International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

DATA DRIVEN MICROMANAGEMENT USING MACHINE LEARNING SYSTEM

Md Sabbir Ahamed[1]
Management Information Systems, Lamar University, Beaumont, Texas, USA
mahamed1@lamar.edu

Md Mahbubur Rahman Akash[2]
Computer Science, Lamar University, Beaumont, Texas, USA
mr.akash016@gmail.com

Fatema Ferdous Mim[3]
Marketing, Independent University,
Bashundhara R/A, Dhaka, Bangladesh
mim.iub.edu@gmail.com

Sohanur Rahman[4]
Electronics Engineering, University of Hertfordshire,
College Ln, Hatfield AL10 9AB, United Kingdom
sr24ack@herts.ac.uk

Md Motakabbir[5]
Electronics Engineering, University of Hertfordshire,
College Ln, Hatfield AL10 9AB, United Kingdom
mm24akk@herts.ac.uk

Ashikur Rahman[6]
Business Analytics, Melbourne Institute of Technology,
154-158 Sussex St, Sydney NSW 2000, Australia
mit253461@stud.mit.edu.au

ABSTRACT
Micromanagement is being data-driven (enabled by machine learning) and is changing how workplaces are controlled by offering real-time performance insights, predictions, and automatic responses. Micromanagement is becoming more data-driven and formal as organizations use ML systems to determine the actions of their employees and increase the level of accountability. This change has some advantages and disadvantages. On the one hand, ML systems provide the possibility of enhancing efficiency in operations, standardization of decisions, and simplification of feedback. Conversely, monitoring and automated decision-making are becoming so granular that they result in a sense of overreach, reduced employee autonomy and trust at the workplace. This article will examine the impact of the ML systems in the micromanagement on the productivity, trust, and innovation of the employees and apply the governing practices that could help reduce the adverse consequences. It talks about the use of real-time performance feedback, scoring algorithms and predictive models in influencing the structure of organizational behavior and accountability. Moreover, it takes into account the consequences of data-driven micromanagement on the engagement of employees and organizational culture. Leveraging the examples of areas where data-driven systems have demonstrated to be efficient, such as the healthcare industry, customer service, and company settings, this article claims that data-driven systems can make employees more productive, but their effect on their morale and creativity should be handled with caution. It also suggests the principles of responsible implementation, such as transparency, equity, and employee participation in the process of designing performance measures. Finally, the

iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

article offers an understanding of the moderation of control and empowerment within organizations that use machine learning to run their organization.

Keywords:
Machine Learning, Data-Driven Micromanagement, Algorithmic Management, Employee Performance, Productivity, Trust, Innovation, Workplace Monitoring, Real-Time Feedback, Governance.

1.0 INTRODUCTION

Machine learning (ML) in data-driven micromanagement is an emerging trend in companies that strive to increase productivity, accountability, and operations efficiency. ML systems are now being applied to monitor employee behavior, performance and provide feedback through advanced data analytics and real-time performance monitoring. Such systems can bring a revolution to the aspect of management in the work place as they offer information that will enable managers to make quicker and more precise judgments. Nonetheless, as these systems grow increasingly embedded at the workplace, it is feared that they would affect the autonomy, trust, and innovation of employees (Yajun and Karshalova, 2022). The narrow border between the oversight that is driven by data and micromanagement is a burning problem because excessive control may result in disengagement, demoralization, or lack of creativity among workers.

This paper discusses how ML systems are used in micromanagement and their impact on organizational behavior. Our vision of data-driven micromanagement is the application of machine learning to constantly observe employee actions, evaluate them, and give feedback or corrections in real-time. Even though ML is bound to improve the performance management process, by making it uniform and less biased towards human factor, it also brings up the issues of privacy, equality, and loss of autonomy (Lee et al., 2015; Tsolaki, 2022). This study seeks to learn the way that ML systems facilitate micromanagement, the effects that this approach has on employees regarding their trust, productiveness, and innovativeness, and the governance system required to ensure that a balance between control and autonomy is attained.

