MSELS
Management Systems Evolution and Leadership Studies
VOL. 2 | NO. 4 | 2025

The Transformation of Decision-Making Leadership in Data-Driven Organizations: An Interpretive Study

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Abstract

This study aimed to interpret how leadership decision-making is transformed when organizations shift from experience-based and authority-centered decision practices toward data-driven, analytics-supported, and evidence-mediated forms of managerial judgment. This qualitative interpretive study was conducted among senior managers, middle managers, data analysts, digital transformation specialists, and organizational development experts working in data-driven organizations in Tehran. Participants were selected through purposive sampling based on their direct involvement in strategic, operational, or analytical decision-making processes. Data were collected through semi-structured interviews with 21 participants, and theoretical saturation was reached after the eighteenth interview, with three additional interviews conducted to confirm conceptual adequacy. Interviews were transcribed verbatim and analyzed using thematic analysis supported by NVivo software. Coding proceeded through open coding, category development, theme refinement, and interpretive integration. The analysis produced five main categories: evidence-mediated leadership judgment, hybrid human–analytics decision architecture, redistribution of decision authority, data culture as a leadership practice, and ethical reflexivity in data-driven decisions. Participants described the transformation of leadership not as the replacement of managerial judgment by data, but as the reconstruction of judgment through evidence, dashboards, predictive indicators, and cross-functional interpretation. Data-driven decision-making changed who participates in decisions, how authority is justified, how risk is discussed, and how leaders balance speed, accountability, and contextual understanding. The findings suggest that decision-making leadership in data-driven organizations evolves from individual authority toward interpretive orchestration, where leaders are expected to translate data into meaning, question algorithmic outputs, create collective analytical capacity, and preserve ethical responsibility. Effective data-driven leadership therefore depends not only on technological infrastructure, but also on cultural readiness, interpretive competence, transparency, and human accountability.

Keywords: Data-driven decision-making; decision leadership; digital transformation; analytics capability; interpretive study; organizational leadership; Tehran.

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HOW TO CITE

Sharifi, K. (2025). Management System Evolution Through Organizational Learning: Developing a Dynamic Capability Framework. *Management Systems Evolution and Leadership Studies,* 2(4), 29-39.

1. Introduction

Decision-making has always been central to leadership, but the meaning of leadership decision-making is being fundamentally transformed in contemporary organizations. Classical views of managerial decision-making emphasized authority, experience, bounded rationality, administrative coordination, and the capacity of leaders to make choices under uncertainty. Simon's theory of bounded rationality challenged the assumption of fully rational managerial actors by arguing that decision-makers operate under cognitive, informational, and environmental constraints and therefore rely on satisficing rather than perfect optimization (Simon, 1997). Later organizational theories expanded this view by showing that decisions are shaped not only by individual cognition but also by routines, coalitions, politics, institutional pressures, and organizational learning (March, 1991). In this traditional understanding, leaders were expected to interpret incomplete information, rely on professional experience, negotiate ambiguity, and assume responsibility for the consequences of their choices. However, the rise of digital transformation, big data analytics, artificial intelligence, and real-time information infrastructures has introduced a new decision environment in which leaders are increasingly expected to justify decisions through data, metrics, dashboards, predictive models, and algorithmic recommendations.

The movement toward data-driven decision-making has altered the epistemic basis of leadership. Data-driven decision-making refers to organizational practices in which decisions are informed by systematically collected, processed, analyzed, and interpreted data rather than being based primarily on intuition, hierarchy, or precedent. Early managerial discussions of analytics emphasized that firms could compete by embedding statistical analysis, predictive modeling, and fact-based decision processes into core business functions (Davenport, 2006; Davenport & Harris, 2007). Empirical research has also suggested that firms adopting data-driven decision-making practices may achieve higher productivity and performance than comparable firms that rely less heavily on data (Brynjolfsson et al., 2011; Brynjolfsson & McElheran, 2016). Yet the transformation is not merely technical. It changes how leaders define problems, evaluate alternatives, build legitimacy, communicate with subordinates, and defend decisions before stakeholders. Leadership in data-driven organizations therefore requires more than access to information systems; it requires the interpretive capacity to convert data into organizationally meaningful judgments.

