

Leadership in Autonomous Organizations: Exploring New Managerial Roles in AI-Based Work Systems

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Abstract

This study aimed to explore how leadership roles are reconstructed in autonomous organizations where AI-based work systems participate in task allocation, workflow coordination, decision support, performance monitoring, and managerial control. A qualitative interpretive design was used to examine managerial experiences in AI-enabled organizations in Tehran. Data were collected through semi-structured interviews with 24 participants, including senior managers, middle managers, HR managers, AI project leaders, operations supervisors, and data-oriented decision makers who had direct experience with AI-based work systems. Participants were selected through purposive and snowball sampling. Interviews continued until theoretical saturation was achieved, with saturation reached after the twenty-first interview and confirmed through three additional interviews. All interviews were audio-recorded with consent, transcribed verbatim, and analyzed using thematic analysis. NVivo software was used to organize transcripts, generate initial codes, compare patterns, and develop final themes. Credibility was strengthened through member checking, peer review, and repeated comparison between codes and interview excerpts. The analysis identified five main categories that explain the changing nature of leadership in autonomous organizations: algorithmic orchestration of work, managerial sensemaking in AI-mediated decisions, human-centered trust and transparency building, capability development for human–AI collaboration, and ethical governance of autonomous systems. Participants described leadership as shifting from direct supervision to system calibration, exception handling, interpretive judgment, employee protection, and continuous learning. While AI improved speed, prediction, coordination, and operational consistency, managers emphasized that human leadership remained essential for contextual interpretation, ethical accountability, conflict resolution, and maintaining organizational meaning. The findings suggest that AI-based work systems do not eliminate leadership but transform its core functions. In autonomous organizations, effective leaders act as orchestrators, interpreters, trust builders, capability architects, and ethical governors who align algorithmic efficiency with human judgment, employee agency, and organizational responsibility.

Keywords: autonomous organizations; artificial intelligence; AI-based work systems; algorithmic management; digital leadership; human–AI collaboration; qualitative research; managerial roles

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“ HOW TO CITE

Niazi, F. (2025). Leadership in Autonomous Organizations: Exploring New Managerial Roles in AI-Based Work Systems. *Management Systems Evolution and Leadership Studies*, 2(6), 33–42.

1. Introduction

Artificial intelligence has become one of the most significant forces reshaping contemporary organizations, not only because it automates tasks but because it changes how work is coordinated, evaluated, and governed. In traditional organizations, leadership has usually been understood as a human-centered process through which managers influence employees, allocate resources, interpret uncertainty, make decisions, and maintain organizational direction. In autonomous organizations, however, many of these functions are increasingly mediated by AI-based work systems. These systems can recommend decisions, assign tasks, predict demand, monitor employee performance, detect operational anomalies, automate administrative processes, and support strategic planning. As a result, leadership is no longer exercised only through direct interpersonal authority but



through hybrid arrangements in which human managers, data infrastructures, algorithmic systems, and digital platforms jointly shape organizational action.

The term “autonomous organization” does not necessarily refer to an organization without human managers. Rather, it refers to an organizational form in which AI-based systems perform or support managerial functions with varying degrees of independence. These systems may automate workflow scheduling, personalize employee dashboards, recommend hiring or promotion decisions, optimize resource allocation, generate performance analytics, support customer-service decisions, or coordinate cross-functional projects. Prior research on algorithmic management has shown that algorithms can perform functions historically associated with managers, including monitoring, goal setting, performance management, scheduling, compensation, and even termination-related recommendations (Parent-Rochelleau & Parker, 2022). This shift indicates that the central question is not whether AI replaces managers, but how managerial authority, responsibility, and judgment are redistributed when autonomous systems become embedded in work processes.

The emergence of AI-based work systems is closely connected to broader debates on automation and augmentation. Earlier discussions of workplace automation often emphasized substitution: machines replace human labor when tasks are routine, codifiable, and predictable. More recent scholarship, however, highlights the complementarity between human and artificial intelligence. Jarrahi (2018) argues that AI and humans contribute different strengths to organizational decision making: AI is strong in computational processing, pattern recognition, and prediction, whereas humans remain essential in ambiguity, contextual judgment, ethical reasoning, and sensemaking. This complementarity is especially important in managerial work because management rarely involves purely technical decisions. Strategic, operational, and people-related decisions are embedded in organizational culture, power relations, emotions, values, and uncertainty.