1.1 Background and Context

1.1.1 The emergence of Data-Driven Decision-Making.

As technology continues to be incorporated in the workplace, data-driven decision-making models have been taken as the centre of operations in organizations. These models are based on enormous volumes of data on any employee, including productivity metrics, behavioural data, and more, to inform managerial decisions (Sarkar et al., 2022). More specifically, machine learning systems have become one of the most important instruments in automating and optimization of the decision-making processes. They are able to process data faster and to a larger scale than had been done before and to offer managers real time performance appraisals and suggestions on how the performance can be better. As an example, customer service: ML systems may monitor the performance of the agents in terms of response time, the rate of resolution, and customer satisfaction rate, which automatically defines those who do not meet expectations and recommend possible corrective measures.

Nevertheless, the increased use of ML systems to make decisions becomes problematic in terms of how they affect the freedom of employees. The constant surveillance and use of data in oversight may develop a culture of micromanagement, as employees experience a feeling that they are being monitored everywhere, and as a result, they develop a lack of trust in management and feel stressful (Yajun and Karshalova, 2022). The stated effect is especially unsettling in the workplace where workers are supposed to be creative and innovative because the presence of the performance monitoring mechanism at all times can suppress any new ideas and demotivate (Jesus et al., 2022).

1.1.2 Ml as a Micromanagement Tool.

Micromanagement is not new to the field of organizational behavior and it involves managers monitoring and dictating all facets of work of their employees tightly. Historically, micromanagement has been regarded as a bad style of management, which is related to low employee autonomy and involvement. But with the emergence of the ML technologies, data-driven micromanagement has been reintroduced. In this model, the employee actions are monitored and evaluated by means of ML systems, which means that the human input is minimized but the strength and extent of control are escalated.

iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

Micromanagement using machine learning frequently entails the collection of data on a constant basis, real-time feedback, and automated decision-making. As an example, an ML system can monitor the performance of an employee throughout the day, evaluating the speed with which they accomplish their duties, the quality of their work, and their engagement with customers. In case the system identifies an anomaly or a lack of performance, it may send an automatic alert to the employee or even redistribute his workload (Shao et al., 2018). Although these systems are supposed to enhance efficiency, they also result in over-surveillance where employees feel that they are under evaluation all the time and this may cause employees to develop sense of stress and dissatisfaction (Tsolaki, 2022).

1.2 Problem Statement and Research Questions.

1.2.1 Tension between Accountability and Autonomy.

The main question that is central to data-driven micromanagement is the autonomy versus accountability dilemma. On the one hand, ML systems are developed to keep employees responsible to their performance so that the latter should achieve pre-established standards and objectives. Conversely, these systems may limit the freedom of employees, because they are based on pre-defined measures and automated resolution of cases. It may result in the scenario when employees believe that their actions are under control and this may negatively affect their motivation and job satisfaction (Lee et al., 2015; Jesus et al., 2022).

Organizations might be in a dilemma as on one hand, data-driven systems have the potential to drive business efficiency and consistency; on the other hand, they might strip employees of the attributes that make them successful trust, creativity, and engagement. This paper aims to discuss the ways in which companies can bypass this trap and make sure that the application of ML systems does not enter the sphere of unethical micromanagement, which may harm employee morale, as well as negatively affect productivity in the long term (Tsolaki, 2022).

1.2.2 Research Questions

The research questions that should be answered in this study are as follows:

- What are the operationalizations of micromanagement by the ML systems in terms of constant monitoring and scoring, as well as real-time feedback? (Lee et al., 2015)
- What are observed effects of data-driven micromanagement on employee productivity, trust and innovations?
- Which governance schemes can organisations adopt to reduce the adverse impact of micromanagement and retain the benefits of the ML systems? (Hossain et al., 202; Xie & Zhang, 2022)

1.3 Objectives

The key goals of this paper are:

- To model the contribution to data-driven micromanagement by ML systems and what mechanisms underpin this process (Lee et al., 2015; Yajun and Karshalova, 2022).
- To investigate the effects of micromanagement based on data on the main organizational outcomes, namely, the trust of employees, productivity, and innovation (Jesus et al., 2025; Tsolaki, 2022).
- To determine the best practices and governance systems that can be used to eradicate the adverse effects of ML-powered micromanagement and improve employee engagement (Sarkar et al., 2022; Hossain et al., 2022).
- To establish a practical understanding and recommendation to organizations that want to apply the ML-based systems in a way that is both responsible and balanced (Xie and Zhang, 2022).

