Ethical Leadership in Algorithmic Management Systems: A Qualitative Exploration of Managerial Accountability

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Abstract

This study aimed to explore how managers understand, experience, and enact ethical leadership and accountability in organizations that use algorithmic management systems for monitoring, evaluation, coordination, and decision support. This qualitative study was conducted using an interpretive thematic design. Data were collected through semi-structured interviews with 24 managers, supervisors, human resource professionals, operations managers, and digital transformation specialists working in Tehran-based organizations that had implemented algorithmic tools in employee evaluation, scheduling, customer-service monitoring, recruitment screening, productivity analytics, or performance dashboards. Participants were selected through purposive sampling, and recruitment continued until theoretical saturation was reached. Interviews lasted between 45 and 75 minutes and focused on managers' experiences of algorithmic decision-making, ethical responsibility, transparency, fairness, employee voice, and human oversight. All interviews were transcribed verbatim and analyzed using thematic analysis with the support of NVivo software. Trustworthiness was enhanced through member checking, peer debriefing, audit trail documentation, and repeated comparison of codes and themes. Analysis generated five main categories: ethical sensemaking under algorithmic opacity, fragmented managerial accountability, fairness and dignity in data-driven evaluation, human oversight and employee contestability, and institutionalizing ethical governance. Participants described algorithmic management as increasing efficiency and consistency, but also as creating moral ambiguity when decisions were technically produced yet managerially enforced. Managers reported tension between trusting automated outputs and protecting employees from biased, decontextualized, or opaque evaluations. Ethical leadership emerged as a relational and procedural practice requiring explanation, listening, intervention, and willingness to accept responsibility rather than shifting blame to technology. The study shows that ethical leadership in algorithmic management depends on managers' capacity to translate abstract AI ethics principles into everyday accountability practices. Algorithmic accountability is not achieved by technical design alone; it requires accountable leaders, transparent procedures, contestable decisions, and organizational governance mechanisms that preserve human judgment, fairness, and employee dignity.

Keywords: ethical leadership; algorithmic management; managerial accountability; artificial intelligence; qualitative research; organizational ethics; human oversight; Tehran

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1. Introduction

Algorithmic management has become one of the most consequential transformations in contemporary organizational life. In contrast to conventional management systems in which supervisors directly observe, coordinate, evaluate, and discipline employees, algorithmic management refers to the use of data-driven and computational systems to allocate tasks, monitor performance, rank employees, predict behavior, recommend decisions, and standardize managerial control. These systems may appear in platform work, call centers, logistics, financial services, recruitment, customer relationship management, digital sales, and knowledge-based organizations. Their appeal is clear: they promise speed, consistency, scalability, real-time visibility, and reduction of subjective managerial bias. Yet the same systems also create new ethical tensions because decisions affecting employees may be generated by opaque models, incomplete data, automated rules, or predictive metrics that are difficult for both workers and managers to understand. Kellogg, Valentine, and Christin (2020) argue that algorithms reshape the contested terrain of organizational control by changing how work is directed, evaluated, and resisted, while Lee et al. (2015) show that workers often experience algorithmic systems as managerial actors that assign, evaluate, and constrain work practices.

The rise of algorithmic management requires renewed attention to ethical leadership. Ethical leadership has traditionally been defined as the demonstration of normatively appropriate conduct through personal actions and interpersonal relationships, as well as the promotion of such conduct through communication, reinforcement, and decision-making (Brown et al., 2005). This definition is important because it locates ethical leadership not only in personal integrity but also in visible managerial practices. Treviño et al. (2003) similarly emphasize that ethical leadership includes both the “moral person” dimension, such as honesty and fairness, and the “moral manager” dimension, such as setting standards, communicating expectations, rewarding ethical behavior, and holding people accountable. In algorithmic environments, however, the visibility of moral agency becomes more complicated. Managers may not design the algorithm, may not fully understand the model, and may be required to enforce outputs produced by systems developed by vendors, data teams, or senior executives. This creates a practical and moral question: when a managerial decision is mediated by an algorithm, who is ethically accountable for its consequences?

