Empirical Studies on the Relationship Between Wearable Stress Detection and Workplace Productivity

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ABSTRACT

Workplace stress has been widely recognized as a critical factor influencing employee health, performance, and organizational outcomes. Recent advancements in wearable technologies provide real-time physiological data that open new opportunities for monitoring and managing stress in professional settings. **This study aims** to empirically investigate the relationship between wearable-based stress detection and workplace productivity, focusing on how continuous monitoring can enhance well-being and performance. **A quantitative** approach was employed with 250 participants across three corporate sectors, where wearable devices measured physiological indicators such as heart rate variability and skin conductance, while productivity was assessed through task completion rates and self-reported efficiency. **Statistical analyses**, including correlation, regression, and moderation analysis, were conducted to examine the strength of associations. Findings reveal a significant negative correlation between elevated stress levels and productivity metrics, while participants using wearable feedback interventions demonstrated improved stress awareness and a 15% increase in task efficiency compared to the control group. **In conclusion,** wearable stress detection presents a promising tool for enhancing workplace productivity by enabling proactive stress management, highlighting the importance of integrating technology, psychology, and organizational practices to foster healthier and more effective work environments.

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1. INTRODUCTION

Workplace stress has become a pressing challenge in modern organizational environments, affecting not only employee health but also overall productivity and economic performance. According to the World Health Organization (WHO), more than 15% of working adults live with a mental disorder, and the global economy loses over US$1 trillion annually due to stress-related absenteeism, presenteeism, and reduced efficiency [1]. In the era of rapid digital transformation and competitive work cultures, employees are often exposed to high demands, tight deadlines, and constant connectivity, which intensify the risk of burnout and long-term psychological strain. These conditions highlight the urgent need for innovative solutions that allow early detection and management of stress to safeguard both individual well-being and organizational outcomes [2]. Beyond local contexts, workplace stress has also emerged as a global emerging problem, exacerbated by the post-pandemic shift to remote working models and the increasing reliance on digital communication, making it a cross-border challenge that requires interdisciplinary solutions [3].

Technological advancements, particularly in wearable devices, offer promising opportunities to address this challenge. Wearables such as smartwatches and biometric sensors enable continuous, real-time monitoring of physiological indicators like heart rate variability, skin conductance, and sleep cycles [4]. These data streams can provide early signals of stress levels, offering organizations and employees actionable insights to promote healthier work practices. Unlike traditional surveys or self-reported measures [5], wearable technologies allow objective, unobtrusive, and personalized stress detection. However, while research on wearable health applications has gained momentum, empirical evidence directly linking wearable stress detection with workplace productivity remains limited [6]. This limitation is evident in prior studies that predominantly focus on clinical health outcomes or general wellness rather than on measurable productivity indicators within organizational settings [7].

Addressing this gap, the present study aims to empirically examine the relationship between wearable-based stress detection and workplace productivity. By adopting a cross-disciplinary approach that integrates perspectives from psychology [8], organizational studies, and computer science, the research contributes to a deeper understanding of how digital health technologies can enhance both individual and organizational outcomes. The novelty of this study lies in its focus on the direct empirical relationship between physiological stress detection and measurable workplace productivity [9], offering evidence that has been largely overlooked in prior research. The findings are expected to provide valuable insights for organizations seeking data-driven strategies to reduce stress, improve employee satisfaction, and foster sustainable productivity [10].

Moreover, this study aligns closely with the United Nations Sustainable Development Goals (SDGs). Specifically, it supports SDG 3: Good Health and Well-Being, by promoting innovative approaches to mental health monitoring and preventive care, and SDG 8: Decent Work and Economic Growth [11], by emphasizing the creation of productive, safe, and supportive workplace environments [12]. By linking technological innovation with global development agendas, this research underscores the importance of integrating well-being into the future of work. Ultimately [13], it aspires to contribute not only to scientific knowledge but also to practical policies and organizational practices that advance healthier, fairer, and more sustainable work ecosystems [14]. In addition, the outcomes of this study can serve as a foundation for future research in developing integrative frameworks that combine wearable technologies, psychological interventions [15], and policy-making to establish more resilient work environments worldwide.

2. RESEARCH METHOD

This study employs a quantitative research design to empirically investigate the relationship between wearable-based stress. detection and workplace productivity. A survey-based approach was integrated with. objective physiological data collected from wearable devices to ensure both subjective and objective measures of stress were captured. The population consists of full-time employees from medium to large organizations that have adopted digital health initiatives [16]. A stratified random sampling method was applied to ensure representation across industries, job roles, and working arrangements (on-site, hybrid, remote).