The literature on big data analytics capability has provided an important foundation for understanding this transformation. Big data analytics capability refers to the organizational ability to acquire, integrate, process, analyze, and use data resources for strategic and operational purposes. Studies have shown that analytics capability depends on technological infrastructure, data quality, analytical talent, management support, and alignment with business strategy (Akter et al., 2016; Mikalef et al., 2018; Wamba et al., 2017). Other studies have linked analytics capability with dynamic capabilities, innovation, operational responsiveness, and competitive performance (Mikalef et al., 2020; Wamba et al., 2017). These findings are important because they show that data-driven organizations are not simply organizations that possess large datasets or advanced software; rather, they are organizations that develop routines, structures, and capabilities for transforming data into action. However, much of this literature focuses on organizational performance, technological capability, or strategic alignment, while less attention has been given to how leaders themselves experience and reconstruct decision-making authority in data-rich environments.

Digital transformation has also changed the social architecture of decision-making. In many organizations, decision processes are no longer confined to senior executives or formal managerial roles. Data scientists, business intelligence specialists, platform managers, process owners, and algorithmic systems increasingly participate in decision-making. This creates hybrid decision structures in which human judgment and computational outputs interact. Shrestha et al. (2019) argue that artificial intelligence changes organizational decision-making by introducing new combinations of human and machine judgment, including full delegation, sequential decision-making, and aggregated decision structures. Similarly, Jarrahi (2018) emphasizes that human and artificial intelligence should be understood as complementary rather than simply substitutive: machines are powerful in computation, pattern recognition, and scalability, whereas humans remain important for contextual interpretation, ethical judgment, creativity, and ambiguity management. These arguments suggest that the future of leadership is not a simple transition from human decision-making to machine decision-making, but rather the emergence of hybrid decision leadership.

This hybridity creates both opportunities and tensions. On the one hand, data-driven decision-making can reduce bias, increase transparency, accelerate learning, and improve coordination across departments. Leaders can use analytics to identify patterns that are invisible to intuition, test assumptions, forecast risks, and monitor performance in real time. On the other hand, data-driven systems can create new forms of dependency, surveillance, fragmentation, and algorithmic opacity. Research on algorithmic management has shown that algorithms may reshape organizational control by recording, rating, recommending, restricting, rewarding, or replacing human actions (Kellogg et al., 2020). Faraj et al. (2018) similarly note that learning algorithms may transform work by producing black-boxed performance, anticipatory quantification, comprehensive digitization, and hidden politics. These studies indicate that data-driven decision-making is not neutral. It changes power relations, accountability mechanisms, and the meaning of managerial responsibility. Leaders in data-driven organizations must therefore learn not only how to use analytics, but also how to question analytics, contextualize outputs, and protect human agency.

A further issue concerns the relationship between data and intuition. The shift from intuition-based to analytics-based decision-making is often presented as a linear movement from subjective judgment to objective evidence. However, this binary distinction is too simplistic. Managerial decisions frequently involve incomplete data, conflicting indicators, uncertain futures, and value-laden trade-offs. Korherr et al. (2022) show that the transition from intuitive to data-driven decision-making involves different managerial archetypes, including analytical thinkers, coaches, guides, and strategists. This suggests that leaders do not merely abandon intuition; rather, they reconfigure intuition in relation to analytical evidence. Experienced leaders may use data to challenge assumptions, but they also use contextual knowledge to evaluate whether data are relevant, incomplete, biased, or misleading. Thus, the transformation of decision-making leadership involves a movement from unexamined intuition toward disciplined interpretation.