This question is especially urgent because algorithmic management often produces a redistribution of authority without a corresponding redistribution of accountability. Algorithms can classify employees as high or low performers, flag anomalies, predict turnover, prioritize applicants, recommend disciplinary action, or shape incentive structures. However, when employees challenge these outputs, responsibility may become dispersed among line managers, HR departments, data analysts, software providers, and executive decision-makers. Bovens (2007) conceptualizes accountability as a relationship in which an actor is obliged to explain and justify conduct to a forum that can question, evaluate, and potentially sanction that conduct. In algorithmic management systems, this accountability relationship may be weakened when no identifiable actor can adequately explain how a decision was produced or why a particular employee was affected.

The ethical challenge is not simply that algorithms are sometimes inaccurate or biased. Rather, the deeper problem is that algorithmic systems can obscure the social, political, and organizational values embedded in managerial decisions. Faraj et al. (2018) describe learning algorithms as consequential for work and organizing because they involve black-boxed performance, comprehensive digitization, anticipatory quantification, and hidden politics. These features are highly relevant to managerial accountability. Black-boxed performance limits interpretability; comprehensive digitization converts work into data traces; anticipatory quantification turns prediction into intervention; and hidden politics makes value choices appear technically neutral. Therefore, ethical leadership in algorithmic systems requires more than passive compliance with digital tools. It requires managers to recognize that algorithmic outputs are not morally neutral facts but organizational judgments mediated through data, design assumptions, and institutional priorities.

Previous studies on platform labor illustrate these concerns. Rosenblat and Stark (2016), in their study of Uber drivers, show how algorithmic systems can exercise indirect control while preserving a discourse of flexibility and independence. Drivers were managed through ratings, information asymmetries, dynamic pricing, and automated coordination, even though formal managerial authority was often displaced into the platform architecture. Similarly, Lee et al. (2015) found that algorithmic allocation and evaluation shaped workers' perceptions of fairness and autonomy. These studies are significant because they show that algorithmic management is not only a technological system but also a power relation. However, much of the existing literature has focused on workers' experiences, platform labor, and system-level governance. Less attention has been paid to how organizational managers themselves interpret ethical responsibility when they must lead through systems they may not fully control.

AI ethics literature provides useful principles for understanding these problems but does not fully resolve the managerial question. Jobin et al. (2019) identify recurring principles in AI ethics guidelines, including transparency, justice and fairness, non-maleficence, responsibility, and privacy. Floridi et al. (2018) similarly propose principles such as beneficence, non-maleficence, autonomy, justice, and explicability as foundations for responsible AI. Yet Mittelstadt (2019) warns that principles alone cannot guarantee ethical AI because high-level consensus often fails to translate into robust institutional duties, professional norms, implementation methods, or accountability mechanisms. This criticism is particularly relevant for algorithmic management because managers may be familiar with abstract values such as fairness and transparency but lack procedures for applying these values when an employee is harmed by a dashboard score, automated ranking, or predictive recommendation.

Algorithmic accountability literature has therefore emphasized the need for auditability, documentation, explainability, and institutional review. Kroll et al. (2017) argue that accountable algorithms require mechanisms that allow decisions to be examined, verified, and governed. Raji et al. (2020) further propose internal algorithmic auditing as an end-to-end framework for identifying and addressing risks throughout the development and deployment lifecycle. Diakopoulos (2015) also highlights the importance of investigating algorithmic power structures, mistakes, biases, and impacts. These contributions are essential, but they often emphasize technical, legal, or institutional accountability. In organizational practice, however, employees frequently encounter accountability through managers. When workers ask why they received a low score, why their schedule changed, why they were screened out, or why their performance was flagged, they usually do not interact with the algorithm designer; they interact with a supervisor, HR manager, or operations manager. Therefore, managerial accountability remains a critical but underexplored layer of algorithmic governance.

The integration of artificial intelligence into human resource management intensifies these concerns. Tambe et al. (2019) note that AI applications in HR create opportunities for improved prediction and efficiency but also generate challenges related to data quality, fairness, explainability, and employee trust. Algorithmic management in HR and operations can reduce inconsistency in managerial judgment, but it may also institutionalize bias when historical data reflect unequal opportunities, subjective evaluations, or organizational inequities. Barocas and Selbst (2016) show that data mining can produce disparate impacts even when discrimination is not intentional, because biased data, proxy variables, and uneven data representation can reproduce social inequality. This means that ethical leadership must involve active scrutiny of the data and assumptions behind algorithmic recommendations rather than simple reliance on the appearance of objectivity.