The automation–augmentation paradox further complicates the leadership challenge. Raisch and Krakowski (2021) argue that automation and augmentation cannot be separated cleanly in management contexts because AI systems may simultaneously enhance human decision making and reduce human involvement in action. For example, a predictive analytics system may initially support managers by offering recommendations, but over time managers may rely on the system so heavily that their own interpretive and critical capacities weaken. Conversely, excessive human control may prevent organizations from benefiting from AI speed and scalability. Leadership in autonomous organizations therefore requires balancing automation and augmentation rather than choosing one over the other. Managers must decide when to trust AI outputs, when to question them, when to override them, and when to redesign the system itself.

This transformation also affects the foundations of organizational control. Algorithmic management research demonstrates that AI-based systems can reshape how organizations direct, evaluate, reward, discipline, and replace workers. Kellogg, Valentine, and Christin (2020) conceptualize algorithms at work as a new contested terrain of control, emphasizing that algorithmic systems can make control more immediate, opaque, interactive, and difficult to contest. Lee et al. (2015), in their study of data-driven management in ride-sharing platforms, showed how workers experience algorithmic assignment, evaluation, and coordination as forms of management even when no human supervisor is physically present. These studies are important because they reveal that AI does not merely support existing management; it may become a managerial actor embedded in the technological architecture of work.

At the same time, AI-based work systems are not neutral tools. They are designed, trained, implemented, interpreted, and governed within organizational contexts. Faraj, Pachidi, and Sayegh (2018) describe learning algorithms as systems that introduce new forms of black-boxed performance, comprehensive digitization, anticipatory quantification, and hidden politics into organizing. These features create new leadership problems. When managers cannot fully explain how an AI system produces a recommendation, they face the challenge of maintaining accountability without complete technical transparency. When AI systems quantify employee behavior, managers must decide how to prevent data from becoming a narrow substitute for human understanding. When algorithms anticipate future behavior, leaders must prevent prediction from turning into deterministic judgment.

The rise of AI also transforms managerial roles within human–AI teams. Siemon (2022) found that AI-based teammates may occupy roles such as coordinator, creator, perfectionist, and doer in collaborative settings. This suggests that AI systems are increasingly designed not only as tools but as quasi-team members with specialized functions. In such contexts, leaders must manage human–AI collaboration as a socio-technical arrangement. They must clarify which tasks belong to humans, which tasks belong to AI, and which tasks require joint decision making. They must also manage role ambiguity, employee anxiety, accountability gaps, and trust calibration. Effective leadership therefore depends on designing collaboration rather than simply adopting technology.

Despite the rapid expansion of AI in organizations, much of the leadership literature still relies on assumptions developed for human-centered managerial systems. Traditional leadership theories emphasize vision, motivation, communication, influence, empowerment, ethical conduct, and change management. These dimensions remain important, but they are insufficient for understanding organizations in which algorithmic systems participate in managerial functions. For example, a leader in an AI-based work system may not personally assign tasks; instead, the leader may supervise the logic by which tasks are assigned. The leader may not directly observe employee performance; instead, the leader may interpret AI-generated performance dashboards. The leader may not make every operational decision; instead, the leader may determine thresholds for human review, escalation, and override. Thus, leadership becomes less about direct command and more about configuring, interpreting, legitimizing, and governing autonomous work systems.

This shift is especially relevant in knowledge-intensive, digitally transforming, and data-driven organizations. AI-based systems are increasingly integrated into project management, customer relationship management, human resource analytics, supply chain coordination, financial forecasting, marketing personalization, and risk assessment. In each of these domains, the managerial role changes from information gatekeeping to interpretive judgment. Since AI systems can process large volumes of data faster than human managers, the distinctive value of leadership becomes the ability to connect AI outputs to organizational purpose, employee experience, ethical standards, and strategic priorities. Managers become translators between algorithmic outputs and human action.