The cultural dimension of data-driven leadership is equally important. Organizations cannot become data-driven only by purchasing analytics platforms or hiring data scientists. Data-driven decision-making requires a culture in which evidence is valued, assumptions are questioned, data quality is protected, and decision processes are open to learning. LaValle et al. (2011) found that organizations able to convert analytics into value tend to embed analytics in decision processes and managerial practices rather than treating analytics as a separate technical function. Data-driven culture also requires psychological safety because employees must be willing to challenge senior leaders when data contradict prior beliefs. Without such a culture, analytics may become symbolic rather than substantive: dashboards may be displayed in meetings, but decisions may still be dominated by hierarchy, politics, or retrospective justification. Therefore, the transformation of leadership involves cultural work: leaders must model evidence-based inquiry, encourage data literacy, and prevent data from becoming either ignored or blindly worshipped.

Despite growing attention to analytics, digital transformation, and artificial intelligence, there remains a need for qualitative and interpretive research on how leaders experience decision-making transformation in specific organizational contexts. Quantitative studies can measure associations between analytics capability and performance, but they often cannot capture the lived meanings, tensions, and interpretive practices through which leaders make sense of data-driven decision-making. An interpretive approach is particularly suitable because decision-making leadership is not only a technical process but also a social, symbolic, and cultural practice. Leaders must interpret what data mean, decide whose interpretation counts, negotiate conflicts between data and experience, and determine how much authority should be delegated to analytical systems. These issues require close attention to participants' narratives, meanings, and organizational experiences.

The Iranian organizational context, particularly Tehran as the country's major economic, technological, administrative, and corporate center, provides a relevant setting for examining this phenomenon. Many organizations in Tehran are increasingly adopting enterprise resource planning systems, customer analytics, business intelligence dashboards, digital platforms, and AI-supported decision tools. However, these organizations often operate within hybrid managerial cultures where hierarchical authority, expert judgment, informal networks, regulatory uncertainty, and emerging data infrastructures coexist. This makes the transformation of decision-making leadership especially complex. Leaders may be expected to be data-driven while still navigating centralized authority, limited data integration, uneven digital skills, and cultural resistance to transparency. Studying this context can contribute to the broader literature by showing how data-driven leadership is interpreted and enacted in organizations undergoing digital transition rather than in fully mature analytics environments.

Accordingly, this study adopts a qualitative interpretive design to explore how decision-making leadership is transformed in data-driven organizations in Tehran. Instead of treating data-driven decision-making as a purely technological or performance-oriented phenomenon, the study examines it as an organizational meaning-making process. It asks how leaders understand the changing role of data in decisions, how they balance analytics and judgment, how decision authority is redistributed, and what ethical and cultural tensions emerge. The aim of this study was to interpret the transformation of decision-making leadership in data-driven organizations by identifying the main meanings, practices, and tensions through which leaders reconstruct authority, judgment, and accountability in analytics-supported decision environments.

2. Methods and Materials

This study used a qualitative interpretive research design to explore how leadership decision-making is transformed in data-driven organizations. The interpretive approach was selected because the purpose of the study was not to test predetermined hypotheses, but to understand how managers and specialists make sense of decision-making changes in organizational contexts where data, analytics, dashboards, and digital platforms increasingly shape managerial practice. Qualitative interpretive inquiry is appropriate when the phenomenon under investigation is complex, socially constructed, and embedded in organizational meanings, routines, and relationships (Creswell & Poth, 2018; Lincoln & Guba, 1985).

The research population consisted of managers, senior experts, and digital transformation professionals working in data-driven organizations in Tehran. Participants were selected through purposive sampling. Inclusion criteria were: at least five years of professional experience, direct involvement in managerial or analytical decision-making, experience with data dashboards or analytics-based reporting systems, and willingness to participate in an audio-recorded interview. Participants came from technology firms, financial service organizations, retail platforms, consulting firms, manufacturing companies, and service-sector organizations that had implemented business intelligence, customer analytics, performance dashboards, or digital decision-support tools. The final sample included 21 participants. Theoretical saturation was reached after the eighteenth interview, when no substantially new codes or conceptual categories emerged; three additional interviews were conducted to confirm saturation and refine the interpretation.