Ethical leadership in algorithmic management also requires attention to employee dignity. When work is continuously tracked, quantified, and ranked, employees may feel reduced to metrics rather than recognized as moral agents with contextual circumstances, tacit contributions, and legitimate expectations of voice. Algorithmic tools may overlook invisible labor, emotional labor, teamwork, mentorship, creativity, and ethical restraint because these contributions are difficult to quantify. If managers rely exclusively on measurable indicators, they may unintentionally reward narrow productivity while neglecting fairness, learning, collaboration, and well-being. Shneiderman (2020) argues for human-centered AI that supports reliability, safety, and trustworthiness, while Dignum (2019) emphasizes that responsible AI must consider responsibility across design, deployment, and use. These perspectives imply that managers should not treat algorithmic systems as substitutes for ethical judgment but as tools requiring interpretation, contextualization, and responsible intervention.

The present study is situated in Tehran-based organizations that are increasingly adopting digital dashboards, AI-assisted evaluation tools, recruitment screening systems, customer-service analytics, productivity monitoring, and workflow optimization software. Although the global literature on algorithmic management has expanded rapidly, empirical research in non-Western organizational contexts remains comparatively limited. Local managerial interpretations matter because accountability practices are shaped by organizational culture, regulatory awareness, technological maturity, employee relations, and managerial authority structures. In contexts where algorithmic tools are imported, adapted, or implemented without mature governance frameworks, managers may face significant uncertainty regarding transparency, appeal rights, data quality, and ethical responsibility. Therefore, qualitative inquiry is especially appropriate because it can capture the meanings, tensions, and moral reasoning processes that managers experience in practice.

This study contributes to the literature in three ways. First, it links ethical leadership theory with algorithmic management, showing how moral person and moral manager dimensions are reconfigured when managerial decisions are mediated by opaque digital systems. Second, it extends algorithmic accountability research by focusing on the lived experiences of managers who must interpret, justify, and sometimes challenge algorithmic outputs. Third, it provides qualitative evidence from Tehran-based organizations, offering context-sensitive insight into how ethical leadership is enacted in emerging algorithmic management environments. The aim of this study was to explore how managers in Tehran-based organizations understand and enact ethical leadership and managerial accountability in algorithmic management systems.

2. Methods and Materials

This study used a qualitative research design based on interpretive thematic analysis. The qualitative approach was selected because the purpose of the study was not to measure the statistical effect of algorithmic management but to explore managers' lived experiences, ethical interpretations, and accountability practices in organizations where managerial decisions were mediated by algorithmic systems. The study population consisted of managers and organizational professionals working in Tehran-based organizations that had implemented algorithmic or data-driven management tools in at least one managerial function, including employee performance evaluation, recruitment screening, work scheduling, productivity monitoring, customer-service analytics, workflow allocation, or managerial dashboards.

Participants were selected through purposive sampling. Inclusion criteria were: having at least three years of managerial or professional experience, direct involvement with algorithmic or data-driven management systems, employment in a Tehran-based organization, and willingness to participate in an audio-recorded interview. Participants who had only general awareness of digital systems but no direct experience with algorithmic management tools were excluded. The final sample included 24 participants. Theoretical saturation was reached after the twenty-first interview, when no substantially new codes or categories emerged; three additional interviews were conducted to confirm saturation and refine category boundaries. Participants included senior managers, middle managers, HR managers, operations managers, digital transformation specialists, and data governance professionals from technology firms, financial services, online retail, telecommunications, logistics, and service organizations.

Data were collected through semi-structured interviews. The semi-structured format allowed the researcher to maintain consistency across interviews while also giving participants space to describe specific experiences, ethical dilemmas, and organizational practices in depth. The interview guide included open-ended questions about participants' experiences with algorithmic management systems, perceived benefits and risks, ethical concerns, accountability practices, transparency, employee reactions, human oversight, and managerial decision-making. Sample interview questions included: "How are algorithmic tools used in managerial decisions in your organization?", "Can you describe a situation in which an algorithmic recommendation created an ethical concern?", "Who is considered responsible when an algorithmic decision harms or disadvantages an employee?", "How do employees challenge or appeal algorithmic decisions?", and "What does ethical leadership mean when management decisions are influenced by algorithms?"