The Iranian organizational context provides a meaningful setting for exploring this issue. Tehran is the country's major economic, technological, administrative, and service-sector hub. Organizations in Tehran increasingly adopt digital platforms, business intelligence systems, automation tools, AI-enabled customer analytics, HR dashboards, and decision-support systems. However, AI adoption often occurs within complex institutional conditions, including regulatory ambiguity, uneven digital maturity, skill gaps, data-quality problems, hierarchical management traditions, and cultural expectations regarding authority and accountability. These

contextual characteristics make Tehran an important site for studying how managers experience the transition toward AI-based work systems.

The present study addresses the following research question: How are managerial roles reconstructed in autonomous organizations that use AI-based work systems? This question is important for three reasons. First, it moves beyond the technical question of AI implementation and examines the organizational meaning of AI-mediated leadership. Second, it contributes to leadership studies by identifying new managerial roles that emerge when AI participates in coordination, control, and decision making. Third, it offers practical insights for organizations attempting to integrate AI without weakening human judgment, employee trust, and ethical accountability.

Accordingly, this qualitative study explores the lived managerial experiences of leaders, supervisors, HR managers, operations managers, AI project leaders, and data-oriented decision makers in Tehran-based organizations. By using semi-structured interviews and thematic analysis, the study identifies the core categories through which leadership is redefined in AI-based work systems. The aim of this study is to develop a qualitative understanding of the new managerial roles required for leading autonomous organizations in which AI-based work systems reshape decision making, coordination, employee supervision, and organizational accountability

2. Methods and Materials

This study used a qualitative interpretive research design to explore how managerial roles are reconstructed in autonomous organizations using AI-based work systems. A qualitative approach was appropriate because the study focused on participants' experiences, interpretations, and meaning-making processes rather than statistical measurement. The interpretive orientation allowed the researcher to examine how managers understood AI-mediated coordination, algorithmic decision support, digital monitoring, role ambiguity, accountability, and trust in their daily organizational practices. Qualitative inquiry is particularly suitable for investigating emerging organizational phenomena where concepts are still developing and where participants' subjective accounts provide rich insight into process, context, and meaning (Creswell & Poth, 2018).

The participants consisted of 24 professionals working in Tehran-based organizations that had implemented AI-based or algorithmically supported work systems. Participants were selected through purposive sampling because the study required individuals with direct experience of AI-mediated managerial or operational processes. Snowball sampling was also used after initial interviews, as participants introduced other managers or specialists who had relevant experience. Inclusion criteria were: at least three years of professional experience, at least six months of direct engagement with AI-based decision-support or workflow systems, employment in a Tehran-based organization, and willingness to participate in an audio-recorded interview. Participants included senior managers, middle managers, HR managers, operations supervisors, AI project leaders, business intelligence specialists, and data analytics managers. The final sample size was determined by theoretical saturation. Saturation was reached after 21 interviews, when no substantially new categories emerged, and three additional interviews were conducted to confirm the stability of the thematic structure. This approach is consistent with qualitative saturation logic, in which data collection continues until additional interviews no longer produce meaningfully new themes (Guest et al., 2006; Hennink & Kaiser, 2022).

Data were collected through semi-structured interviews. The interview protocol included open-ended questions about participants' experiences with AI-based work systems, changes in leadership responsibilities, decision-making practices, employee monitoring, trust in AI recommendations, ethical concerns, skill requirements, and the future role of managers in autonomous organizations. Sample questions included: "How has AI changed the way managerial decisions are made in your organization?", "Which leadership tasks are now performed or supported by AI systems?", "How do managers respond when AI recommendations conflict with human judgment?", and "What new capabilities do leaders need in AI-based work systems?" Interviews lasted between 45 and 75 minutes. All interviews were conducted in a private setting or through secure online communication, depending on participant availability. With participants' consent, interviews were audio-recorded and transcribed verbatim. Participants were assigned codes from P01 to P24 to protect confidentiality.

