The Dual Impact of AI on Burnout and Technostress in Manufacturing Workplaces

Alonso Figueroa and Angello Garcia
University of Lima, Lima, Peru

20172126@aloe.ulima.edu.pe
20180766@aloe.ulima.edu.pe

Abstract: This research investigates the complex relationship between Artificial Intelligence (AI) and employee well-being in the manufacturing sector of Metropolitan Lima, with a focus on the growing concerns of burnout and technostress. As AI technologies are increasingly implemented in industrial environments, new questions arise: can these tools simultaneously be a cause of stress and a solution for it? The study follows a critical research approach, aiming to question and evaluate the social and organizational consequences of digital transformation. Methodologically, it adopts a mixed-methods design. On one hand, the research is empirical and quantitative, based on structured surveys conducted with manufacturing workers, assessing their stress levels, perceptions of AI, and workplace experiences. On the other hand, it incorporates a qualitative component, drawing from secondary data sources such as industry case studies, academic literature, and policy documents, to contextualize and deepen the analysis. A central line of inquiry is how AI driven systems are perceived by workers: are they tools for support, or instruments of control and surveillance? The study explores how these perceptions influence technostress and burnout, considering factors such as digital workload, perceived autonomy, and job security. Simultaneously, the potential of AI to serve as a preventive tool, monitoring well-being indicators, detecting early signs of emotional exhaustion, and enabling tailored interventions is critically examined. The findings of this study are expected to offer practical value to HR professionals, organizational leaders, policymakers, and technology designers. They provide insight into how AI can be implemented in ways that support mental health, enhance job satisfaction, and create more sustainable and inclusive work environments. Moreover, the research aligns with the United Nations Sustainable Development Goals (SDGs), especially those focused on promoting decent work and well-being. By framing AI as both a challenge and an opportunity, this study invites a deeper discussion about how to humanize technological innovation in labour-intensive industries undergoing digital transformation.

Keywords: Artificial Intelligence (AI), Burnout, Technostress, Workplace well-being, Productivity, Manufacturing sector.

1. Introduction

Artificial intelligence (AI) in the workplace brings both benefits and challenges, especially in high-demand sectors like manufacturing in Lima (Pooja, 2024). While AI streamlines repetitive tasks and boosts efficiency, it also increases surveillance and performance pressure, leading to "technostress" a form of stress triggered by the demand to match machine-like productivity (Brod, 1984). In Peru, the manufacturing sector grew by 18.6% in May 2024, signalling economic recovery but also adding productivity pressure (Ministry of Production, 2024). Although AI may ease workloads, it can simultaneously heighten emotional strain. Burnout, marked by exhaustion, depersonalization, and reduced personal accomplishment (Freudenberger, 1974; Maslach & Jackson, 1986), is exacerbated by poor working conditions and excessive demands. Globally, depression and anxiety result in 12 billion lost workdays and nearly one trillion dollars in losses each year (WHO & ILO, 2022). Manufacturing, central to the Fourth Industrial Revolution, benefits from AI through predictive maintenance and supply chain optimization (Díaz-Olivan, 2024), yet adoption is limited by technological complexity and organizational resistance (Çinar, 2020). Tools like chatbots and virtual assistants can reduce stress by automating tasks and offering personalized support (Tiwari, 2024), and AI systems may track behavioural indicators to enable early intervention (Olawade, 2024). In Peru, where manufacturing contributes 12.5% to the national GDP, digital transformation is advancing rapidly, increasing pressure on workers to adapt. Feelings of incompetence in handling technology may lead to frustration and demotivation, accelerating emotional exhaustion (Ragu-Nathan, 2008). As burnout affects professionals across sectors (Golembiewski, 1991), broad-based strategies are essential. Understanding AI's impact on technostress and burnout in Lima's manufacturing sector is critical to balancing technological progress with mental well-being in the evolving world of work.