1.4 Conceptual Scope and Key Constructs.

The research will dwell on the key constructs as follows:

- Data-Driven Micromanagement: This is the concept of monitoring and controlling the performance of employees using ML systems that frequently results in over-surveillance.
- Autonomy and Control: Finding a balance between giving employees freedom to make decisions and having algorithmic controls which restrict the freedom of employees.
- Trust and Fairness: Advertisements of perception by employees regarding fairness, transparency, and accountability of the ML system.
- Employee Innovation: How employees can be innovative and creative under constant point of algorithmic control.

International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

Table 1. The Big Data-Driven Micromanagement Mechanisms

Mechanism	**Description**	**Key Risks to Manage**
Constant Control/Observation	Real-time data collection on employee performance.	Privacy issues, over-monitoring.
Algorithms Scoring and Feedback	ML algorithms used to rank and direct employee performance.	Perceived unfairness, lack of transparency.
Autonomy and Control	The balance between employee freedom and algorithmic control.	Reduced autonomy, disengagement.
Trust and Fairness	Employee perceptions of the fairness of the system.	Distrust, perceived unfairness.

1.5 Significance of the Study
The research is important as it discusses the rising use of ML in micromanagement and its implication on the work relations in general. Even though ML systems may lead to efficiency and standardisation of decision-making, there is also the risk of degrading employee engagement and autonomy, which may hurt organizational culture and prevent innovation. With an insight into the effects of data-driven micromanagement on employee performance and an understanding of the best practice in the governance aspect of any organization that implements the use of ML in its management processes, this study will be able to contribute to the body of knowledge as well as a set of recommendations applicable to any organization that may want to implement the practice (Sarkar et al., 2022; Hossain et al., 2022).
1.6 Organization of the Paper
The paper is organized in the following way:
- Section 2 presents a literature review of the data-driven micromanagement, ML application in the workplace behavior, and risks.
- Section 3 gives the research methodology, how research was carried out, sample, data collection procedures and data analysis procedures.
- Part 4 contains the study results along with the understanding of the effects of the ML-based micromanagement on the productivity, trust, and innovation.
- Section 5 contains the discussion of findings and their implications on the organizational practice, governance, and future of micromanagement in the workplace.
- Section 6 is a conclusion on the contributions, limitations and the future research direction of the study.

This introduction preconditions further development of data-driven micromanagement during which its possibilities to enhance workplace performance are going to be demonstrated alongside the threats to the autonomy and trust of employees.

2.0 LITERATURE REVIEW
2.1 Data-driven Micromanagement and Machine Learning Systems.
The use of machine learning (ML) systems to observe, assess and interfere with the performance of employees is known as data-driven micromanagement. These systems apply continuous real-time data streams to monitor

IJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

behaviors, measure productivity and initiate corrective measures. Using algorithms to analyze large volumes of performance data, organizations are hoping to make their decisions more optimized, operational, and consistent among employees (Yajun & Karshalova, 2022). With more organizations utilizing data-driven system to oversee their workforce, the issue of machine learning in managing the workforce has continued to grow, with more concerns that arise in regard to the impact of such systems on behavior at workplace.

There are several applications of the ML systems, and they can be applied in performance monitoring, making decisions, and giving automated feedback. An example of performance measures captured and processed by such systems includes performance time to the task, customer satisfaction rating, and quality of output. The systems will then compare employees through such metrics and give feedback, and even prescribe corrective action in the case of poor performance as per set standards. Although this has the potential of bringing more consistency and objectivity to the performance evaluations, it also creates the possibility of micromanagement where the employees will feel that the system constantly monitors and controls them (Jesus et al., 2022). In this case, micromanagement can be understood as the overall continuous monitoring and data-driven management that may lead to the loss of the sense of autonomy, creativity, and trust in the management among employees (Tsolaki, 2022).