Interviews were conducted individually in a private setting or through secure online platforms according to participants' preference. Each interview lasted between 45 and 75 minutes. Before the interview, participants were informed about the purpose of the study, voluntary participation, confidentiality, and their right to withdraw at any time. Written informed consent was obtained. With permission, interviews were audio-recorded and then transcribed verbatim. All identifying information, including names of individuals and organizations, was removed during transcription. Participants were assigned codes from P1 to P24 to preserve confidentiality. Field notes were written after each interview to document contextual impressions, emerging analytic ideas, and possible follow-up issues.

Data were analyzed using thematic analysis with the support of NVivo software. The analysis followed a systematic process of familiarization, initial coding, code comparison, category development, theme refinement, and final interpretation. First, all transcripts were read several times to gain a holistic understanding of the data. Second, meaningful units related to ethical leadership, algorithmic opacity, fairness, responsibility, employee voice, human oversight, and organizational governance were coded line by line. Third, similar codes were grouped into preliminary categories. Fourth, categories were reviewed against the original transcripts to ensure that they accurately represented participants' accounts. Fifth, the final categories were named and defined based on their conceptual relevance to the research aim.

NVivo software was used to organize transcripts, store codes, compare coding patterns, retrieve quotations, and manage analytic memos. The use of software did not replace researcher interpretation but supported systematic data management and transparency. To enhance trustworthiness, several strategies were used. Credibility was strengthened through member checking with selected participants and peer review of emerging themes. Dependability was supported by maintaining an audit trail of coding decisions, category revisions, and analytic memos. Confirmability was enhanced through reflexive notes documenting the researcher's assumptions and interpretations. Transferability was addressed by providing detailed descriptions of the participants, organizational context, and analytic categories.

3. Findings

The demographic characteristics of the participants showed diversity in gender, age, managerial level, sector, and professional background. Of the 24 participants, 14 were men and 10 were women. Participants' ages ranged from 30 to 52 years, with 6 participants aged 30–35, 9 aged 36–42, 6 aged 43–48, and 3 aged 49–52. In terms of organizational role, 8 participants were senior managers, 7 were middle managers, 4 were HR managers, 3 were operations managers, and 2 were digital transformation or data governance specialists. Regarding work experience, 5 participants had 3–7 years of managerial experience, 10 had 8–12 years, and 9 had more than 12 years. Participants worked in technology companies (n = 6), financial services (n = 5), online retail and platform-based services (n = 4), telecommunications (n = 3), logistics and delivery services (n = 3), and customer-service-oriented organizations (n = 3). All participants reported direct experience with at least one algorithmic management tool, including performance dashboards, automated productivity scoring, employee ranking systems, recruitment screening tools, customer-service analytics, or work-allocation systems.

The first main category was **ethical sensemaking under algorithmic opacity**. Participants explained that algorithmic management systems often produced outputs that appeared precise but were difficult to interpret ethically. Managers described dashboards, scores, alerts, and rankings as "objective" at first glance, but many became uncertain when employees questioned the logic behind a result. This opacity created ethical discomfort because managers were expected to justify decisions that they did not fully understand. One participant stated, "The system gives a score, but the employee asks me why the score is low. I can explain the policy, but I cannot always explain the algorithm" (P7). Another manager noted, "Sometimes the number looks scientific, but behind it there are assumptions that nobody in the management meeting discusses" (P12). Participants reported that ethical leadership began with acknowledging uncertainty rather than hiding behind technical language. Managers who acted ethically tried to ask additional questions, consult technical teams, and avoid presenting algorithmic outputs as unquestionable truth. In this category, ethical leadership was experienced as the ability to interpret algorithmic outputs critically and communicate their limitations honestly.