Data were collected through semi-structured interviews. The interview protocol was developed based on the literature on data-driven decision-making, analytics capability, digital transformation, and leadership decision processes. The protocol included broad questions such as: "How has the use of data changed leadership decision-making in your organization?", "What happens when managerial experience conflicts with data?", "Who participates in decision-making when analytics tools are involved?", "How do leaders justify decisions in a data-driven environment?", and "What ethical or cultural challenges emerge when decisions are based on data?" Follow-up questions were used to clarify meanings, elicit examples, and explore contradictions in participants' accounts.

Interviews lasted between 45 and 75 minutes and were conducted in a confidential setting selected by participants, either in person or through secure online platforms. All interviews were recorded with informed consent and transcribed verbatim. Participants were assured that their names, organizational identities, and any commercially sensitive information would remain confidential. To protect anonymity, interviewees were coded as P1 to P21. Data collection continued until theoretical saturation was achieved. Field notes were written after each interview to record contextual impressions, emerging analytical ideas, and reflexive observations.

Data were analyzed using thematic analysis supported by NVivo software. Thematic analysis was selected because it provides a flexible and systematic method for identifying, analyzing, and reporting patterns across qualitative data (Braun & Clarke, 2006). The analysis followed several stages. First, interview transcripts were read repeatedly to achieve familiarization. Second, initial open codes were generated inductively from participants' statements. Third, related codes were grouped into preliminary categories. Fourth, categories were compared across interviews to identify recurring patterns, tensions, and interpretive meanings. Fifth, categories were refined into main themes that represented the transformation of decision-making leadership in data-driven organizations.

NVivo was used to organize transcripts, manage codes, compare coding frequencies, retrieve relevant quotations, and examine relationships among categories. The coding process was iterative rather than linear. Codes were revised as new meanings emerged, and earlier transcripts were re-examined in light of later interviews. To enhance trustworthiness, the study used member checking with six participants, peer review by two qualitative research experts, prolonged engagement with the data, and maintenance of an audit trail. Credibility was strengthened through direct quotations, transferability through thick description of the organizational context, dependability through systematic documentation of coding decisions, and confirmability through reflexive memo writing (Lincoln & Guba, 1985). The final thematic structure consisted of five main categories.

3. Findings and Results

The participants included 21 individuals working in data-driven organizations in Tehran. In terms of gender, 13 participants were male and 8 were female. Regarding age, 5 participants were between 30 and 35 years old, 9 were between 36 and 45 years old, and 7 were older than 45. In terms of education, 4 participants held bachelor's degrees, 13 held master's degrees, and 4 held doctoral degrees. With respect to organizational role, 6 participants were senior managers, 5 were middle managers, 4 were data analysts or business intelligence specialists, 3 were digital transformation managers, and 3 were organizational development or strategy experts. Professional experience ranged from 6 to 24 years. This diversity made it possible to examine the transformation of decision-making leadership from managerial, analytical, and organizational perspectives.

The first main category was evidence-mediated leadership judgment. Participants repeatedly stated that leadership decisions were no longer accepted merely because they came from seniority, personal experience, or hierarchical authority. Instead, leaders were increasingly expected to support their decisions with data, performance indicators, customer behavior metrics, financial dashboards, or predictive reports. This did not mean that experience disappeared; rather, experience had to be articulated through evidence. One senior manager explained, “Before, if a director said, ‘I know the market,’ that was enough. Now everyone asks, ‘What does the data show?’ The leader still decides, but the decision must speak the language of evidence” (P4). Another participant noted, “Data has made leadership more accountable. You cannot hide behind intuition as easily as before” (P11). Participants interpreted this change as a shift from authority-centered judgment to evidence-mediated judgment. Leaders were still responsible for decisions, but their legitimacy increasingly depended on their ability to interpret and communicate data. However, several participants warned that evidence could also be used selectively. One digital transformation expert stated, “Some managers use dashboards only when the numbers support what they already wanted to do. Data-driven decision-making becomes decorative if leaders do not really question themselves” (P16). Thus, the transformation of judgment involved both greater transparency and the risk of instrumental data use.

