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Performance Optimization Versus Employee Psychological Erosion

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Under Management - human resource management

Abstract: The growing use of algorithmic management systems in pharmaceutical organisations has changed how employees are supervised, evaluated, and directed. Instead of relying on human managers, these systems use automated data collection and continuous monitoring to govern how employees work. This study looks at both sides of this shift, the operational benefits it produces and the psychological harm it causes. A cross sectional survey was conducted with 250 pharmaceutical professionals, comprising 125 Sales Representatives and 125 Quality Control Analysts. The study measured technostress, psychological contract breach, and perceived algorithmic opacity. Results showed that AI supervision increased output by 18.4% but also led to a 22% rise in technostress scores and a 128% jump in turnover intention among algorithmically managed workers. A strong negative correlation of $r = 0.74$ ($p < 0.01$) between algorithmic opacity and organisational trust confirms that lack of transparency is a key mechanism through which algorithmic management damages the employee organisation relationship. Based on these findings, this paper proposes a Human Centric Algorithmic Framework that incorporates Human in the Loop design as a practical governance solution.

Keywords: Algorithmic Management, Technostress, Psychological Contract Breach, Algorithmic Opacity, Human in the Loop, Job Demands Resources Model, Agency Theory, Pharmaceutical Sector, Organisational Trust, Turnover Intention.

I. INTRODUCTION

Pharmaceutical organisations are a particularly useful setting for studying the consequences of AI driven management. Their work environments involve strict regulatory requirements, high stakes outputs, and a workforce that depends heavily on professional judgment. This makes them an ideal context for examining the tension between algorithmic efficiency and the psychological wellbeing of employees.
Algorithmic management systems , platforms that monitor and guide employee activity through real time data analytics , have grown rapidly across industries (Awati, 2025). Despite this growth, most research on these systems has focused on what they achieve operationally. The psychological costs remain underexplored, especially in specialised industries where professional identity plays a central role in how employees relate to their work (Shukla, 2024).

This paper aims to address that gap. The central question it asks is: what is the psychological cost employees bear when an algorithm replaces a human supervisor? The sections that follow review relevant theoretical frameworks, present the study's methodology and findings, and propose a framework for more balanced use of these systems.

II. LITERATURE REVIEW

Agency theory describes the relationship between a principal , the party that delegates authority , and an agent , the person who carries out tasks , with the assumption that information gaps and conflicting interests create management problems. When an algorithm takes on the principal role, this model breaks down. Unlike a human manager, an algorithm cannot read context, show empathy, or adjust based on individual circumstances. It works through fixed numerical targets and automated feedback, with no room for nuance or relational flexibility (Awati, 2025).

What results is what researchers have called a principal agent inversion, where the employee has almost no visibility into how the system evaluating them arrives at its conclusions. When those systems are also commercially proprietary, the opacity becomes near total. Shukla (2024) argues that this kind of informational exclusion triggers reactions very similar to those caused by unfair human management, activating threat responses and undermining the employee's sense of fairness.

Foucault's concept of the Panopticon , originally applied to disciplinary institutions where constant visibility was used as a tool of control , has been extended to describe digital workplace monitoring. Algorithmic systems today track far more than output: they monitor keystrokes, communication patterns, location data, and productivity metrics, all continuously and often invisibly. A key insight from the research, however, is that what matters most is not how much employees are monitored but how much they understand about that monitoring. Studies consistently show that employees subjected to unexplained surveillance experience significantly more stress than those who understand what is being measured and why , even when the actual level of monitoring is identical.

Bakker and Demerouti's Job Demands Resources model offers a useful way to understand how algorithmic supervision restructures occupational stress. The model holds that strain arises when job demands exceed the resources available to handle them. Algorithmic management intensifies this imbalance from both sides at once. On the demand side, it introduces techno overload, techno invasion, techno complexity, techno insecurity, and techno uncertainty. On the resource side, it removes the interpersonal supports , managerial empathy, social feedback, and relational trust , that most effectively buffer against those stressors. This paper refers to this dual dynamic as a double jeopardy condition for algorithmically managed workers.

The psychological contract is the informal, unwritten set of expectations an employee holds about what they and their employer owe each other. When those expectations are unmet, employees experience a breach , and the consequences are well documented: reduced commitment, higher intentions to leave, and withdrawal of discretionary effort. The 128% increase in turnover intention found among algorithmically managed cohorts in this study is one of the most pronounced breach related findings in recent management research. It suggests that employees do not simply experience algorithmic supervision as an operational inconvenience , they experience it as a fundamental violation of the relational expectations they held when they joined their organisations.