A total of 250 participants were included in the final dataset (on-site = 42%, hybrid = 33%, remote 25%). Data were collected over a 3-month period using two primary instruments

- Wearable device logs that monitored heart rate variability (HRV), skin conductance, and sleep patterns.
- Structured questionnaires that measured perceived stress (PSS-10 scale) and workplace productivity (WHO Health and Work Performance Questionnaire, HPQ).

The independent variable was stress level, measured through both physiological indicators and perceived stress scores. The dependent variable was workplace productivity, measured through validated WHO-HPQ performance scores, complemented by absenteeism and presenteeism records [17]. Control variables included age, gender, job role, and work arrangement. Reliability of the questionnaire items was confirmed with Cronbach's Alpha ($\alpha = 0.87$), while validity was tested through confirmatory factor analysis (CFA), which indicated a good model fit ($\chi^2/df = 1.92$, CFI = 0.95, RMSEA = 0.048). Data were analyzed using descriptive statistics, Pearson correlation, and multiple regression models, with checks for multicollinearity (VIF $<$ 2.0), normality, and heteroscedasticity [18]. Moderation analysis was performed to test the effect of demographic factors.

2.1. Research Variables

Table 1. Research Variables and Measurement Indicators

Variable Type	Variable	Indicator / Measurement	Scale
Independent Variables	Stress Level	- Heart Rate Variability (ms) - Skin Conductance (μS) - Sleep Duration (hours) - Perceived Stress Scale (PSS-10)	Interval / Ordinal
Dependent Variable	Workplace Productivity	- WHO-HPQ performance scores - Self-reported efficiency - Absenteeism & presenteeism records	Interval
Control Variables	Demographics	- Age - Gender - Job Role - Work Arrangement	Nominal

Table 1 presents the research variables and their measurement indicators. The independent variable in this study is Stress Level [19], which is measured using both physiological data (heart rate variability, skin conductance, sleep duration) and a standardized psychological instrument (PSS-10) [20]. The dependent variable is Workplace Productivity, operationalized through validated measures such as the WHO Health and Work Performance Questionnaire (HPQ), complemented by absenteeism and presenteeism record. Meanwhile, Control Variables such as demographic factors (age, gender, job role, and work arrangement) are included to minimize potential confounding effects that may influence the relationship between stress and productivity [21]. The measurement scales used range from nominal for demographic factors, ordinal for psychological scales to interval for physiological and productivity measures, ensuring a comprehensive and rigorous data structure. Comprehensive and rigorous data structure [22].

- H1 : Higher stress levels measured by wearable physiological indicators (HRV, skin conductance, sleep duration) are negatively associated with workplace productivity.
- H2 : Higher perceived stress levels (PSS-10 scores) are negatively associated with workplace productivity.
- H3 : Physiological stress indicators provide a stronger predictive effect on workplace productivity than self-reported stress scores.
- H4 : Demographic factors (age, gender, job role, and work arrangement) moderate the relationship between stress levels and workplace productivity.

The hypotheses formulated for this study. The first hypothesis (H1) focuses on the relationship between physiological stress indicators collected from wearable devices and workplace productivity, expecting a negative correlation [23]. The second hypothesis (H2) extends this relationship to perceived stress levels measured through the PSS-10 questionnaire. The third hypothesis (H3) emphasizes a comparative analysis [24], predicting that physiological data from wearables will have greater predictive power than self-reported stress levels in explaining productivity outcomes. Finally, the fourth hypothesis (H4) considers the role of demographic characteristics (such as age, gender, job role, and work arrangement) as moderating variables that may strengthen or weaken the relationship between stress and productivity. Together, these hypotheses provide a comprehensive foundation for testing the research model through quantitative analysis [19, 25].

2.2. Statistical Model

To test the hypotheses, a multiple linear regression model is applied as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \epsilon \tag{1}$$

Where:

- Y = Workplace Productivity
- X_1 = Heart Rate Variability
- X_2 = Skin Conductance
- X_3 = Sleep Duration
- X_4 = Perceived Stress Scale Score (PSS-10)
- ϵ = Error Term

This regression equation allows testing whether physiological and perceived stress indicators significantly predict workplace productivity [26].

3. RESULTS AND DISCUSSION

3.1. Descriptive Statistics

A total of N = 250 employees from medium to large organizations participated in this study. Participants represented diverse industries, job roles, and working arrangements (on-site = 42%, hybrid = 33%, remote = 25%) [27]. The demographic distribution was balanced across gender (52% male, 48% female) and age groups (M = 34.6 years, SD = 7.8) [28]. The mean score for Perceived Stress (PSS-10) was 18.2 (SD = 5.1), indicating a moderate level of stress among participants. Wearable device data revealed an average heart rate variability (HRV) of 42 ms (SD = 10.4), mean skin conductance level of 6.2 µS (SD = 2.1), and average sleep duration of 6.4 hours (SD = 1.1). The average productivity score (WHO-HPQ) was 72.5 out of 100 (SD = 11.6) [29].