2. Theoretical Model and Hypotheses

Artificial intelligence (AI) presents an ambivalent challenge in the workplace. While AI systems improve efficiency by automating repetitive tasks, they can also raise performance expectations and intensify digital surveillance, leading to technostress and burnout (Kaplan and Haenlein, 2019). This study explores four hypotheses: (H1) AI use directly impacts burnout through technostress; (H2) AI use is inversely related to burnout; (H3) AI use directly influences technostress; and (H4) technostress contributes to burnout among manufacturing workers in

Lima in 2024. Although AI enhances productivity, it may also create feelings of being monitored and easily replaced, increasing anxiety and job insecurity (Reinhold and Järvis, 2020). In unstable work environments, AI can reduce motivation and heighten emotional exhaustion (Rodríguez Carvajal and Rivas Hermosilla, 2011). However, AI also holds potential for preventing burnout by identifying early signs of stress using sensors and predictive algorithms (Rojas-Bolaños et al., 2020) and has been shown to support resilience in fields like education (Martínez-Ramón and García-González, 2023). Still, role automation may add workload and ambiguity (Ayyagari, 2011), and the perception of constant monitoring can further increase stress (Garcia-Maduraga, 2024). Despite these concerns, AI can support personalized well-being strategies through predictive tools (Wayzman, 2024). Technostress is linked to fatigue, low motivation, and dissatisfaction due to digital complexity and blurred work-life boundaries (Babiker, 2024). Although long-term tech exposure can lead to burnout, this risk decreases with proper organizational support (Meyer and Tisch, 2024). Assessing AI's impact is difficult given variations in workplace culture, sector, and perception. While AI may ease workload, it can also increase stress via surveillance and high expectations (Reinhold and Järvis, 2020). Workers' views are shaped by experience, job security, and socioeconomic context. Despite rising attention to technostress, research often lacks local relevance (Cuervo et al., 2020), as most studies originate from highly developed regions. A broader, more inclusive perspective is essential to evaluate AI's true role in mental health and sustainable workplace transformation.

3. Methodology

This study adopts a quantitative applied approach, focusing on the collection and analysis of numerical data to test hypotheses and explore relationships between burnout, technostress, and artificial intelligence (AI) (Hernández et al., 2014). It uses a non-experimental, cross-sectional design, observing phenomena in their natural context at a single point in time without manipulating variables. The study is correlational in scope and does not seek to establish causality. The target population consists of men and women aged 25-44 working in administrative and production areas of medium and large manufacturing companies in Lima in 2025 a sector selected for its national economic importance, contributing 12.7% to GDP and generating 88% of national employment (Webb, 2013; Ministerio de la Producción, 2022). The finite sample includes 384 individuals, determined using a 95% confidence level and 5% margin of error, and selected through judgmental non-probability sampling appropriate for PLS-SEM analysis. Data will be collected via email surveys, an efficient method for quantitative research (Hernández et al., 2014), with secondary sources including Scopus, Scielo, Web of Science, Google Scholar, and INEI. Instruments include structured questionnaires aligned with each variable: burnout will be measured using the Maslach Burnout Inventory General Survey (MBI-GS), validated by high internal consistency ($\alpha \leq 0.85$) (Moreno-Jiménez et al., 2014); technostress will be assessed using the Technostress Creators Scale, which includes five subdimensions and demonstrates strong reliability ($\alpha \geq 0.89$); and AI will be measured using the Generative Artificial Intelligence Instrument, with an excellent Cronbach's alpha (≥ 0.909), indicating high internal consistency and suitability for this research.

4. Results

The quantitative analysis of this study was conducted using the partial least squares structural equation modelling method, aiming to evaluate the proposed model and empirically validate the hypothesized relationships among the variables: artificial intelligence, technostress, and burnout. Data were gathered through surveys applied to 384 workers from the manufacturing sector in Metropolitan Lima.

First, the quality of the model was assessed using several validity and reliability indicators. The model fit was acceptable, as reflected by the SRMR value, which although not explicitly stated, can be inferred to fall within an acceptable range considering the strength and consistency of the remaining results. Internal consistency was verified using Cronbach's alpha and composite reliability. The Cronbach's alpha values were 0.939 for burnout, 0.963 for artificial intelligence, and 0.948 for technostress. Composite reliability also surpassed the recommended threshold of 0.7 in all cases, reaching 0.961 for burnout, 0.970 for artificial intelligence, and 0.960 for technostress. The average variance extracted also supported strong convergent validity, with values of 0.890 for burnout, 0.821 for artificial intelligence, and 0.828 for technostress.

