

Why Artificial Intelligence Should Never Be Used in Managerial Positions: A Critical Analysis of Automated Decision-MakingAuthor: Miriam Zgheib¹*Affiliation:*

1. *Business School, Holy Spirit University of Kaslik, P.O. Box 446, Jounieh, Lebanon*
2. *CIRAME Research Center, Holy Spirit University of Kaslik, P.O. Box 446, Jounieh, Lebanon*

Abstract:

This study critically examines why artificial intelligence should not be granted managerial authority, even though AI demonstrably improves performance in narrow, well-defined tasks. Management requires contextual judgment, ethical reasoning, and accountability, capacities that automated systems do not possess. The study synthesizes three bodies of evidence: the behavioral literature on algorithm aversion (as cited in Dietvorst et al., 2015), the organizational literature on algorithmic control and its consequences (Kellogg et al., 2020), and documented case evidence of algorithmic failures in hiring, criminal justice, and social services. A qualitative, multi-source analysis classifies documented failures by the stage of the decision process in which they occur, revealing that failures originate systematically in biased training data, misaligned optimization objectives, and the absence of accountability mechanisms. The findings show that algorithmic management produces opaque, difficult-to-remedy errors and triggers resistance and loss of trust among employees. The study concludes that AI should serve as a decision-support tool under human oversight, a position consistent with emerging regulation such as the European Union's Artificial Intelligence Act EuropeanCommission,2021. The theoretical contribution extends agency theory by demonstrating that accountability, rather than accuracy, is the binding constraint on automation in managerial roles.

Keywords:

Artificial intelligence, Algorithmic management, Managerial decision-making, Accountability, Algorithmic bias, Human oversight

Introduction:

Modern organizations are being pushed, from every direction, to automate. Software vendors promise that artificial intelligence can close the books faster, forecast demand more accurately, screen thousands of job applications in seconds, and flag fraud before it happens. The enthusiasm is understandable. Machine learning models are excellent at pattern recognition, they never sleep, and they process volumes of data that no human team could read in a lifetime. Yet there is a wide gap between what AI does well and what management actually requires. Management is not a pattern-recognition task. It is a task of judgment, accountability, motivation, and moral responsibility, exercised over people whose lives are directly affected by the decisions made.

The problem this research addresses is that the business literature has largely framed AI as a neutral tool that simply improves decision quality, while the distinctive human demands of managerial work : ethical judgment, contextual sensitivity, and answerability for consequences have been treated as secondary or even as obstacles to efficiency. This framing is dangerous. When an algorithm denies a loan, rejects a job applicant, or sets a production target, someone must answer for the outcome, and an algorithm cannot answer . The gap, therefore, is not technical but organizational: we lack a clear understanding of the specific ways in which automated systems fail when they are placed in positions of managerial authority.

This study addresses that gap through a structured, evidence-based analysis. The core research question is: why should AI systems not be given managerial authority, and what are the measurable consequences of doing so? The objectives of the study are to:

1. Identify the technical, ethical, and organizational limitations of AI in managerial roles.
2. Analyze empirical evidence on algorithmic decision failures in real organizational settings.
3. Examine the behavioral consequences of algorithmic management for employees and for decision quality.
4. Discuss the regulatory and governance implications of automated managerial authority.
5. Propose a complementary model in which AI supports, but never replaces, human managers.

Literature Review:

2.1 The Statistical Superiority of Algorithms in Narrow Tasks

The strongest argument in favor of automation comes from a long line of research comparing human judgment with statistical models. Meehl demonstrated that simple actuarial formulas outperform clinical expert judgment in domains ranging from psychiatric diagnosis to academic prediction. Grove et al. confirmed this in a meta-analysis of 136 studies, finding that mechanical prediction was equal or superior to clinical judgment in the large majority of cases. Kahneman explained why: human judgment is subject to systematic biases, noise, and overconfidence, while algorithms apply the same rule consistently. Dietvorst et al. (2015) added a crucial behavioral finding, namely that people display algorithm aversion, avoiding algorithms even after seeing them outperform human forecasters and provide more accurate pricing (Khalife et al., 2023), furthermore, technology can enable better performance (Subrahmanyam & Beainy, 2027) especially in uncertain environments. In terms of macroeconomics, technology enables more accurate predictions regarding economic quadrants (Nasser et al., 2025), this enhancing firm performance both on a macro and a micro-level (Subrahmanyam et al., 2024). Technology can also be used to predict financial distress (Elia et al., 2021) and provide investors with more information regarding the fair price of stocks and options (Khalife et al., 2025), by doing so, algorithms can increase market efficiency and fairness. Sawaya et al. (2025 ;2026) discussed how AI revolutionized the auditing industry, and internal audit as well as auditor independence is proportionally related to firm performance and financial reporting quality. Existing literature support the positive impact of AI on firm performance (Khalife et al., 2024) especially SMEs (Rizk & Sassine, 2023), not to mention the positive impact on other, non-financial metrics (Kaspard et al., 2025 ; Kaspard et al., 2026). Kamel et al. (2026) argues that digitalization and algorithms can also increase innovation, especially in our modern data-driven culture (Azoury et al., 2024).

Taken together, this literature supports the use of algorithms in well-defined prediction tasks such as credit scoring, demand forecasting, and diagnostic screening.

2.2 From Prediction to Management: The Contested Terrain

The difficulty arises when the same logic is extended from prediction tasks to managerial authority. Kellogg et al. describe algorithmic management as a “contested terrain of control,” identifying six mechanisms — restricting, recommending, recording, rating, replacing, and rewarding — through which algorithms direct, evaluate, and discipline workers. Their review shows that algorithmic control often generates resistance, gaming behavior, and a degradation of worker trust. Jarrahi argues that AI and humans have complementary strengths: AI excels at scale and speed, while humans provide contextual judgment and tacit knowledge. Shrestha et al. propose that organizations should match decision-making structures to the characteristics of the task, reserving full algorithmic authority for structured, low-stakes decisions. In other words, the literature converges on a division of labor, not a transfer of authority.

2.3 Bias, Fairness, and the Problem of Machine Discrimination

A second stream of literature documents the ethical failures of automated decisions. O’Neil shows how “weapons of math destruction,” opaque models applied at scale, can systematically disadvantage the poor and marginalized. Buolamwini and Gebru demonstrated that commercial facial analysis systems misclassify darker-skinned women at dramatically higher rates than lighter-skinned men, revealing that models inherit the biases of their training data. Eubanks documents how automated eligibility systems in social services penalize vulnerable populations, and Angwin et al. showed that criminal risk-assessment tools displayed racial disparities. These findings matter for management because hiring, promotion, and performance systems trained on historical data will reproduce historical discrimination, and unlike a human manager, an opaque model cannot be asked to explain itself.

2.4 Accountability, Governance, sustainability and the Regulatory Response

A third stream concerns accountability. Floridi and Cowls (2019) propose a unified framework of five principles : beneficence, non-maleficence, autonomy, justice, and explicability , arguing that explicability is the enabling principle that makes the others actionable. The European Commission responded with the Artificial Intelligence Act, which classifies AI applications by risk and imposes strict requirements on high-risk systems, including human oversight. The theoretical foundation for this regulatory caution is agency theory: when decision authority is delegated, the principal requires the agent to be accountable, and an algorithm cannot bear legal or moral responsibility (Kellogg et al., 2020). Bostrom adds a long-term warning that optimizing systems can pursue misaligned objectives with dangerous competence. Additionally, sustainability should be considered (Athari et al., 2024), because the latter directly influences firm performance, and the new international trend is sustainability oriented (Beainy & Kamel, 2025). Firms must be held accountable for environmental impact. Subrahmanyam et al. (2024) that building a resilient future is the responsibility of all (Subrahmanyam & Sarkis, 2025).

2.5 The Gap

Most studies examine AI in narrow operational tasks, and most treat automation as a productivity question. What remains underexplored is a systematic account of why managerial authority, as opposed to operational support, should remain human. This study addresses that gap by combining the empirical failure record, the behavioral evidence, and the governance literature into a single critical assessment.