The second main category was **fragmented managerial accountability**. Participants repeatedly described accountability as dispersed across multiple actors, including senior executives, software vendors, HR departments, data teams, and line managers. This fragmentation made it difficult to determine who should answer when employees were harmed by algorithmic decisions. A middle manager explained, “When the system works well, everyone says it is our digital transformation success. When it makes a mistake, everyone says another department is responsible” (P4). Another participant stated, “The employee sees me as the decision-maker, but the criteria are designed somewhere else. Still, I am the person who must deliver the consequences” (P16). Managers experienced this as a moral burden because they were often accountable in interpersonal terms but lacked formal authority to change the system. Ethical leadership in this category involved refusing to transfer blame entirely to the technology. Participants considered accountable managers to be those who accepted responsibility for explaining decisions, escalating concerns, documenting errors, and advocating for corrective action even when the system was designed by others.

The third main category was **fairness and dignity in data-driven evaluation**. Participants acknowledged that algorithmic systems could reduce favoritism and increase consistency, especially in large organizations where direct supervision was uneven. However, they also emphasized that data-driven evaluation could ignore contextual factors such as task difficulty, emotional labor, team support, learning curves, customer behavior, personal crises, or informal contributions. One HR manager stated, “The algorithm sees response time, but it does not see that one employee is solving the most difficult customer problems” (P9). Another participant observed, “If we only reward what is measurable, employees stop doing what is important but invisible” (P18). Managers described ethical leadership as protecting employees from being reduced to numerical indicators. This included reviewing outlier cases, combining quantitative scores with human judgment, discussing evaluation criteria with employees, and recognizing non-quantifiable forms of contribution. Participants believed that fairness required more than equal application of the same metric; it required contextual judgment and respect for employee dignity.

The fourth main category was **human oversight and employee contestability**. Participants emphasized that algorithmic decisions became ethically problematic when employees had no meaningful opportunity to question, appeal, or correct them. In several organizations, managers reported that employees could complain informally, but no formal procedure existed for reviewing algorithmic outputs. One participant stated, “There is a complaint channel, but it is not designed for algorithmic decisions. Employees complain to HR, HR asks IT, IT says the system is working normally” (P2). Another manager explained, “A fair system must have a door for objection. If there is no door, people feel trapped by the machine” (P21). Participants described human oversight as necessary but insufficient unless managers had real authority to pause, override, or revise algorithmic decisions. Ethical leadership in this category involved creating spaces for voice, treating employee challenges as legitimate, and ensuring that human review was substantive rather than symbolic. Managers believed that contestability increased trust because employees were more likely to accept unfavorable decisions when they could understand and challenge the process.

The fifth main category was **institutionalizing ethical governance**. Participants argued that individual ethical intention was important but not enough. Managers needed organizational structures, policies, documentation, and cross-functional collaboration to govern algorithmic systems responsibly. Several participants reported that their organizations adopted algorithmic tools faster than they developed ethical guidelines for using them. One senior manager stated, “We bought the technology before we defined the responsibility model” (P5). Another participant noted, “Ethics cannot depend only on the personality of one manager. There must be a process, a committee, and clear rules” (P23). Participants recommended regular audits, employee communication, data quality review, bias assessment, documented escalation procedures, and defined accountability roles. In this category, ethical leadership was not limited to interpersonal conduct but extended to institution-building. Managers who showed ethical leadership tried to embed responsibility into routines, governance bodies, and organizational learning systems so that algorithmic management could be continuously evaluated rather than accepted as a one-time technical implementation.

4. Discussion

The present study explored how managers in Tehran-based organizations understand and enact ethical leadership and accountability in algorithmic management systems. The findings revealed five interrelated categories: ethical sensemaking under algorithmic opacity, fragmented managerial accountability, fairness and dignity in data-driven evaluation, human oversight and employee contestability, and institutionalizing ethical governance. Together, these findings show that algorithmic management does not eliminate the need for leadership; rather, it changes the moral conditions under which leadership is practiced. Managers in this study did not describe themselves as fully autonomous decision-makers, yet they also did not experience themselves as morally free from responsibility. They occupied an intermediate position between technical systems and human consequences. This position required them to interpret outputs, explain decisions, respond to employee concerns, and sometimes challenge systems that were presented as objective or efficient.