The second category was hybrid human–analytics decision architecture. Participants described decision-making as a process increasingly distributed between human actors and analytical systems. Dashboards, forecasting models, customer segmentation tools, risk scoring systems, and automated reports shaped how problems were identified and alternatives were evaluated. Nevertheless, participants emphasized that analytics did not eliminate the need for human interpretation. A business intelligence specialist stated, “The system can show abnormal customer behavior, but it cannot always explain why it is happening. Managers need to connect the numbers to market reality” (P8). Another participant explained, “Data gives direction, but it does not carry responsibility. At the end, a human leader must decide what is acceptable, strategic, and ethical” (P2). This category shows that data-driven leadership is not simply machine-led leadership. Instead, leadership becomes the orchestration of human and analytical intelligence. Participants reported that effective leaders were those who could ask better questions of data teams, understand the limits of models, and combine analytical outputs with contextual knowledge. One participant summarized this point clearly: “A weak manager asks the dashboard for an answer. A strong manager asks why the dashboard is showing that answer” (P14). Hybrid decision architecture therefore requires analytical literacy, interpretive judgment, and cross-functional communication.

The third category was redistribution of decision authority. Participants reported that data-driven systems changed who had influence in organizational decisions. In traditional structures, decision authority was concentrated in senior managers. In data-driven organizations, however, analysts, technical experts, process owners, and even frontline employees with access to real-time data could influence decision discussions. A middle manager said, “Sometimes a young analyst changes the whole direction of a meeting because they have evidence that senior managers did not expect” (P6). This redistribution created both empowerment and tension. Some participants viewed it positively because decisions became more inclusive and evidence-based. Others noted that senior managers sometimes resisted analytical evidence when it challenged established power relations. One participant stated, “Data democratizes decision-making, but hierarchy does not disappear easily. Some leaders feel threatened when a dashboard contradicts them” (P19). Participants also described new forms of dependency on data teams. Managers who lacked analytical literacy sometimes deferred excessively to analysts, while analysts sometimes produced technically sophisticated insights without sufficient business understanding. Therefore, decision authority was redistributed, but not always balanced. The transformation required new forms of collaboration between managerial authority and analytical expertise.

The fourth category was data culture as a leadership practice. Participants emphasized that data-driven decision-making depended less on technology alone and more on the everyday behaviors of leaders. Data culture was described as a pattern of asking for evidence, sharing information, questioning assumptions, tolerating bad news, and using data for learning rather than punishment. One participant explained, “When managers punish people for every negative number, employees start hiding data. A data culture means we use numbers to learn, not only to blame” (P7). Another stated, “The first signal is how the CEO behaves in meetings. If the CEO asks for evidence and listens when evidence is uncomfortable, everyone understands that data matters” (P13). Participants reported that leadership practices such as transparency, data literacy training, cross-departmental meetings, and open discussion of dashboard indicators helped institutionalize data-driven decision-making. However, they also identified barriers, including poor data quality, fragmented databases, lack of trust in reports, fear of surveillance, and symbolic use of analytics. A strategy expert said, “Many organizations have dashboards, but they do not have data culture. They have numbers on screens, but decisions are still political” (P21). Thus, data culture emerged as a leadership accomplishment rather than a technical by-product.