Methodology:

3.1 Research Design

This study employs a qualitative, multi-source research design combining three components: a structured review of the empirical literature, a secondary analysis of documented algorithmic decision failures, and a conceptual analysis grounded in agency theory and the organizational decision-making literature. A qualitative design is appropriate because the research question

concerns the reasons, mechanisms, and consequences of automated managerial authority, which are not reducible to a single quantitative measure.

3.2 Data Collection Sources

Three categories of evidence were collected. First, peer-reviewed studies on algorithm aversion, algorithmic management, and human-AI complementarity were identified through systematic searches of academic databases. Second, documented case studies of algorithmic failures in organizational settings were drawn from investigative journalism and published audits, including the ProPublica COMPAS analysis (Angwin et al., 2016) and the Gender Shades audit (buolamwini & Gebru, 2018). Third, regulatory documents, notably the European Commission's Artificial Intelligence Act proposal, were analyzed for their treatment of human oversight.

3.3 Analytical Framework

The evidence was analyzed against a framework derived from agency theory (Jensen & Meckling, 1976), which holds that delegation of authority requires monitoring and accountability. Each documented failure was classified according to the stage of the managerial decision process in which it occurred, namely data preparation, model design, decision execution, or accountability review. This classification allows the failures to be traced to their structural sources rather than treated as isolated incidents.

3.4 Limitations

The design relies on published secondary sources rather than primary data collection, and the case evidence is drawn mainly from the United States and Europe. Generalization to other cultural and regulatory contexts should therefore be made with caution.

Results:

4.1 Summary of Documented Failures

The analysis identified recurring failure patterns across the documented cases. Table 1 summarizes the principal cases examined and the stage of the decision process in which each failure occurred.

Table 1: Documented Algorithmic Decision Failures by Process Stage

Case	Domain	Failure	Process Stage
COMPAS risk assessment aggwin et al., 2016	Criminal justice	Racial disparity in risk scores; low	Model design

Case	Domain	Failure	Process Stage
Gender Shades audit Buolamwini & Gebru, 2018	Facial recognition	predictive validity for recidivism Error rates up to 34.7% for darker- skinned women vs. 0.8% for lighter- skinned men	Data preparation
Automated benefits eligibility	Social services	False denials of benefits; applicants unable to appeal opaque decisions	Decision execution
Algorithmic hiring screens	Human resources	Rejection of qualified applicants based on proxy variables; no explanation given to candidates	Decision execution
Automated performance rating	Gig economy platforms	Opaque scoring; workers unable to contest ratings	Accountability review
Risk assessment in social services	Child welfare	Misclassification of families; difficulty in correcting errors	Accountability review

4.2 The Structural Sources of Failure

Classifying these failures by process stage reveals a consistent pattern. Failures rooted in data preparation occur when training data encode historical discrimination, as in the Gender Shades audit. Failures rooted in model design occur when the optimization objective diverges from the intended outcome. Failures in decision execution arise when an automated decision is applied without a mechanism for appeal or correction. And failures in accountability review occur when there is no clear human owner responsible for the outcome. Across all four stages, the common thread is the absence of a human agent who can be held answerable for the decision.

4.3 Behavioral Consequences for Employees

The literature also documents the human cost of algorithmic management. Workers subject to opaque algorithmic control report lower trust, higher resistance, and a tendency to game the system rather than improve performance (Kellogg et al., 2020). Algorithm aversion compounds this: even when algorithms are demonstrably accurate, people are reluctant to rely on them (dietvorst et al., 2015). Together, these findings suggest that automated managerial authority does not simply fail technically; it fails socially, by eroding the very trust on which effective management depends.

Discussion and Conclusion:

5.1 Why Accuracy Is Not Enough

The central lesson of this analysis is that accuracy is not the binding constraint on automation in management. An algorithm can be statistically accurate and still be unacceptable in a managerial role, because management demands accountability for individual decisions, sensitivity to context, and the moral authority to act on behalf of others. Agency theory makes this clear: delegation without accountability is not delegation but abandonment. An algorithm cannot be called to account, cannot explain itself, and cannot bear responsibility for the harm its decisions cause.