Data were analyzed using thematic analysis based on the six-phase procedure proposed by Braun and Clarke (2006): familiarization with data, generation of initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the final report. NVivo software was used to organize transcripts, classify initial codes, retrieve interview segments, compare categories, and refine the final thematic structure. The analysis began with repeated reading of transcripts to develop familiarity with the data. Initial codes were then generated inductively from meaningful units related to leadership, AI-mediated work, managerial change, human judgment, trust, accountability, and employee experience. Similar codes were grouped into subcategories, and subcategories were compared across interviews to identify broader themes. The final themes were reviewed against the original transcripts to ensure that they accurately represented participants' accounts.

To ensure trustworthiness, several strategies were applied. Credibility was strengthened through member checking, in which selected participants reviewed summaries of the interpreted findings. Peer debriefing was used to examine coding decisions and reduce individual researcher bias. Dependability was supported by maintaining an audit trail, including interview guides, coding notes, memos, theme development records, and analytic decisions. Confirmability was enhanced through reflexive memo writing and systematic comparison between findings and direct interview excerpts. Transferability was supported by providing contextual detail about participants, organizational settings, and AI-based work systems. These strategies are consistent with Lincoln and Guba's criteria of credibility, transferability, dependability, and confirmability for qualitative rigor (Lincoln & Guba, 1985; Nowell et al., 2017).

3. Findings and Results

The demographic characteristics of the participants indicated diversity in gender, age, education, managerial level, and organizational sector. Of the 24 participants, 15 were male and 9 were female. In terms of age, 5 participants were between 30 and 35 years old, 8 were between 36 and 40, 7 were between 41 and 45, and 4 were older than 45. Regarding education, 6 participants held bachelor's degrees, 14 held master's degrees, and 4 held doctoral degrees. In terms of professional role, 5 participants were senior managers, 6 were middle managers, 4 were HR managers, 4 were operations supervisors, 3 were AI or digital transformation project leaders, and 2 were business intelligence or data analytics managers. Participants represented technology, banking and financial services, telecommunications, online retail, logistics, healthcare services, and consulting organizations in Tehran.

Their professional experience ranged from 6 to 22 years, and their experience with AI-based work systems ranged from 8 months to 6 years.

The first main category was **algorithmic orchestration of work**. Participants explained that AI-based systems had become central to task allocation, workflow sequencing, scheduling, demand forecasting, and operational prioritization. Managers no longer controlled all routine coordination activities manually; instead, they increasingly supervised algorithmic systems that allocated tasks, ranked priorities, and generated workflow recommendations. One operations supervisor stated, “Before the AI dashboard, I decided the daily workload based on my own experience. Now the system proposes the sequence, and my job is to check whether the sequence makes sense in real conditions” (P07). This category shows that leadership was shifting from direct task assignment to orchestration of algorithmic coordination. Managers described their role as “calibrating the system,” “checking exceptions,” and “making sure the algorithm understands organizational reality.” While participants appreciated the efficiency of automated coordination, they also emphasized that AI systems sometimes ignored informal knowledge, employee fatigue, customer sensitivity, or unexpected contextual constraints. Therefore, managerial leadership remained necessary to interpret and adjust algorithmic workflows.

The second main category was **managerial sensemaking in AI-mediated decisions**. Participants reported that AI systems produced recommendations, risk scores, customer predictions, employee performance indicators, and operational alerts, but these outputs did not automatically translate into decisions. Managers had to interpret what the recommendation meant, assess its relevance, and decide whether to accept, modify, or reject it. One senior manager explained, “The AI gives us a probability, not wisdom. It tells us what may happen, but it does not understand why it matters for this customer, this employee, or this situation” (P03). Participants repeatedly distinguished between “data-based recommendation” and “managerial judgment.” AI was valued for speed and pattern recognition, but managers believed that decision legitimacy required contextual interpretation. This category indicates that leaders in autonomous organizations become sensemakers who translate algorithmic outputs into responsible organizational action. They must understand enough about AI logic to ask critical questions while also understanding enough about people and strategy to prevent mechanical decision making.