The category of ethical sensemaking under algorithmic opacity is consistent with research showing that algorithmic systems often appear authoritative while remaining difficult to interpret. Kellogg et al. (2020) argue that algorithmic technologies reshape control because they alter how managerial authority is exercised and contested. Faraj et al. (2018) similarly describe learning algorithms as involving black-boxed performance and hidden politics. The present findings extend this literature by showing that opacity is not only a technical limitation but also a leadership problem. Managers felt ethically exposed when they had to justify outcomes that they could not fully explain. This finding also supports Mittelstadt’s (2019) argument that AI ethics principles are insufficient without implementation mechanisms. Transparency, in practice, was not simply a principle written in a policy document; it was a managerial interaction in which employees asked for reasons and managers had to decide whether to acknowledge uncertainty, investigate the system, or hide behind technical authority.

The finding on fragmented managerial accountability aligns strongly with Bovens' (2007) conceptualization of accountability as a relationship involving explanation, justification, questioning, and consequences. In the organizations studied, algorithmic management often weakened this relationship by separating decision production from decision communication. Data teams, vendors, executives, and managers each controlled part of the process, but no single actor always accepted full responsibility. Similar concerns are found in algorithmic accountability literature, where Kroll et al. (2017) emphasize the need for systems that enable review and verification, and Raji et al. (2020) argue for internal auditing across the AI lifecycle. The present study adds a managerial layer to these debates. Even when technical accountability mechanisms are necessary, employees often experience accountability through their immediate managers. Therefore, ethical leadership requires managers to resist the temptation to use algorithms as moral shields. Participants viewed accountable managers as those who remained answerable to employees even when responsibility was structurally distributed.

The category of fairness and dignity in data-driven evaluation supports previous studies showing that algorithmic management can produce both consistency and injustice. Lee et al. (2015) found that workers' perceptions of algorithmic fairness are shaped by how systems allocate, support, and evaluate work. Rosenblat and Stark (2016) also showed that platform workers may be managed through information asymmetries and indirect forms of control. The present study confirms that managers recognize similar risks in organizational settings beyond platform labor. Participants valued the consistency of data-driven evaluation but warned that metrics may ignore context, invisible work, and qualitative contributions. This finding is also consistent with Barocas and Selbst's (2016) argument that data-driven systems can reproduce inequality through biased data and proxy variables. Ethical leadership therefore requires more than equal application of metrics. It requires contextual fairness, recognition of human dignity, and willingness to examine whether measurable indicators actually represent valuable work.

The finding on human oversight and employee contestability highlights the procedural dimension of ethical leadership. Participants believed that employees should have meaningful opportunities to question algorithmic decisions. This aligns with AI ethics literature emphasizing explainability, accountability, and human-centered design (Dignum, 2019; Floridi et al., 2018; Shneiderman, 2020). However, the findings also show that human oversight can become symbolic if managers lack authority to intervene. Some participants described complaint channels that existed formally but failed practically because HR, IT, and management passed responsibility among one another. This supports critiques of superficial

AI governance, in which organizations adopt ethical language without giving employees enforceable rights or managers actionable procedures. Ethical leadership in algorithmic management must therefore include contestability: employees need not only explanations but also accessible mechanisms for correction, appeal, and review.

The category of institutionalizing ethical governance extends ethical leadership theory by showing that moral conduct must be embedded in organizational systems. Brown et al. (2005) define ethical leadership as both personal conduct and the promotion of ethical conduct through communication, reinforcement, and decision-making. Treviño et al. (2003) similarly emphasize that ethical leaders are moral managers who use organizational systems to guide behavior. The present findings suggest that in algorithmic environments, the moral manager role must expand to include algorithmic governance. Managers must help build policies, accountability matrices, audit routines, data review processes, employee communication procedures, and cross-functional ethics committees. This finding is consistent with Raji et al. (2020), who argue for internal auditing across development and deployment, and with Jobin et al. (2019), who show that responsibility and transparency are central but variably implemented AI ethics principles. In this study, managers understood that individual conscience alone could not compensate for absent governance structures.