The fifth category was ethical reflexivity and interpretive vigilance. Participants argued that data-driven decisions raise ethical concerns related to privacy, bias, transparency, employee monitoring, and customer profiling. Several participants noted that leaders often focus on accuracy and efficiency while neglecting the social consequences of data use. A digital transformation manager stated, “Just because we can measure something does not mean we should use it for decisions. Leaders must ask what kind of behavior the metric will create” (P10). Another participant explained, “Algorithms can make discrimination look scientific if nobody checks the assumptions behind the model” (P17). Ethical reflexivity refers to the leader’s capacity to question not only whether data are useful, but also whether their use is fair, transparent, and responsible. Interpretive vigilance refers to continuous awareness that data are produced through choices: what is measured, how it is categorized, which variables are excluded, and whose interests are served. Participants believed that responsible data-driven leadership requires leaders to preserve human accountability even when decisions are supported by automated systems. One senior manager concluded, “Data can recommend, but it cannot be morally accountable. Accountability must stay with leadership” (P5).

4. Discussion and Conclusion

The purpose of this study was to interpret how decision-making leadership is transformed in data-driven organizations. The findings showed that this transformation is multidimensional and cannot be reduced to the adoption of digital tools or analytics platforms. Instead, data-driven decision-making changes the basis of leadership legitimacy, the relationship between human judgment and analytical systems, the distribution of decision authority, the cultural practices of leadership, and the ethical responsibilities of organizational actors.

These findings align with prior research suggesting that data-driven decision-making improves organizational capability only when it is embedded in managerial routines, strategic alignment, and organizational culture (Akter et al., 2016; Davenport & Harris, 2007; LaValle et al., 2011; Wamba et al., 2017). The present study extends this literature by showing how leaders themselves interpret the transformation of decision-making authority in organizations undergoing data-driven change.

The first category, evidence-mediated leadership judgment, indicates that leadership legitimacy increasingly depends on the ability to justify decisions through evidence. This finding is consistent with research on data-driven decision-making showing that organizations using data and analytics systematically may achieve stronger performance outcomes (Brynjolfsson et al., 2011; Brynjolfsson & McElheran, 2016). It also supports Davenport's (2006) argument that analytics becomes a basis of competitive advantage when it is embedded in decision processes rather than used as a peripheral reporting activity. However, the findings also show that data do not automatically create rational decision-making. Participants described cases in which leaders used data selectively to support predetermined preferences. This supports Simon's (1997) notion of bounded rationality and March's (1991) view that organizational decisions are shaped by interpretation, learning, and competing logics. Data may reduce uncertainty, but it does not eliminate ambiguity, bias, or politics. Therefore, data-driven leadership should be understood as evidence-mediated judgment rather than pure objectivity.

The second category, hybrid human–analytics decision architecture, demonstrates that leadership decision-making increasingly occurs through interaction between human actors and analytical systems. This finding strongly aligns with Jarrahi's (2018) argument that humans and artificial intelligence possess complementary strengths in organizational decision-making. Machines can process large datasets, detect patterns, and generate predictions, but human leaders remain necessary for contextual interpretation, ethical reasoning, and judgment under ambiguity. The finding also supports Shrestha et al. (2019), who argue that AI-based decision-making creates different structural combinations of human and machine judgment. In the present study, participants did not view analytics as replacing leadership; they viewed it as changing what leadership requires. Leaders must now be able to ask analytical questions, understand model limitations, interpret outputs, and decide when data should be followed, questioned, or supplemented. This suggests that the future of decision-making leadership is not automation alone but interpretive orchestration.

The third category, redistribution of decision authority, shows that data-driven organizations alter power relations. When analysts, technical experts, and frontline employees possess relevant data, they can influence decisions that were previously controlled by senior managers. This finding aligns with research on algorithmic and data-mediated work, which shows that digital systems reshape organizational control, expertise, and authority (Faraj et al., 2018; Kellogg et al., 2020). However, the redistribution observed in this study was not purely democratic. Participants described tensions between hierarchy and evidence, managerial resistance to uncomfortable data, and dependency on technical specialists. This suggests that data-driven decision-making decentralizes some forms of knowledge while potentially recentralizing control through systems, dashboards, and algorithmic infrastructures. Leaders must therefore manage the political consequences of data. They need to create decision forums in which analytical expertise and managerial responsibility are integrated rather than placed in competition.