The third main category was **human-centered trust and transparency building**. Participants emphasized that employees did not automatically trust AI-based work systems, especially when these systems affected performance evaluation, scheduling, workload, promotion, or rewards. Managers had to explain how the system was used, clarify that AI outputs were not the only basis for decisions, and create channels for questioning or appealing algorithmic judgments. An HR manager noted, “Employees were afraid that a number on the dashboard would become their identity. We had to explain that the AI score is only one input, not the whole story” (P11). Trust was therefore not understood as blind acceptance of technology but as confidence that AI would be used fairly, transparently, and with human oversight. Participants also noted that lack of transparency created resistance. When employees could not understand why a system assigned certain tasks or produced certain evaluations, they interpreted the system as unfair or punitive. Leaders had to act as trust builders who mediated between technical systems and employee perceptions.

The fourth main category was **capability development for human–AI collaboration**. Participants described new competency requirements for both managers and employees. Leaders needed AI literacy, data interpretation skills, ethical awareness, critical thinking, change management capability, and the ability to redesign work around human–AI collaboration. One AI project leader stated, “The biggest problem is not the algorithm; it is that

managers either trust it too much or reject it completely. We need leaders who know how to work with AI without becoming dependent on it” (P18). Participants believed that AI-based work systems required a new leadership profile: technically informed but not purely technical, strategically oriented but operationally engaged, and able to combine analytical reasoning with human sensitivity. Several participants also noted that employees needed training to understand AI recommendations, use dashboards, interpret alerts, and communicate with managers about system limitations. This category shows that leadership in autonomous organizations includes building organizational capability for productive human–AI interaction.

The fifth main category was **ethical governance of autonomous systems**. Participants were concerned about accountability, bias, privacy, over-monitoring, and the possibility that AI systems could intensify control over employees. Managers reported that AI could improve fairness by standardizing decisions, but it could also reproduce bias if data were incomplete, historical patterns were discriminatory, or system logic was not reviewed. One participant stated, “If the AI makes a wrong recommendation, employees do not blame the machine; they blame management. So responsibility cannot be outsourced to the system” (P05). Participants believed that leaders must define boundaries for AI autonomy, determine which decisions require human review, protect employees from excessive surveillance, and ensure that AI-based decisions remain aligned with organizational values. This category indicates that the managerial role is expanding toward ethical governance. Leaders must not only use AI but also regulate its organizational consequences.

4. Discussion and Conclusion

The findings of this study show that leadership in autonomous organizations is not disappearing; rather, it is being reconstructed around new forms of socio-technical responsibility. The first major finding, algorithmic orchestration of work, indicates that AI-based systems increasingly perform coordination tasks traditionally handled by human managers. This finding aligns with Parent-Rochelleau and Parker’s (2022) argument that algorithmic management systems can perform core managerial functions such as monitoring, scheduling, goal setting, and performance management. It also supports Lee et al. (2015), who demonstrated that algorithmic systems can organize work practices even in the absence of direct human supervision. In the present study, managers did not describe themselves as replaced by AI; instead, they described their role as supervising the conditions under which AI coordinates work. This suggests that the managerial role is moving upward from routine allocation to meta-coordination. Leaders become responsible for evaluating whether automated workflow decisions are contextually appropriate, operationally realistic, and socially acceptable. This finding contributes to leadership studies by showing that coordination is no longer only interpersonal or bureaucratic; it is increasingly algorithmic and requires managerial oversight at the level of system design, calibration, and exception handling.

The second finding, managerial sensemaking in AI-mediated decisions, shows that AI outputs require interpretation before they can become legitimate organizational decisions. This result is consistent with Jarrahi’s (2018) theory of human–AI symbiosis, which emphasizes that AI is powerful in data processing and prediction but that humans remain essential in ambiguity, contextual judgment, and equivocal decision environments. The participants’ statements also align with Raisch and Krakowski’s (2021) automation–augmentation paradox. AI systems can augment managerial decision making by providing predictive insights, but they may also automate judgment if managers accept recommendations uncritically. The present findings suggest that effective leadership

requires active sensemaking: managers must ask what an AI recommendation means, what assumptions are embedded in it, what contextual variables it may ignore, and what consequences may follow if it is implemented. This supports the view that leadership in AI-based work systems is increasingly interpretive. Managers are not simply decision makers; they are translators between machine-generated probabilities and human-centered organizational realities.