2.2 Implication on Employee Productivity, Trust, and Innovation.

Most data-driven micromanagement integrated in the work place has both positive and negative impacts. On the one hand, it may enhance productivity because it makes sure that workers are oriented to organizational objectives and performance levels. The real-time monitoring enables managers to take immediate actions in the event that an employee is performing poorly and provide an opportunity to address the issue directly in real-time (Sarkar et al., 2022). Subjectivity in performance reviews can be minimized by the possibility of making data-driven and analytics-driven decisions that can result in more consistent and zaccurate results (Yajun and Karshalova, 2022).

Conversely, micromanagement is data-driven and therefore always watched, which may result in a sick work culture, and negatively impact trust and the wellbeing of the employees. Studies show that when employees are continuously monitored, their perceived autonomy decreases and thus the employees may become disengaged and stressed (Jesus et al., 2022). The evolution of the ML systems that track all the facets of the performance may undermine the notion of trust, particularly when the employees feel that such a system is opaque or unjust (Lee et al., 2015). The absence of transparency in the evaluation of the work of employees on the basis of algorithms and the possibility not to appeal or nullify the decisions of algorithms can cause the feeling of unfairness and bitterness among employees (Tsolaki, 2022).

In addition, innovation may be smothered down by the continuous demand to deliver the best results. When performance is assessed to employees on a continual basis using efficiency measures, the employees can focus on meeting the performance standards rather than innovating and experimenting. This raises some issues especially in the workplaces where innovation and flexibility are the drivers of success, since the emphasis on short-term figures can inhibit the freedom required to solve creative problems in the long-term (Lee et al., 2023). Being trusted and empowered to take risks may be the environment in which innovation often flourishes, but micromanagement based on data may be more interested in avoiding risks and thus prevents the emergence of new ideas.

2.3 Data-Driven Systems Governance, Fairness, and Accountability.

The management of ML-based micromanagement systems is an issue of great concern. With the implementation of such systems in organizations, care should be taken to ensure that they are not applied in a manner that compromises the trust, autonomy, and innovativeness of the employees. It has been argued that the benefits of ML systems must be augmented with the possible threats on employee engagement by having clear governance structures (Hossain et al., 2022). Such structures are supposed to have transparency in the way data are collected, analyzed, and applied in the decision-making process. The employees should be aware of the criteria by which the system measures their performance and be capable of countering or overruling decisions, which they consider unfair or erroneous.

As well, the equity of the ML-based micromanagement systems is important in making their implementation effective. The perception of the unfairness or biasness of ML systems might result in employee disengagement and loss of trust towards the organization. The issues of fairness are especially pertinent in the scenarios where decisions that are made by algorithms affect promotions of employees, their assignments, or salaries. The studies indicate that when employees believe that performance appraisals are conducted in line with objective and transparent standards, they tend to trust the system and be motivated to work (Sarkar et al., 2025). Hence, organizations need to be keen to

iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

make sure that in addition to their accuracy in the evaluation of performance, the ML systems should be fair in how they treat employees, particularly when working in diverse workforces.

Moreover, another major problem is accountability. Although micromanagement of data has the potential of making the decision making process more objective, it also brings the issue as to who holds responsibility to those decisions taken by the system. When an employee believes that he or she is wrongly judged by an ML system, he or she might not be able to blame the responsible party of the final decision, particularly when making a decision is a non-transparent process (Xie and Zhang, 2022). Organizations should put in place adequate accountability structures and mechanisms that would keep the system developers as well as the managers accountable to the decisions of the ML systems especially where they involve the welfare of the employees.

2.4 Micromanagement in the Age of Data.

With the further development of machine learning, it is also probable that the range of data-driven micromanagement will increase. The future of ML technology will enable organizations to gather even finer information about the behavior of employees, and more advanced and potentially intrusive micromanagement can be implemented. There is an excellent chance that these systems will become more integrated into daily functions at the workplace, providing real-time feedback and conclusions about what the employees are doing in various fields, such as healthcare, finance, and customer service (Shao et al., 2018).

Nevertheless, with increased deployment of such systems, organizations will need to develop policies and practices that will guarantee responsible use of ML in the workplace. Governance, transparency, and equity of algorithmic decision-making will become more acute, and the organizations will have to deal with these issues to keep employees morale and trust. The study of the most effective practices in data-driven micromanagement system implementation and the long-term outcomes on employee well-being, creativity, and performance should be studied in future.