The fourth category, data culture as a leadership practice, supports the argument that analytics capability is fundamentally organizational rather than merely technological. Prior studies have emphasized that big data analytics capability depends on resources, skills, processes, and management support (Mikalef et al., 2018; Wamba et al., 2017). The present findings add that leaders create data culture through repeated practices: asking for evidence, accepting uncomfortable findings, encouraging data literacy, and using metrics for learning rather than punishment. This is consistent with LaValle et al. (2011), who found that organizations generate value from analytics when analytics is integrated into decision-making and managerial behavior. The participants' distinction between "having dashboards" and "having data culture" is particularly important. It suggests that technology adoption can remain superficial if leaders do not change the social norms of decision-making. Data culture requires trust, psychological safety, and a learning orientation. Without these conditions, employees may manipulate indicators, hide negative data, or treat analytics as a ritual rather than a basis for inquiry.

The fifth category, ethical reflexivity and interpretive vigilance, highlights the moral dimension of data-driven leadership. This finding aligns with studies warning that algorithmic systems may reproduce hidden biases, create opacity, intensify monitoring, and reshape organizational control (Faraj et al., 2018; Kellogg et al., 2020). It also supports Jarrahi's (2018) emphasis on the continuing importance of human judgment in uncertain and equivocal decision contexts. Participants argued that leaders must remain accountable even when decisions are supported by models or automated systems. This is important because data-driven organizations may be tempted to transfer responsibility to "the system" or "the algorithm." However, algorithms do not possess moral accountability. Leaders must ask whether data were collected fairly, whether models are explainable, whether metrics encourage harmful behavior, and whether decisions respect employees, customers, and stakeholders. Ethical data-driven leadership therefore requires not only compliance but also reflexive questioning of the assumptions embedded in data systems.

Taken together, the findings suggest that the transformation of decision-making leadership involves a shift from decision-maker as authoritative chooser to decision-maker as interpretive orchestrator. Traditional leadership emphasized experience, position, and personal judgment. Data-driven leadership still requires judgment, but this judgment is now exercised through evidence, analytics, cross-functional interpretation, and ethical reflection. This supports Korherr et al. (2022), who show that the transition from intuitive to data-driven decision-making involves different managerial roles and archetypes rather than a single universal leadership model. In the present study, effective leaders were not those who blindly followed data, nor those who defended intuition against analytics. They were leaders who could integrate evidence and experience, empower analytical expertise without abandoning responsibility, and build cultures where data informed learning. This finding contributes to leadership studies by conceptualizing data-driven leadership as a relational, interpretive, and ethical capability.

Another important contribution concerns the context of Tehran-based organizations. The findings show that data-driven transformation in this context occurs within organizations that often combine emerging digital infrastructures with hierarchical managerial traditions. This creates a distinctive tension: leaders are expected to become evidence-based while organizational culture may still reward authority, seniority, and informal influence. This tension is not unique to Tehran, but it may be more visible in transitional organizational environments where data systems are growing faster than data culture. The study therefore suggests that data-driven leadership development should not focus only on technical analytics training. It should also address authority relations, communication routines, decision rights, ethical governance, and cultural readiness.

The findings also have implications for the theory of dynamic capabilities. Analytics capability becomes valuable when it enables organizations to sense changes, seize opportunities, and reconfigure routines. However, the present study indicates that these dynamic capabilities depend heavily on leadership interpretation. Data may reveal patterns, but leaders must decide what the patterns mean, which actions are legitimate, and how organizational members should respond. This supports studies linking big data analytics capability with dynamic and operational capabilities (Mikalef et al., 2020; Wamba et al., 2017), while adding that leadership decision-making acts as an interpretive bridge between analytics resources and organizational action. Without such leadership, analytics may produce information without transformation.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

Acknowledgments

Authors thank all who helped us through this study.

Conflict of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

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