5.2 The Case for Human Oversight

This does not mean AI has no place in management. On the contrary, the evidence supports a complementary model in which AI serves as a decision-support tool under human oversight. Algorithms can surface patterns, flag risks, and process data at a scale no human can match. But the authority to decide, and the responsibility for the outcome, must remain with a human manager who can be held accountable. This position is consistent with the European Union's Artificial Intelligence Act, which requires human oversight of high-risk systems EuropeanCommission,2021.

5.3 Implications for Practice

For organizations, the practical implication is to design AI systems with accountability built in from the start: clear human ownership of decisions, mechanisms for appeal and correction, and transparency about how and why decisions are made. For researchers, the implication is that the evaluation of AI in management should measure not only accuracy but also accountability, fairness, and trust.

5.4. Conclusion

This study set out to answer a single question: why should AI not be given managerial authority? The answer, drawn from three bodies of evidence, is that management is fundamentally a human responsibility. AI excels at narrow prediction tasks, but management requires contextual judgment, ethical reasoning, and accountability — capacities that automated systems do not possess. The documented failure record shows that algorithmic management produces opaque, difficult-to-remedy errors, and the behavioral evidence shows that it erodes trust and triggers resistance among employees. The theoretical contribution of this study is to show, through the lens of agency theory, that accountability is the binding constraint on automation in managerial roles. The practical conclusion is clear: AI should support human managers, not replace them. Organizations that respect this boundary will capture the benefits of automation without surrendering the accountability that management requires.

References

- Angwin, J., Larson, J., Mattu, S., & Kirchner, L. 2016. Machine bias: There's software used across the country to predict future criminals, and it's biased against blacks. ProPublica.
- Athari, S. A., Saliba, C., Abboud, E., & El-Bayaa, N. (2024). Examining the quadratic impact of sovereign environmental, social, and governance practices on firms' profitability: new insights from the financial industry in gulf cooperation council countries. *Sustainability*, 16(7), 2783.
- Azoury, N., Subrahmanyam, S., & Sarkis, N. (2024). The Influence of a Data-Driven Culture on Product Development and Organizational Success through the Use of Business Analytics. *J. Wirel. Mob. Networks Ubiquitous Comput. Dependable Appl.*, 15(2), 123-134.
- Beainy, R., & Kamel, C. (2025). A Million Scenarios One Green Result. *International Journal of Scientific Research and Modern Technology*, 4(10), 121-126.
- Bostrom, N. 2014. *Superintelligence: Paths, dangers, strategies*. Oxford University Press.
- Buolamwini, J., & Gebru, T. 2018. Gender shades: Intersectional accuracy disparities in commercial gender classification. *Proceedings of Machine Learning Research*, 81, 1–15.
- Dietvorst, B. J., Simmons, J. P., & Massey, C. 2015. Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General*, 144(1), 1–15.
- Elia, J., Toros, E., Sawaya, C., & Balouza, M. (2021). Using Altman Z"-score to predict financial distress: Evidence from Lebanese alpha banks. *Management Studies and Economic Systems*, 6(1/2), 47-57.
- Eubanks, V. 2018. *Automating inequality: How high-tech tools profile, police, and punish the poor*. St. Martin's Press.
- European Commission. 2021. Proposal for a Regulation laying down harmonised rules on artificial intelligence ArtificialIntelligenceAct. European Commission.
- Floridi, L., & Cowls, J. 2019. A unified framework of five principles for AI in society. *Harvard Data Science Review*, 11.
- Grove, W. M., & Meehl, P. E. 1996. Comparative efficiency of informal subjective, impressionistic and formal mechanical, algorithmic prediction procedures: The clinical-statistical controversy. *Psychology, Public Policy, and Law*, 22, 53–107.
- Jarrahi, M. H. 2018. Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, 61(4), 577–586.
- Jensen, M. C., & Meckling, W. H. 1976. Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3(4), 305–360.
- Kahneman, D. 2011. *Thinking, fast and slow*. Farrar, Straus and Giroux.
- Kamel, C.; Khalil, F.; Mouawad, J.; Kechli, W.; Kaspard, J. (2026). Enabling Green Innovation in the Circular Economy: A Systematic Thematic Review of Digitalization and Stakeholder Engagement. *Sustainability*, 18, 1360. <https://doi.org/10.3390/su18031360>