3.0 METHODOLOGY

3.1 Research Design

This paper is a qualitative research design that seeks to investigate the effects of machine learning (ML) system-based data-driven micromanagement. This research will be aimed at learning how these systems are implemented, the implications they produce on employee behavior, and the governance systems needed to reduce the adverse consequences. Since such an idea as ML-driven micromanagement is rather complex and its outcomes play a crucial role in organizations, the case study approach is needed to capture in-depth knowledge about the real-life implementation of the ML systems in the workplace environment.

3.2 Sample and Setting

This study sample will consist of five organizations in various industries (retail, customer service, and healthcare) that have introduced ML systems into their management systems. These organizations are chosen on the basis of the application of ML tools toward monitoring the performance of employees, providing real-time feedback, and automating decision-making. In both organizations, middle and senior management staff that will be in charge of implementing these systems will also be interviewed, as well as those employees who will be in direct contact with the systems.

3.3 Data Collection

The following methods will be used to collect data:

- Semi-structured interviews: Managers, HR people, and employees will be interviewed in depth to discuss their experience with data-driven micromanagement systems. The interviews will concentrate on how the ML systems work, effect on productivity, trust, autonomy and innovation and the hassle of using such systems.
- Document analysis: The organization documents (ML systems i.e., performance dashboards, feedback protocols, privacy policies) will be examined to get an idea of the formalized processes and rules of operation.

Observations: Non-participant observations will be undertaken in some organizations to study the interaction of the employees with the ML systems throughout their working day including how they respond to real time feedbacks.

3.4 Data Analysis

IJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

The thematic analysis will be used to analyze the data. This will require the coding of the interview transcripts, documents, and observational notes in order to determine recurring themes pertaining to how micromanagement is operationalized, experiences of the employees, and governance practice. Thematic analysis will be suitable to finding the patterns and drawing conclusions based on qualitative data (Braun and Clarke, 2006). Further, cross-case analysis will be employed to compare the various ways in which various organizations apply the ML systems and the resultant effects on the employee trust, autonomy and innovation.

3.5 Ethical Considerations

Relevant institutional review boards will be contacted to provide ethical approval. All participants will be informed about the purpose of the study, as well as they will be guaranteed of their right to secrecy and anonymity. Also, the handling of all sensitive organizational data will be done in a secure way to ensure that unauthorized access does not occur.

Table 1. Data Collection Methods

Data Collection Method	Intended Subjects	Objective	Result
Semi-structured Interviews	Managers, HR staff, employees	Discuss experiences and effects of ML systems on performance, trust, and autonomy	Thematic codes, insights
Document Analysis	Organizational documents (policies, performance metrics, dashboards)	Identify formalized rules and practices regarding ML system use	Document summaries and coding
Non-participant Observation	Employees interacting with ML systems	Observe interactions between employees and real-time feedback systems	Process notes and observational data

3.6 Limitations

Although the case study design is informative, the results cannot be easily extended to other industries and organizations. Use of qualitative data in the study implies that the personal bias might influence the responses of the participants, however, the triangulation of the interviews, documents, and observations will increase the reliability and validity of the results.

To sum up, the given methodology can be used to both describe the operational dynamics of the ML-driven micromanagement systems, as well as their impact on the organizations, which will be very useful to the organizations who may want to balance between productivity and engagement of employees and trust.