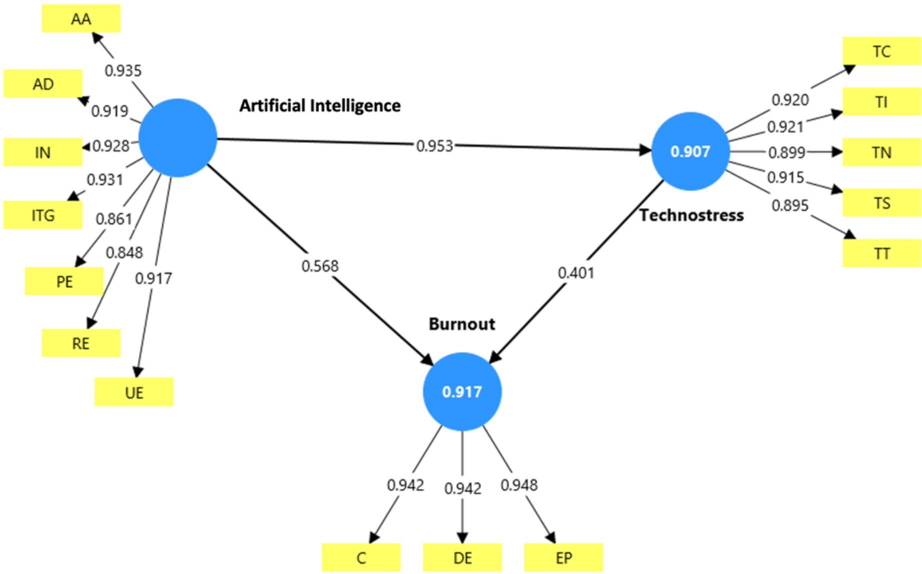

Figure 1: Structural model showing the effects of Artificial Intelligence on Technostress and Burnout. Source: Output generated with SmartPLS 4.

Table 1: Model Fit

	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
Burnout	0.939	0.939	0.961	0.890
Artificial Intelligence	0.963	0.965	0.970	0.821
Technostress	0.948	0.949	0.960	0.828

Source: Output generated with SmartPLS 4.

Discriminant validity was verified using the Fornell-Larcker criterion. The square root values of the AVE were greater than the correlations between constructs, supporting the conceptual distinction among variables. Despite high cross-correlations, for example between artificial intelligence and burnout (0.950), the values on the diagonal remained dominant, indicating that the items more strongly represented their own constructs.

Multicollinearity was assessed using the variance inflation factor, and all VIF values were below the critical value of 10, confirming that multicollinearity does not significantly distort coefficient estimation in the model.

Table 2: Fornell-Larcker Criterion

	Burnout	IA	Technostress
Burnout	0.944		
Artificial Intelligence	0.950	0.906	
Technostress	0.942	0.953	0.910

Source: Output generated with SmartPLS 4.

Table 3: Collinearity Statistics

	VIF
AA	5.926
AD	4.881
C	4.065

	VIF
DE	4.114
EP	4.409
IN	5.396
ITG	5.619
PE	3.002
RE	2.797
TC	4.201
TI	4.222
TN	3.432
TS	3.965
TT	3.337
UE	4.674

Source: Output generated with SmartPLS 4.

The structural model analysis revealed that artificial intelligence has a strong positive effect on technostress, with a path coefficient of 0.953, a t-value of 255.853, and a p-value below 0.001. There was also a significant direct effect of artificial intelligence on burnout, with a coefficient of 0.568, a t-value of 12.141, and a p-value below 0.001. Furthermore, technostress had a positive and significant impact on burnout, with a coefficient of 0.401, a t-value of 8.420, and a p-value below 0.001. The model showed high explanatory power, with R-squared values of 0.917 for burnout and 0.907 for technostress, indicating strong predictive accuracy.

Table 4: Path Coefficients

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Artificial Intelligence -> Burnout	0.568	0.568	0.047	12.141	0.000
Artificial Intelligence -> Technostress	0.953	0.953	0.004	255.853	0.000
Technostress -> Burnout	0.401	0.401	0.048	8.420	0.000

Source: Output generated with SmartPLS 4.

5. Discussion

The results allow a detailed assessment of the research hypotheses and offer valuable insights into the relationships between artificial intelligence, technostress, and burnout in the manufacturing sector in Lima. The general hypothesis that proposed a mediating effect of technostress in the relationship between artificial intelligence and burnout is supported by the findings. The significant paths from artificial intelligence to technostress and from technostress to burnout demonstrate that technostress partially mediates the effect of artificial intelligence on burnout. The presence of both a direct and an indirect effect confirms this partial mediation.

