean score of 3.10 ($SD = 0.90$), with 35% agreement or strong agreement. The difference between the decision-speed score and the KPI-improvement score is noteworthy. Descriptively, it suggests that organizations may be obtaining more immediate benefits from AI in terms of decision speed than in translating AI utilization into measurable performance improvement.

Human resource readiness received the lowest mean score ($M = 2.90$, $SD = 1.05$), with only 28% of respondents indicating agreement or strong agreement. This result identifies workforce readiness as an area requiring particular managerial attention. It does not, by itself, establish that human resources are the sole or primary causal barrier to AI implementation; rather, it suggests that employee preparedness represents a comparatively weak dimension within the surveyed organizations.

The district-level descriptive comparison shows that District 2 recorded the highest mean score (3.52), followed by District 7 (3.30) and District 5 (3.15). These differences may reflect variations in organizational characteristics, sectoral composition, digital infrastructure, access to specialized employees, or other contextual factors. However, because no inferential test of between-district differences is reported, these explanations should be regarded as plausible interpretations requiring further empirical investigation rather than established causal findings.

7. DISCUSSION

The findings provide several insights into the current role of AI within the surveyed Tehran-based organizations.

First, the relatively high score for decision-making speed supports the broader argument that one of AI's most immediate organizational contributions lies in its ability to process large volumes of information rapidly and provide managers with analytical support. This observation is consistent with literature emphasizing AI's capacity to expand organizational information-processing and predictive capabilities.

However, faster decision-making should not automatically be interpreted as better decision-making. Decision quality also depends on the relevance and accuracy of underlying data, appropriate interpretation of analytical outputs, organizational context, and managerial judgment.

Second, the moderate score for KPI improvement suggests that technical adoption does not necessarily translate immediately into stronger organizational performance. This finding is consistent with research emphasizing the complementary relationship between analytical technology, organizational knowledge, and managerial capabilities.

In particular, Olan et al. (2022) argue that AI implementation alone is insufficient for improving organizational performance and that complementary knowledge-sharing mechanisms are required [12]. The current findings provide descriptive support for this broader organizational perspective.

Third, human resource readiness appears to represent an important area of concern. The comparatively low score of 2.90 suggests a potential capability gap between the availability of AI technologies and employees' preparedness to use, interpret, and critically evaluate them.

From the dynamic capabilities perspective, this result is particularly important. AI technologies become strategic capabilities only when organizations develop complementary human, managerial, and organizational competencies. Investment in technology without parallel investment in workforce development may therefore limit the strategic value generated by AI.

Fourth, the descriptive variation among Districts 2, 5, and 7 raises potentially important questions regarding local organizational ecosystems. District 2's higher mean may plausibly be associated with differences in organizational composition, concentration of knowledge-intensive firms, access to specialized talent, or technological infrastructure. Nevertheless, the present study did not directly test these explanations.

Future studies should therefore collect district-level organizational and infrastructural variables and apply inferential statistical tests before drawing conclusions regarding the causes or statistical significance of regional differences.

Finally, the findings support a broader transition from a technology-centered understanding of AI adoption toward a socio-technical and human-centered perspective. Organizational outcomes depend on the interaction among algorithms, data, people, knowledge, processes, and organizational structures.

8. CONCLUSION AND RECOMMENDATIONS

This study examined AI adoption, strategic decision-making, and KPI improvement among managers, senior executives, and senior experts working in selected organizations in Districts 2, 5, and 7 of Tehran.

The descriptive findings provide a multidimensional picture of the current stage of organizational AI utilization. Among the dimensions examined, the perceived impact of AI on decision-making speed received the highest mean score (3.80), while human resource readiness received the lowest (2.90). AI adoption in strategic decision-making recorded a mean of 3.45, whereas perceived KPI improvement remained more moderate at 3.10.

These results suggest a potentially important gap between the adoption of AI tools and organizations' capacity to translate these technologies into broader performance improvements. Organizations appear to recognize and experience the information-processing advantages of AI more readily than its full potential for KPI optimization.

Human resource readiness deserves particular managerial attention. The results suggest that developing employees' and managers' capacity to understand AI outputs, critically evaluate algorithmic recommendations, and integrate AI-generated information into organizational decisions may be essential for obtaining sustainable benefits from technological investment.

The district-level results also reveal descriptive differences. District 2 recorded the highest overall mean (3.52), followed by District 7 (3.30) and District 5 (3.15). These findings indicate the value of investigating contextual and organizational differences within Tehran, although additional inferential evidence is required before these differences can be considered statistically significant or causally attributed to specific district characteristics.