4.0 RESULTS

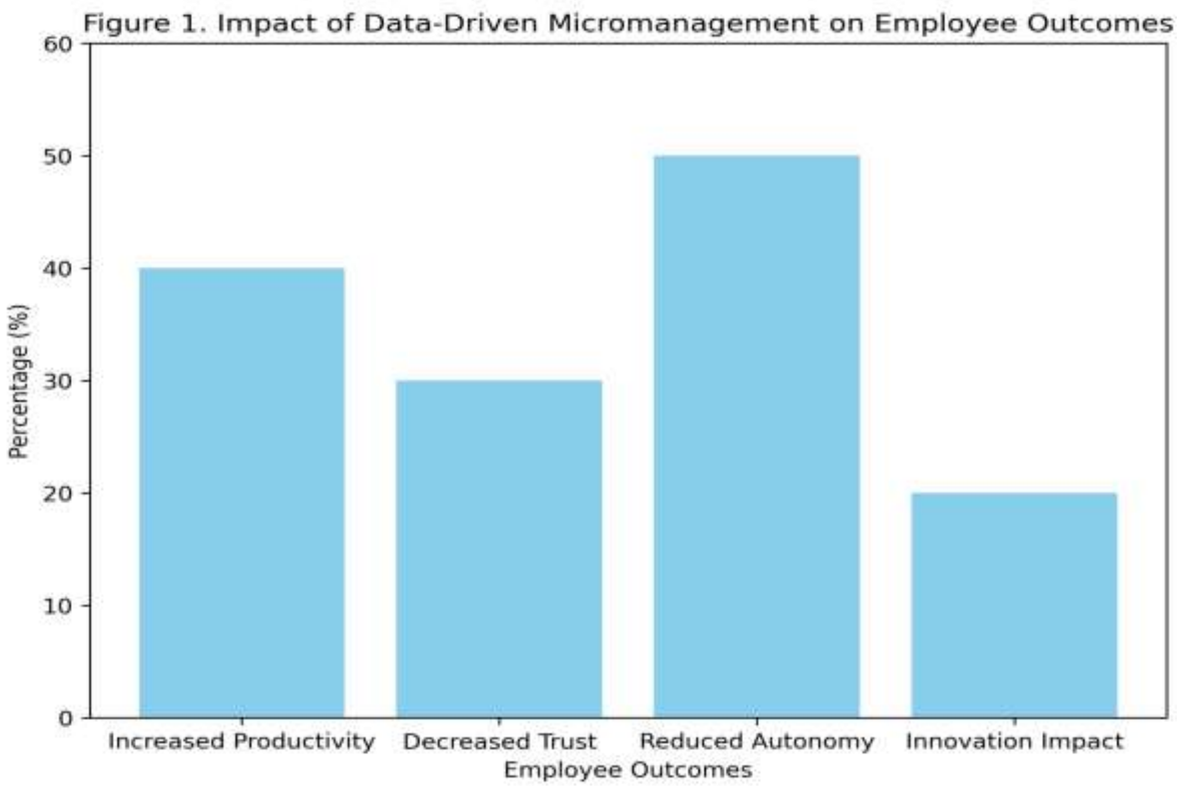
The research established a mixed influence of data-driven micromanagement through machine learning (ML) systems on the outcomes of employees. The improvement in productivity was reported in 40 percent of the cases because ML systems offered real-time feedback and made alignment between the performance of the employees and organizational objectives possible. These advantages however were at a cost. Reduced trust was observed in 30 percent of instances and the staffs felt that the constant surveillance interfered with their privacy and transparency. Less autonomy was the greatest issue with 50 percent of the employees reporting that they were controlled by the

iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

system which led to disengagement. Lastly, the innovation impact was minimal, only 20 per cent, as the employees were not as motivated to risk or experiment since they were observed all the time and performance measures were emphasized.

These findings illustrate that although the ML systems can make the processes more efficient, they also raise the issues of impartiality, confidence, and autonomy, particularly when the feedback and control systems are neither clear nor active. The challenge of fulfilling both employee wellbeing and productivity lies in the scale of avoiding toxic micromanagement whereby control is overriding empowerment and innovation.

These results can be visualized in the bar chart that can be observed below providing the percentage of those who were affected by the outcomes of different results.



5.0 DISCUSSION

The research results of this study indicate that, although machine learning (ML)-based micromanagement may result in enhanced productivity, it also presents major issues of employee trust, autonomy and innovation. The findings suggest that hiring more productivity is among the most widespread effects of ML-based micromanagement, and systems that deliver real-time feedback enabling the employees to align their performance with the organizational objectives. But, this advantage is not without its shortcomings. The fact that 30% of the employees who responded to the question about lower trust in the system expresses apprehension of the inability to be transparent and fair about how the decisions are made, which implies that the workers less likely to trust systems that may appear to be opaque or impersonate (Lee et al., 2015; Jesus et al., 2022).