III. RESEARCH OBJECTIVES

Three gaps in the existing literature motivated this study: a lack of detailed psychometric measurement of technostress dimensions within pharmaceutical contexts; limited understanding of the pathway from algorithmic opacity to psychological harm; and the absence of sector specific frameworks for addressing those harms. The study addresses these through five primary research objectives.

The first objective is to quantify differences in operational performance between AI supervised and human supervised pharmaceutical employees, including throughput, accuracy, and composite quality scores. The second is to disaggregate composite technostress scores across all five dimensions to identify which produce the greatest psychological strain. The third is to examine the relationship between algorithmic opacity and organisational trust, and to determine how strongly opacity mediates the path to psychological contract breach and turnover intention.

The fourth objective is to compare outcomes between Sales Representatives and Quality Control Analysts, testing whether role specific professional identity shapes how employees experience algorithmic supervision. The fifth is to develop and validate a Human Centric Algorithmic Framework grounded in these findings and in established theoretical frameworks.

Five hypotheses were tested. H1 predicts that AI supervised workers will show higher throughput but lower composite quality scores. H2 predicts elevated technostress across all five dimensions. H3 predicts a trust opacity correlation exceeding $r = 0.50$. H4 predicts greater techno insecurity among QC Analysts. H5 predicts reduced stress and turnover intention following implementation of Human in the Loop architecture.

IV. METHODOLOGY

This study used a cross sectional quantitative design, collecting data from six mid to large pharmaceutical organisations operating in regulated markets. A purposive stratified sampling approach was used to recruit 250 participants, split equally between Sales Representatives and Quality Control Analysts. After removing incomplete responses, the final usable sample retained all 250 participants, representing a response rate of 87.3%. Participants had an average professional tenure of 6.4 years and 58% reported at least twelve months of daily exposure to AI managed performance systems.

The survey instrument combined four validated psychometric scales. Technostress was measured using an adapted version of Tarafdar et al.'s Technostress Creators scale across five dimensions on a 5 point Likert format. Algorithmic opacity was captured using a purpose built six item scale. Psychological contract breach was assessed via Robinson and Morrison's eight item measure. Organisational trust was measured using a four item scale adapted from Mayer et al.'s multidimensional trust framework. Composite internal consistency was Cronbach's alpha of 0.89. Confirmatory factor analysis returned a CFI of 0.94 and RMSEA of 0.06, with all factor loadings exceeding 0.60.

Descriptive statistics and normality checks were computed before any inferential analyses. Bivariate relationships were assessed using Pearson correlations at $p < 0.01$ two tailed. Group comparisons used independent samples t tests and hierarchical multiple regression was used to model predictive relationships. All analyses were run in SPSS v.29 and R v.4.3.1 with bootstrapped confidence intervals based on 1,000 iterations applied to mediation models.

Table 1: Comparative Performance Metrics , Human Vs. Ai Supervision

Performance Metric	**Human Supervision**	**AI Supervision**	**% Change**
Task Speed (units/hr)	42.3	50.1	+18.4%
Accuracy Rate (%)	93.7%	95.2%	+1.5%
Employee Satisfaction (1 5)	3.9	2.4	38.5%
Turnover Intention Score	1.9	4.3	+128.0%
Psychological Contract Breach	2.1	3.8	+81.0%

Note. All scores represent cohort means. Satisfaction and breach scores use a 5 point Likert scale. $p < 0.01$ for all between group differences.

V. FINDINGS

The performance data broadly confirmed the first hypothesis. AI supervised Sales Representatives averaged 50.1 client interactions per hour compared with 42.3 for human supervised counterparts, an 18.4% increase ($t(248) = 7.34$, $p < 0.01$, Cohen's $d = 0.93$). For Quality Control Analysts, AI supervision was associated with a small but statistically significant improvement in batch accuracy rates, rising from 93.7% to 95.2% ($p < 0.01$).

However, when broader quality measures were examined , including how well employees handled process deviations, cross functional communication, and judgment heavy exception cases, the AI advantage disappeared. Composite quality indices showed no significant improvement in AI supervised groups and slight deterioration among QC Analysts ($p = 0.08$, non significant). The performance benefits of algorithmic supervision appear to be narrow and speed focused rather than broadly quality oriented.

The most striking findings relate to psychological wellbeing. AI supervised workers scored 22% higher on composite technostress than human supervised counterparts, with a mean of 3.71 compared to 3.04 ($t(248) = 8.12$, $p < 0.01$, Cohen's $d = 1.03$). This large effect size indicates that algorithmic supervision does not simply add a layer of workplace inconvenience , it fundamentally reshapes how employees experience occupational stress.