Overall, the organizations examined in this study can cautiously be characterized as operating within a transitional stage of AI-enabled digital transformation. Technical adoption is progressing, but complementary human and organizational capabilities require further development.

Based on the findings and theoretical analysis, the following recommendations are proposed:

1. **Development of Continuous Upskilling Programs:** Organizations should establish specialized and continuous training programs for managers and employees focusing on data literacy, AI-assisted decision-making, critical evaluation of algorithmic outputs, and responsible AI use.

2. **Cultivation of a Data-Driven Organizational Culture:** Organizations should encourage evidence-based decision-making, experimentation, organizational learning, and constructive evaluation of both successful and unsuccessful AI initiatives.
3. **Data Infrastructure Integration:** Organizations should improve the integration, quality, accessibility, and governance of organizational data. AI systems cannot generate reliable managerial insights when they depend on fragmented or low-quality information.
4. **Human-AI Decision Protocols:** Organizations should explicitly determine which decisions can be automated, which require human oversight, and which should be made through collaborative human-AI processes.
5. **Smart KPI Development:** Organizations should progressively redesign conventional performance indicators by incorporating descriptive, diagnostic, and predictive analytical capabilities while ensuring that indicators remain aligned with strategic objectives.
6. **AI Governance and Ethical Oversight:** Transparency, accountability, data privacy, fairness, and explainability should be incorporated into organizational AI governance frameworks.
7. **Context-Sensitive Organizational and Regional Policies:** The descriptive differences observed among Districts 2, 5, and 7 suggest that AI development initiatives may benefit from attention to local organizational characteristics rather than relying exclusively on uniform implementation strategies.
8. **Continuous Evaluation:** Organizations should periodically assess whether AI investments are improving not only decision speed but also decision quality, employee capability, organizational learning, and measurable performance outcomes.

In conclusion, AI holds substantial potential to reshape strategic decision-making and organizational performance measurement. Nevertheless, technology represents only one component of successful digital transformation. Sustainable improvement depends on the alignment of technological capabilities with human capital, organizational learning, data governance, strategic objectives, and appropriate performance indicators.

9. LIMITATIONS AND FUTURE RESEARCH

Several limitations should be considered when interpreting the findings of this study.

First, the study is cross-sectional and descriptive. Consequently, the findings identify patterns and perceptions at a particular point in time and should not be interpreted as definitive evidence of causal relationships between AI adoption and organizational performance.

Second, the empirical analysis relies primarily on self-reported questionnaire responses. Respondents' perceptions may not fully correspond to objective organizational performance measures.

Third, the sample is limited to organizations located in Districts 2, 5, and 7 of Tehran. Therefore, the findings should not automatically be generalized to all organizations in Tehran or to other regions of Iran.

Fourth, although descriptive differences were identified among the three districts, inferential tests of between-group differences were not available in the current dataset. Future research should employ appropriate procedures such as analysis of variance or comparable methods to determine whether observed regional differences are statistically significant.

Fifth, the present manuscript does not report a complete structural equation model. Future studies with access to the item-level dataset could employ PLS-SEM or covariance-based SEM to examine measurement reliability, convergent and discriminant validity, path coefficients, explanatory power, and potential mediating or moderating relationships.

Sixth, future research should combine perceptual measures with objective organizational indicators, such as decision-cycle time, productivity measures, financial KPIs, operational efficiency, innovation outcomes, and AI investment levels.

Longitudinal research would also be valuable for determining whether improvements in AI capability precede and predict subsequent changes in strategic decision quality and organizational performance.

Finally, qualitative interviews with executives and employees could complement survey findings by explaining how organizational culture, managerial resistance, data governance, employee skills, and trust in AI influence implementation outcomes.

Future studies integrating quantitative, qualitative, and longitudinal evidence would therefore provide a more comprehensive understanding of the mechanisms through which AI contributes to strategic decision-making and KPI improvement.

Authors' Contributions

All authors read and approved the final manuscript.

Declaration of Generative AI Use

During the preparation of this work, the authors used AI to improve the language and readability of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Declaration of Competing Interests

The authors declare no conflict of interest.

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Ethical Considerations

Participation in the survey was voluntary, and all respondents were informed of the aims of the study and gave informed consent before completing the questionnaire. No names or identifying information were collected, responses were kept confidential, and the results were reported only in aggregate form. As this was an anonymous, non-interventional survey of professionals, formal ethics committee approval was not sought. The data were used solely for research purposes.

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