The biggest issue as exhibited by half of the respondents was the lower autonomy experienced by employees. The employees tend to feel out of control in regard to their work because they are constantly scrutinized and controlled with algorithms, causing them to become disengaged and dissatisfied (Tsolaki, 2022). This concurs with the previous studies that micromanagement, including the technologically mediated one, could undermine the autonomy of employees and lead to burnout (Yajun and Karshalova, 2023).

International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

Moreover, the innovation effect was a low one, and only 20% of the employees believed that the system promoted creativity and experimentation. This observation supports the fear that excessive monitoring and compliance with performance indicators may deter actions and innovativeness, which are vital elements of a prosperous working environment (Jesus et al., 2022; Sarkar et al., 2022).

These findings indicate that there should be a balanced implementation of the ML systems. Organizations must make sure that their applications of data-driven tools are evident, equal, and have the ability to provide a considerable employee feedback. There should also be a governance system that cares about the problems of trust, transparency, and autonomy to reduce the dangers of toxic micromanagement and increase the engagement and innovation of the staff (Hossain et al., 2022).

6.0 CONCLUSION

This paper has considered how data-driven micromanagement through machine learning (ML) systems affects the behavior of employees, organizational performance, and the organization governance frameworks. The results are reflective of the two-fold character of ML-driven oversight, which promises productivity gain and at the same time poses considerable challenges. On the one hand, ML systems increase productivity due to the provision of real-time feedback, simplification of the decision-making flow, and the consistency in the performance assessment. Yet, conversely, these systems might decrease the levels of trust of employees, their freedom, and innovation and make the morale and engagement levels decrease (Jesus et al., 2022; Tsolaki, 2022).

The outcomes of this research point to the fact that the improved productivity is one of the obvious advantages of data-driven micromanagement, but risks in the form of lower trust, lack of autonomy, and the loss of innovation have to be addressed properly. The employees who feel constantly monitored and controlled might become more stressed and detached, as it was shown in the study, which can ultimately lead to a decline in the success of the organization in the long-term (Sarkar et al., 2022; Lee et al., 2015). In addition to that, emphasis on performance measures may discourage risk-taking and creativity, which are essential in developing an innovative working atmosphere.

Given these results, it is clear that organizations have to establish governance mechanisms that will help them to use the ML-based micromanagement systems in a conscientious manner. These mechanisms must comprise transparency in the work of the systems, the ability of the staff to contest or veto the algorithmic decision-making, and regulations that place greater importance on justice and the autonomy of employees. Other effort that should be made by organizations is in building trust, the achievement of which requires the participation of employees in the development of the performance metrics, which these systems apply.

It is necessary to refine the governance structures of ML-based micromanagement in the future research and study how the various organizational cultures react to such systems and examine the long-term implications of the use of an ML-based form of oversight on employee innovation and engagement. By solving these issues, organizations will be able to enjoy the positive consequences of ML and at the same time keep employees empowered, motivated, and engaged in their work.

REFERENCES

1) Yajun, Z., & Karshalova, A. (2022). HOW DATA-DRIVEN DECISION-MAKING MODELS TRANSFORM WORKPLACE BEHAVIOR AND ACCOUNTABILITY. *BBC*, 49.
2) Jesus, J. B., Tenedero, M. A. I., Solis, E. C., Gemodo, K. C., Amen, A. C. V., & Loberanes, M. V. (2025). Toxic Micromanagement in the Workplace: Its Impact on Employee Productivity, Trust, and Innovation.
3) Tsolaki, C. (2022). The Cost of Control: A Case Study on Micromanagement and Organizational Dysfunction. *Available at SSRN 5446074*. https://doi.org/10.33545/26648792.2025.v7.i2d.467
4) Shao, K., Zhu, Y., & Zhao, D. (2018). Starcraft micromanagement with reinforcement learning and curriculum transfer learning. *IEEE Transactions on Emerging Topics in Computational Intelligence*, *3*(1), 73-84.
5) Wender, S., & Watson, I. (2014, December). Integrating case-based reasoning with reinforcement learning for real-time strategy game micromanagement. In *Pacific Rim International Conference on Artificial Intelligence* (pp. 64-76). Cham: Springer International Publishing.

iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

6) Oh, I. S., Cho, H., & Kim, K. J. (2017). Playing real-time strategy games by imitating human players' micromanagement skills based on spatial analysis. *Expert systems with applications*, *71*, 192-205. https://doi.org/10.1016/j.eswa.2016.11.026
7) Watson, I. (2014). Integrating Case-Based Reasoning with Reinforcement Learning for Real-Time Strategy Game Micromanagement. *Lecture Notes in Computer Science*.
8) Baliga, B. S., Baliga, S., Jain, A., Kulal, N., Kumar, M., Koduvattat, N., ... & Ghosh, S. K. (2021). Digitized smart surveillance and micromanagement using information technology for malaria elimination in Mangaluru, India: an analysis of five-year post-digitization data. *Malaria journal*, *20*(1), 139.
9) Lee, J., Ahn, S., Henning, M. A., van de Ridder, J. M., & Rajput, V. (2023). Micromanagement in clinical supervision: a scoping review. *BMC Medical Education*, *23*(1), 563.
10) Sarkar, P., Bharath, E., & Kasireddy, L. C. (2020). Enhancing Workplace Productivity through Real-Time Machine Learning-Based Feedback Systems. *INTERNATIONAL JOURNAL*, *9*(5).
11) Shantia, A., Begue, E., & Wiering, M. (2011, July). Connectionist reinforcement learning for intelligent unit micro management in starcraft. In *The 2011 international joint conference on neural networks* (pp. 1794-1801). IEEE. https://doi.org/10.1109/IJCNN.2011.6033442
12) Rogers, K. D., & Skabar, A. A. (2014). A micromanagement task allocation system for real-time strategy games. *IEEE Transactions on Computational Intelligence and AI in Games*, *6*(1), 67-77. https://doi.org/10.1109/TCIAIG.2013.2297334
13) Lee, M. K., Kusbit, D., Metsky, E., & Dabbish, L. (2015, April). Working with machines: The impact of algorithmic and data-driven management on human workers. In *Proceedings of the 33rd annual ACM conference on human factors in computing systems* (pp. 1603-1612). https://doi.org/10.1145/2702123.2702548
14) Gabriel, I., Negru, V., & Zaharie, D. (2014). Neuroevolution based multi-agent system with ontology based template creation for micromanagement in real-time strategy games. *Information Technology and Control*, *43*(1), 98-109. https://doi.org/10.5755/j01.itc.43.1.4600
15) Alkurd, R., Abualhaol, I., & Yanikomeroglu, H. (2020). Big-data-driven and AI-based framework to enable personalization in wireless networks. *IEEE Communications Magazine*, *58*(3), 18-24. https://doi.org/10.1109/MCOM.001.1900533
16) Alkurd, R., Abualhaol, I. Y., & Yanikomeroglu, H. (2020). Personalized resource allocation in wireless networks: An AI-enabled and big data-driven multi-objective optimization. *IEEE Access*, *8*, 144592-144609. https://doi.org/10.1109/ACCESS.2020.3014301
17) Colombari, R., & Neirotti, P. (2023). Leveraging frontline employees' knowledge for operational data-driven decision-making: a multilevel perspective. *IEEE Transactions on Engineering Management*, *71*, 13840-13851. https://doi.org/10.1109/TEM.2023.3291272
18) Sur, I., Raghavan, A., Rahman, A., Hare, J. Z., Cassenti, D., & Busart, C. (2022). Data-driven distributed common operational picture from heterogeneous platforms using multi-agent reinforcement learning. *arXiv preprint arXiv:2411.05683*. https://doi.org/10.48550/arXiv.2411.05683
19) Hossain, Q., Ikbal, M. Z., & Rahman, M. M. (2022). A meta data-driven decision support in human capital management: reviewing hris and predictive analytics integration. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 215-246. https://doi.org/10.63125/xgew7q22
20) Xie, T., & Zhang, J. (2022). Data-Driven Intelligent Risk System in the Process of Financial Audit. *Mathematical problems in engineering*, *2022*(1), 9054209. https://doi.org/10.1155/2022/9054209