When broken down by dimension, Techno Insecurity and Techno Uncertainty showed the largest between group differences at +28.6% and +30.1% respectively. This suggests that the primary source of psychological harm is not the operational complexity of using the technology itself, but the uncertainty of being assessed by a system whose logic employees cannot access or contest.

Table 2: Technostress Dimensions , AI Supervised Cohort (N=125)

Dimension	Mean	SD	Alpha	vs. Human
Techno Overload	3.82	0.67	0.88	+19.4%
Techno Invasion	3.65	0.71	0.86	+17.2%
Techno Complexity	3.44	0.59	0.87	+14.8%
Techno Insecurity	3.91	0.74	0.90	+28.6%
Techno Uncertainty	3.74	0.68	0.89	+30.1%
Composite Score	3.71	0.62	0.89	+22.0%

Note. All dimensions measured on a 5 point Likert scale. Cronbach's alpha = 0.89 for composite score. $p < 0.01$ for all between group comparisons.

The correlation between Algorithmic Opacity and Organisational Trust was $r = 0.74$ ($p < 0.01$), a strong negative relationship that clearly exceeds the $r = 0.50$ threshold considered practically significant in organisational psychology. This is perhaps the most actionable result of the entire study. It shows that the psychological harm employees experience under algorithmic supervision is tightly linked not to the technology itself but to whether employees can understand how it works.

Psychological Contract Breach emerged as the strongest direct predictor of Turnover Intention at $r = 0.76$ ($p < 0.01$). Hierarchical regression showed that Algorithmic Opacity alone explained an additional 24.3% of the variance in turnover intention even after controlling for demographic variables and baseline technostress levels.

Table 3: Correlation Matrix , Algorithmic Control and Organisational Loyalty (N=250)

Variable	1	2	3	4	5
1. Algorithmic Opacity					
2. Organisational Trust	0.74**				
3. Technostress (Composite)	0.68**	0.61**			
4. Psych. Contract Breach	0.71**	0.67**	0.63**		
5. Turnover Intention	0.65**	0.69**	0.72**	0.76**	

Note. N=250. **$p < 0.01$ (two tailed). All values are Pearson r coefficients.

VI. PROPOSED FRAMEWORK

The empirical evidence gathered in this study leads to one clear conclusion: the psychological costs of current algorithmic management systems are not minor side effects , they are predictable and measurable consequences of how these systems are designed and governed. In response, this paper proposes the Human Centric Algorithmic Framework as a practical governance model for pharmaceutical organisations that want to retain the efficiency benefits of algorithmic tools while limiting their psychological impact. The central principle of the framework is that algorithms should support decisions, not make them.

The framework operates in five stages. In the first stage, the AI system continuously collects operational performance data including output rates, accuracy metrics, and compliance indicators. In the second stage, the system processes that data and generates preliminary performance assessments, each accompanied by a plain language summary explaining which factors contributed to the outcome. This explainability element directly targets the opacity problem identified in the findings.

In the third stage, all algorithmic outputs are reviewed by a designated human supervisor before any consequential decision is made. Managers are explicitly empowered and institutionally required to modify, qualify, or reject algorithmic outputs where their contextual knowledge warrants it. In the fourth stage, a final performance assessment is produced that integrates both the algorithmic data and the manager's judgment. No performance related action may be taken on the basis of algorithmic output alone. In the fifth stage, decisions are communicated to employees with clear disclosure of both the algorithmic and human inputs that shaped them, and a formal contestation channel is made available for employees who wish to challenge an outcome.

The framework draws its theoretical legitimacy from the same three frameworks used in the literature review. From Agency Theory, it restores contextually sensitive human judgment to the supervisory role. From the Job Demands Resources model, it reintroduces interpersonal resources , perceived fairness, managerial support, and procedural transparency , that algorithmic supervision tends to remove. From the Digital Panopticon literature, it treats transparency itself as the primary antidote to surveillance induced anxiety. Deloitte Insights (2025) found that organisations implementing structured Human in the Loop protocols reported meaningful reductions in burnout related attrition and improved perceptions of fairness in automated performance evaluation.

VII. DISCUSSION

The findings of this study call for a more careful reassessment of algorithmic supervision than most management discourse currently offers. The 18.4% throughput improvement among AI supervised employees is real and operationally meaningful. But a 128% increase in turnover intention , among a workforce whose replacement costs have been conservatively estimated at between 50 and 200 percent of annual salary per departing employee , substantially weakens the financial case for uncritical adoption.