The third finding, human-centered trust and transparency building, highlights the relational dimension of leadership in autonomous organizations. Participants emphasized that employees often experience AI systems through their consequences: workload distribution, monitoring, evaluation, ranking, and reward decisions. This finding is strongly aligned with Kellogg et al. (2020), who argue that algorithms create new forms of workplace control through mechanisms that may be opaque and difficult for workers to contest. It also supports Faraj et al. (2018), who identify black-boxed performance and hidden politics as important features of learning algorithms in organizations. In the present study, trust did not emerge from the technical sophistication of AI; it emerged from managerial communication, procedural fairness, and the availability of human review. Leaders were expected to explain AI use, protect employees from reductionist measurement, and ensure that data did not become a substitute for dialogue. This finding adds to the leadership literature by demonstrating that trust in AI is partly trust in management. Employees may not understand the algorithm, but they evaluate whether leaders use the algorithm responsibly.

The fourth finding, capability development for human–AI collaboration, suggests that autonomous organizations require a new leadership capability architecture. Participants described AI literacy, data interpretation, critical judgment, ethical awareness, and change leadership as essential capabilities. This finding aligns with Wilson and Daugherty's (2018) concept of collaborative intelligence, which emphasizes that organizations gain value from AI when humans and machines complement each other. It also aligns with Siemon's (2022) finding that AI-based teammates can occupy different roles in human–AI collaboration and that role clarity is necessary for effective hybrid teamwork. In this study, managers emphasized that employees and leaders must learn how to work with AI rather than merely receive AI outputs. This means that leadership development must include the ability to design human–AI workflows, identify appropriate levels of AI autonomy, and prevent both overreliance and resistance. The finding contributes to management research by framing leadership capability not only as individual competence but as the organizational capacity to combine human and artificial intelligence.

The fifth finding, ethical governance of autonomous systems, demonstrates that AI-based leadership is inseparable from accountability. Participants were concerned about bias, privacy, excessive monitoring, and responsibility for AI-generated errors. This finding corresponds with Berente et al. (2021), who argue that managing AI introduces new organizational challenges because AI systems are autonomous, inscrutable, and continuously evolving. It also supports Asatiani et al. (2021), who emphasize the need for socio-technical approaches to deploying inscrutable AI systems in organizations. The participants' view that responsibility cannot be outsourced to AI is particularly important. Even when AI systems generate recommendations, human leaders remain accountable for how those recommendations are used. Therefore, leadership in autonomous organizations includes establishing ethical boundaries, review mechanisms, escalation procedures, and accountability structures. This finding expands the concept of managerial responsibility from supervising people to governing intelligent systems that influence people.

Overall, the findings suggest that AI-based work systems transform leadership from a primarily supervisory function into a multi-dimensional governance function. The leader of an autonomous organization must operate as an orchestrator, sensemaker, trust builder, capability architect, and ethical governor. This model differs from traditional leadership models that focus mainly on vision, motivation, and interpersonal influence. Those elements remain relevant, but they must be integrated with AI literacy, algorithmic accountability, system-level thinking, and socio-technical design. In autonomous organizations, leadership is distributed across humans and systems, but accountability remains human. This creates a new managerial paradox: leaders control less of the routine work directly but become more responsible for the architecture through which work is controlled.

The study also suggests that autonomous organizations require a careful balance between efficiency and human agency. AI-based systems can increase speed, standardization, and predictive accuracy, but they can also reduce employee voice, intensify surveillance, and narrow managerial attention to measurable indicators. The participants' concerns show that leadership must prevent algorithmic rationality from dominating organizational life. AI should support decision making without eliminating deliberation; it should improve coordination without erasing informal knowledge; it should enhance performance without reducing employees to data points. This balance is especially important in organizations where technological adoption is faster than cultural adaptation. Managers must therefore lead not only technical implementation but also meaning reconstruction, explaining why AI is used, how it affects work, and where human judgment remains decisive.

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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