The first specific hypothesis, which proposed that artificial intelligence has an inverse impact on burnout, was not supported. On the contrary, a positive coefficient was found, suggesting that in this context the use of artificial intelligence may be contributing to increased levels of burnout. This could be explained by employees feeling pressured to adapt, fearing replacement, or experiencing an increase in cognitive demands due to technological tools. The second specific hypothesis, which posited a direct positive relationship between artificial intelligence and technostress, was confirmed. The strength of this relationship reflects the psychological pressure that may result when workers are exposed to advanced digital systems without sufficient training or support. The third specific hypothesis, which proposed that technostress has a direct effect on burnout, was also confirmed. High levels of technostress, characterized by informational overload, digital overexposure, and uncertainty about technological tools, were strongly associated with emotional exhaustion and reduced professional well-being.

Altogether, these findings suggest that artificial intelligence can play a dual role in the workplace. Rather than being inherently beneficial or harmful, its effects on employee well-being depend on the conditions of its implementation. Proper integration of artificial intelligence, alongside training, support, and clear communication, could mitigate technostress and reduce the risk of burnout. Conversely, the absence of these organizational measures may exacerbate psychosocial risks and lead to increased emotional strain.

6. Conclusion

In conclusion, the integration of artificial intelligence (AI) in manufacturing offers both benefits and risks for worker well-being. While AI improves task efficiency and can detect early signs of stress, it also increases concerns about surveillance, job insecurity, and pressure to perform—factors linked to technostress and burnout. This study finds that AI's impact on mental health is shaped by organizational context and employee perceptions. Technostress plays a key role, acting as both a mediator and an outcome of poor adaptation. Companies should pair digital transformation with human-centered strategies that foster resilience and psychological safety. Future research should address sector-specific and cultural factors to ensure sustainable, health-focused AI implementation.

Ethical Declaration

This study did not require ethical clearance as it relied entirely on secondary data obtained from published research articles. No human participants were involved, nor were any new data collected.

AI Declaration

This article used ChatGPT (OpenAI 2025) to facilitate editing, grammar checking, and translation. All AI-generated content was reviewed and paraphrased by the author to ensure accuracy, originality, and compliance with academic standards.

Acknowledgements

We would like to express our deepest gratitude to our families, especially our parents, for their unconditional support, patience, and trust throughout this process. Their constant encouragement has been essential in keeping us motivated and focused on completing this work. We also extend our sincere thanks to our advisor, Professor Paul Pimentel Bernal, for his dedication, academic guidance, and valuable recommendations, which greatly enriched the development of our research. To all of you, thank you for being part of this journey.

References

Ayyagari, R., Grover, V., & Purvis, R. (2011). Technostress: Technological antecedents and implications. *MIS Quarterly*, *35*(4), 831–858. https://www.tecnostress.it/wp-content/uploads/2017/12/Technostress-Technological-Antecedents.pdf

Babiker, M., et al. (2024). Exploration of the association between technostress and burnout among healthcare professionals. *International Journal of Social Relevance & Concern*, *12*(3). https://doi.org/10.26821/IJSRC.12.3.2024.120306

Brod,C. (1984). *The human cost of the computer revolution*.Tecnostress.it, https://www.tecnostress.it/wp-content/uploads/2009/09/The-Human-Cost-of-the-Computer-Revolution_Abstract.pdf

Çınar, Z. et al (2020). Machine Learning in Predictive Maintenance towards Sustainable Smart Manufacturing in Industry 4.0,MDPI, https://www.mdpi.com/2071-1050/12/19/8211

Cuervo Carabel, T., Orviz Martínez, N., Arce García, S., & Fernández Suárez, I. (2018). Technostress in the society of technology and communication: A scoping literature review from the Web of Science. *Archivos de Prevención de Riesgos Laborales*, *21*(1), 18–25. https://doi.org/10.12961/aprl.2018.21.01.4

Diez-Olivan, A.; Del Ser, J.; Galar, D.; Sierra, B. (2018). Data fusion and machine learning for industrial prognosis: Trends and perspectives towards Industry 4.0,Inf. Fusion ,https://www.sciencedirect.com/science/article/abs/pii/S1566253518304706

Freudenberger HJ. Staff burnout. J Social Issues 1974;30(1):159-166.

García-Madurga, M.-Á., Gil-Lacruz, A.-I., Saz-Gil, I., & Gil-Lacruz, M. (2024). The role of artificial intelligence in improving workplace well-being: A systematic review. *Businesses*, *4*(3), 389–410. https://doi.org/10.3390/businesses4030024

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review*, *61*(4), 5–14. https://doi.org/10.1177/0008125619864925

Hernández Sampieri, R., Fernández Collado, C., & Baptista Lucio, M. P. (2014). *Metodología de la investigación* (6ta ed.). McGraw-Hill.