Overall, the findings suggest that ethical leadership in algorithmic management is best understood as a sociotechnical practice. It is social because it involves communication, trust, employee voice, fairness, and responsibility. It is technical because it requires attention to data quality, model limitations, system design, and auditability. It is also organizational because ethical outcomes depend on policies, authority structures, escalation channels, and institutional learning. This interpretation supports the view that responsible AI cannot be reduced to either technical optimization or moral intention. Managers must operate at the intersection of both. They must understand enough about algorithmic systems to question them, enough about ethics to identify harm, and enough about organizational power to create procedures that make accountability real.

The study also has implications for the theory of ethical leadership. Traditional ethical leadership literature emphasizes role modeling, moral communication, fairness, and reinforcement. These elements remain important, but algorithmic management creates new ethical leadership demands. First, leaders must become interpreters of algorithmic systems, explaining not only decisions but also uncertainty and limitations. Second, leaders must become guardians of contestability, ensuring that employees can challenge data-driven decisions. Third, leaders must become institutional designers, embedding accountability into workflows and governance structures. Fourth, leaders must preserve human dignity in environments that increasingly quantify work. These functions suggest that ethical leadership in algorithmic management is less about charismatic moral authority and more about procedural responsibility, reflexive judgment, and accountable intervention.

This study has several limitations. First, the sample was limited to 24 managers and organizational professionals working in Tehran-based organizations. Although the sample was appropriate for qualitative inquiry and theoretical saturation was reached, the findings cannot be statistically generalized to all organizations or national contexts. Second, the study relied on self-reported interview data, which may be influenced by participants' memory, organizational loyalty, social desirability, or desire to present themselves as ethically responsible. Third, the study focused on managerial perspectives and did not include employees, software vendors, data scientists, or senior policymakers. Including these groups could provide a more complete view of algorithmic accountability. Fourth, the study examined multiple organizational sectors rather than one specific industry, which increased diversity but limited detailed sector-specific analysis. Finally, because algorithmic management technologies are rapidly evolving, participants' experiences may reflect the current maturity level of the systems used in their organizations rather than the full range of future algorithmic capabilities.

Future research should examine algorithmic management accountability from multiple stakeholder perspectives, including employees, HR professionals, data scientists, software vendors, legal experts, and senior executives. Comparative studies across industries would help identify how accountability differs in platform work, banking, telecommunications, healthcare, education, logistics, and public administration. Longitudinal research is also needed to examine how ethical leadership practices change as organizations move from early adoption to mature algorithmic governance. Future studies could also compare organizations with formal AI ethics committees and audit procedures to those without such structures. Quantitative research may build on the present qualitative findings by developing and validating scales for ethical leadership in algorithmic management systems. Finally, cross-cultural studies are needed to examine how national culture, labor regulation, technological infrastructure, and managerial traditions shape perceptions of responsibility, transparency, and employee contestability.

Organizations should define clear accountability structures before implementing algorithmic management systems. Managers should not be expected to enforce algorithmic decisions without authority to question, explain, or escalate concerns. Organizations should develop formal procedures for employee appeal, human review, and correction of algorithmic outputs. Algorithmic tools used in evaluation, scheduling, recruitment, or discipline should be regularly audited for bias, accuracy, and unintended consequences. Managers should receive training in AI ethics, data literacy, procedural fairness, and responsible communication. Ethical leadership should also be embedded into governance routines, including cross-functional review committees, documentation of decision rules, employee communication protocols, and periodic assessment of how algorithmic systems affect dignity, trust, and organizational justice. Most importantly, organizations should treat algorithmic management as a human accountability system, not merely a technical efficiency system.

5. Conclusion

This study explored ethical leadership and managerial accountability in algorithmic management systems through qualitative interviews with managers and organizational professionals in Tehran. The findings show that algorithmic management creates new ethical tensions by combining technical authority with distributed responsibility. Managers are often required to justify, communicate, and implement decisions generated by systems they may not fully understand or control. Ethical leadership in this context involves critical sensemaking, acceptance of responsibility, protection of fairness and dignity, creation of meaningful contestability, and institutionalization of ethical governance. The study concludes that responsible algorithmic management cannot be achieved through technical accuracy alone. It requires managers who are willing and able to question algorithmic outputs, explain decisions honestly, listen to employee concerns, intervene when harm occurs, and build organizational systems that make accountability visible, practical, and enforceable.

Ethical Considerations

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

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Conflict of Interest

The authors report no conflict of interest.

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