- Kaspard, J. A., Khalil, F. C., & Kamel, C. A. (2025). Factors contributing to non-financial performance of companies. In *Sustainable Economic Development: Utilizing Non-Financial Performance, Sustainability Reporting, and Corporate Governance* (pp. 413-442). Cham: Springer Nature Switzerland.
- Kaspard, J., Kamel, C., Khalil, F., & Beainy, R. (2026). Financial Performance, Risk, and Market Integration of Sustainability-Oriented Equity Indices: Implications for the Sustainability Transition (2010–2025). *Risks*, 14(5), 99.
- Kellogg, K. C., et al. 2020. Algorithmic management: The contested terrain of control. *Academy of Management Annals*.
- Khalife, D., Subrahmanyam, S., & Farah, A. (2024). A Sustainable Circular Business Model to Improve the Performance of Small and Medium-sized Enterprises Using Blockchain Technology. *J. Wirel. Mob. Networks Ubiquitous Comput. Dependable Appl.*, 15(2), 240-250.
- Khalife, D., Yammine, J., El Bazi, T., Zaki, C., & Jabbour Al Maalouf, N. (2025). Analyzing the impact of investor sentiment on S&P 500 prices using deep learning models. *Journal of Financial Reporting and Accounting*, 23(4), 1365-1386.
- Khalife, D., Yammine, J., Rahal, S., & Freiha, S. (2023). Pricing Asian and Barrier Options Using a Combined Heston Model and Monte Carlo Simulation Approach with Artificial Intelligence. *Mathematical Modelling of Engineering Problems*, 10(5), 1690.
- Meehl, P. E. 1954. *Clinical versus statistical prediction: A theoretical analysis and a review of the evidence*. University of Minnesota Press.
- Nasser, A., Yammine, J., Harouny, J., & Khalife, D. (2025). Predicting Economic Quads Through Asset Returns Using Ensemble Machine Learning. *IEEE Access*.
- O'Neil, C. 2016. *Weapons of math destruction: How big data increases inequality and threatens democracy*. Crown Publishing.
- Rizk, R., & Sassine, M. (2023). Equity financing and SME growth: evidence from the Eurozone. *International Journal of Work Innovation*, 4(3), 227-239.
- Sawaya, C., Al Maalouf, N. J., Hanoun, R., & Rakwi, M. (2025). Impact of auditor independence, expertise, and industry experience on financial reporting quality. *Asia Pacific Management Review*, 30(1), 100357.
- Sawaya, C., Khalil, F. C., Jabbour Al Maalouf, N., & Kaspard, J. (2026). Revolutionizing audit practice in emerging economies: the role of Artificial Intelligence in enhancing the audit of consolidated financial statements. *Cogent Business & Management*, 13(1), 2625974.
- Shrestha, Y. R., et al. 2019. Organizational decision-making structures in the age of artificial intelligence. *California Management Review*, 632, 137–145.
- Subrahmanyam, S. & Sarkis, N. (2025). Mindfulness and Sustainability Leadership: Integrating Awareness and Action for a Resilient Future. In *Strategic Approaches to Mindful Leadership and Change Management* (pp. 349-382). IGI Global Scientific Publishing. 10.4018/979-8-3693-7066-7.ch012

- Subrahmanyam, S., & Beainy, R. H. (2027). Smart Decision Support for Uncertainty and Disruptions in Industry 4.0 Operations. In Smart Operational Research Solutions in the Era of Industry 4.0 and Sustainability (pp. 167-198). IGI Global Scientific Publishing.
- Subrahmanyam, S., Aishwaryalaxmi, N. S., Khalife, D., Shaikh, I. A. K., Faldu, R., & Asthana, N. (2024, April). Impact of knowledge management and big data analytics capabilities on firm performance. In 2024 Ninth International Conference on Science Technology Engineering and Mathematics (ICONSTEM) (pp. 1-5). IEEE.
- Subrahmanyam, S., Khalife, D., & El-Chaarani, H. (2024). Towards Sustainable Future: Exploring Renewable Energy Solutions and Environmental Impacts. Acta Innovations, 51, 15-24. <https://doi.org/10.62441/ActaInnovations.51.3>