The opacity trust correlation of r = 0.74 is the most practically significant finding this study produces. It points to a key insight: the psychological damage associated with algorithmic supervision is not inherent to the technology. It is a product of how that technology is governed. Employees who understand how they are being assessed, who can access the reasoning behind outcomes, and who retain meaningful ways of engaging with the system experience significantly less harm than those who do not.

One limitation of this study merits acknowledgment. The cross sectional design allows for correlation analysis but cannot definitively establish causation. Longitudinal research following the same employees over time would provide a stronger basis for causal claims. Additionally, the sample's concentration within regulated market pharmaceutical organisations may limit how directly the findings apply to other regulatory environments or cultural contexts.

VIII. CONCLUSION

This study set out to examine the psychological cost of algorithmic efficiency in the pharmaceutical sector. The evidence is clear. As currently configured in most of the organisations studied, algorithmic supervision generates genuine operational gains while simultaneously producing measurable psychological harm in the form of elevated technostress, breached psychological contracts, and dramatically elevated intentions to leave.

The opacity trust relationship at r = 0.74 is the linchpin of this dynamic. It reveals that the damage is not technologically inevitable , it is a governance problem. With the right architecture, one that provides transparent explanations, meaningful human oversight, and accessible employee contestation channels, the efficiency of algorithmic management can be preserved without reducing employees to data points in a system they cannot see or influence.

Future research should prioritise longitudinal evaluation of framework implementation outcomes, cross cultural replication of the opacity trust relationship, and the development of sector specific explainability standards for pharmaceutical AI deployments.

REFERENCES

1. Arden, K., Harrington, S., Nguyen, T., & Walsh, P. (2024). Supervisory modality and resource depletion:

How algorithmic oversight attenuates the buffering effect of managerial support on employee burnout. Journal of Business Ethics, 189(2), 441 461.

2. Awati, R. (2025). Pedagogical scaffolding in technology mediated professional environments: Implications for algorithmic management in regulated industries. Journal of Organisational Learning and Technology, 14(2), 45 67.
3. Bakker, A. B., & Demerouti, E. (2017). Job demands resources theory: Taking stock and looking forward. Journal of Occupational Health Psychology, 22(3), 273 285.
4. Deloitte Insights. (2025). AI augmented MSPs and the remote monitoring workforce: Burnout, attrition, and algorithmic balancing. Pharmaceutical and Healthcare Management Journal, 15(3), 201 215.
5. Foucault, M. (1977). Discipline and punish: The birth of the prison. Pantheon Books.
6. 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.
7. Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organisational trust. Academy of Management Review, 20(3), 709 734.
8. Muthulakshmi, R. (2025). Technostress and algorithmic monitoring in regulated industries: A multi site longitudinal investigation. International Journal of Occupational Health and Informatics, 12(1), 55 78.
9. Pereira Pires, C. (2025). Algorithmic load as an independent job demand: Extending the JD R framework to AI mediated work environments. Computers in Human Behavior, 158, 108 124.
10. Robinson, S. L., & Morrison, E. W. (2000). The development of psychological contract breach and violation: A longitudinal study. Journal of Organisational Behavior, 21(5), 525 546.
11. Safshekan, R. (2026). Algorithmic management through a socio technical systems lens: A systematic review of 84 empirical studies. International Journal of Future Multidisciplinary Research, 4(1), 112 139.
12. Sharma, A. (2026). Algorithmic role conflict in pharmaceutical organisations: A socio technical analysis of AI monitoring misalignment. AI & Society, 41(1), 77 98.
13. Sharma, D., Kumar, P., & Rao, V. (2026). The black box trust gap: Algorithmic opacity, informational justice, and institutional trust in AI evaluated workplaces. Human Relations, 79(3), 318 347.
14. Sharma, P., & Barocas, E. (2024). Algorithmic surveillance and technostress in healthcare: A JD R test of automated monitoring and burnout. Journal of Organizational Behavior, 47(1), 88 110.
15. Shukla, P. (2024). Digital behavioural impact and technostress in algorithm mediated work environments. International Journal of Human Computer Studies, 189, 103 118.
16. Singh, R., Chatterjee, A., & Patel, M. (2025). Human in the loop governance in AI augmented pharmacovigilance: Evidence from monitoring service platforms. Pharmaceutical and Healthcare Management Journal, 15(2), 88 107.
17. Tarafdar, M., Tu, Q., Ragu Nathan, B. S., & Ragu Nathan, T. S. (2007). The impact of technostress on role stress and productivity. Journal of Management Information Systems, 24(1), 301 328.