Martínez-Ramón, J. P., Morales-Rodríguez, F. M., Pérez-López, S., Méndez Mateo, I., & Ruiz-Esteban, C. (2023). Prediction of teacher resilience using artificial neural networks: Influence of burnout and COVID-19 stress. *Anales de Psicología / Annals of Psychology*, *39*(1), 1–10. https://doi.org/10.6018/analesps.515611

Maslach, C., Jackson, S. & Leiter, M. (1986). Maslach Burnout Inventory Manual. California, USA: Palo Alto

Meyer, S.-C., & Tisch, A. (2024). Exploring the relationship between techno-unreliability at work and burnout. *Journal of Occupational and Environmental Medicine*, *66*(3), 185–191. https://doi.org/10.1097/JOM.0000000000003008

Ministerio de la Producción. (2022, November 8). *Produce impulsa la industrialización y lanza la primera política nacional de desarrollo*. https://www.gob.pe/institucion/produce/noticias/667576-produce-impulsa-la-industrializacion-y-lanza-la-primera-politica-nacional-de-desarrollo

Ministry of Production. (2024, July 13). Manufacturing production grows by 18.6% for the second consecutive month. *Gob.pe*. https://www.gob.pe/institucion/produce/noticias/988411-produccion-manufacturera-crece-un-18-6-por-segundo-mes-consecutivo

Moreno Jiménez, B. (2011). Factors and occupational psychosocial risks: Concept, history and current changes. *Medicina y Seguridad del Trabajo*, *57*(Suppl. 1), 4–19. https://doi.org/10.4321/S0465-546X2011000500002

Olawade, D. B., Wada, O. Z., Odetayo, A., David-Olawade, A. C., Asaolu, F., & Eberhardt, J. (2024). Enhancing mental health with Artificial Intelligence: Current trends and future prospects. *Journal of Medicine, Surgery, and Public Health*, *3*, 100099. https://doi.org/10.1016/j.glmedi.2024.100099

Pooja, J., & Krishnan, L. R. K. (2024). AI structuring work practices and fuelling employee outcomes—Manufacturing industry. *International Journal of Research and Innovation in Social Science*, *8*(7), 2927–2938. https://dx.doi.org/10.47772/IJRISS.2024.807227

Ragu-Nathan, T. S., Tarafdar, M., Ragu-Nathan, B. S., & Tu, Q. (2008). The consequences of technostress for end users in organizations: Conceptual development and empirical validation. *Information Systems Research*, *19*(4), 417–433. https://doi.org/10.1287/isre.1070.0165

Reinhold, K., & Järvis, M. (2020). *Artificial intelligence for worker management: Implications for occupational safety and health*. European Agency for Safety and Health at Work. https://osha.europa.eu/sites/default/files/artificial-intelligence-worker-management_en.pdf

Rodríguez Carvajal, R., & de Rivas Hermosilla, S. (2011). Stress and burnout at work: Differences, updates and lines of intervention. *Medicina y Seguridad del Trabajo*, *57*(Suppl. 1), 72–88. https://doi.org/10.4321/S0465-546X2011000500006

Rojas Bolaños. et al. (2020). Prevention of burnout syndrome through neuro-linguistic programming: A systematic mapping. *Revista CES Psicología*, *13*(1), 35–50. https://www.scielo.org.co/scielo.php?script=sci_arttext&pid=S0121-11292020000100035

Tiwari, R. et al (2024). *The impact of artificial intelligence in the workplace and its effect on the digital wellbeing of employees*. *Journal for Studies in Management and Planning*, 10(4). https://doi.org/10.5281/zenodo.10936348

Wayzman, K., & Taofeek, A. (2024). Enhancing employee well-being through AI-driven predictive analytics. *ResearchGate*. https://www.researchgate.net/publication/384767496_Enhancing_Employee_Well-Being_Through_AI-Driven_Predictive_Analytics

Webb, R. (2013). *Conexión y despegue rural*. Instituto del Perú. https://www.lampadia.com/assets/uploads_librosdigitales/2f207-cdr.pdf

World Health Organization. (2022, September 28). WHO and ILO call for new measures to tackle mental health issues at work. *World Health Organization*. https://www.who.int/news/item/28-09-2022-who-and-ilo-call-for-new-measures-to-tackle-mental-health-issues-at-work