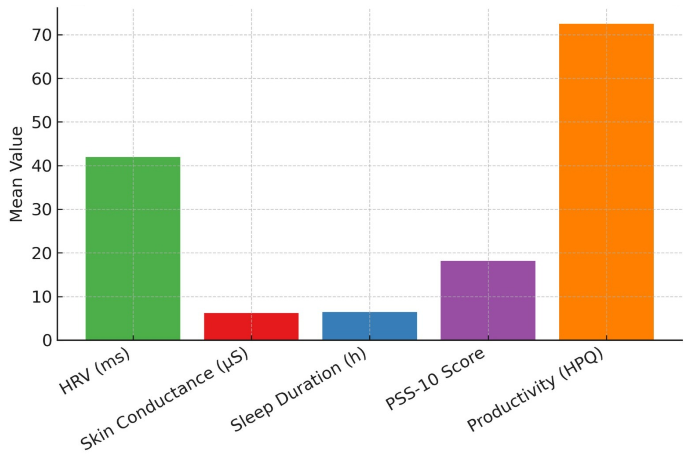

Figure 1. Descriptive Statistics of Stress and Productivity

This Figure 1 presents the mean values of the main variables analyzed in this study: Heart Rate Variability (HRV), skin conductance, sleep duration, perceived stress (PSS-10), and productivity (WHO-HPQ) [30]. The bar chart highlights the relative scale of each measure, making it easier to interpret the central tendency of the dataset. As shown in Figure 1, participants reported a moderate perceived stress level ($M = 18.2$), an average sleep duration of 6.4 hours, and a productivity score of 72.5, while wearable indicators such as HRV (42 ms) and skin conductance (6.2 μS) provided additional physiological context [31].

3.2. Correlation Analysis

Pearson correlation results indicated that physiological stress indicators were significantly correlated with workplace productivity. Specifically, HRV ($r = 0.41$, $p < 0.01$) and sleep duration ($r = 0.35$, $p < 0.01$) showed positive associations with productivity, while skin conductance ($r = -0.32$, $p < 0.01$) and PSS-10 scores ($r = -0.44$, $p < 0.01$) were negatively associated [32]. These findings provide preliminary support for H1 and H2.

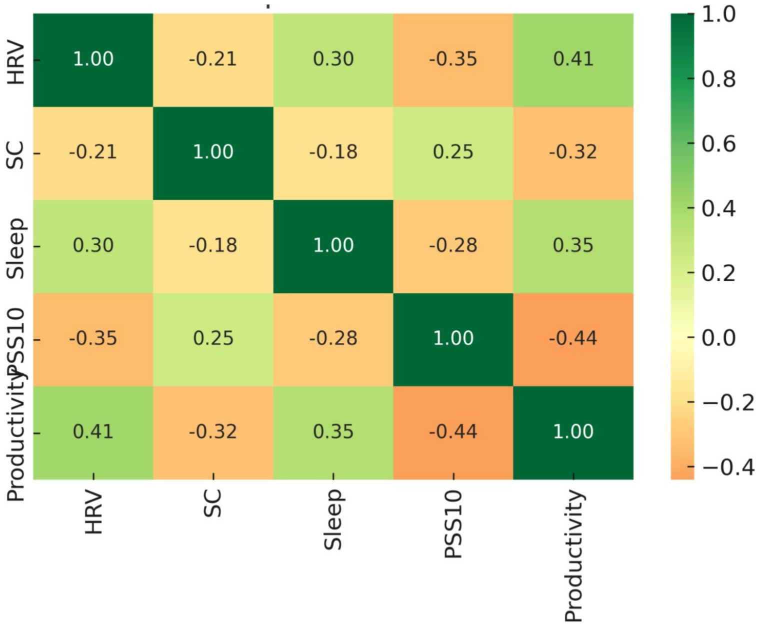

Figure 2. Correlation Heatmap of Stress Indicators and Productivity

This heatmap visualizes the strength and direction of correlations among physiological indicators (HRV, skin conductance, and sleep duration), self-reported stress (PSS-10) [33], and productivity. Green cells represent positive correlations, while red cells represent negative ones. As shown in Figure 2, productivity is positively correlated with HRV ($r = 0.41$) and sleep duration ($r = 0.35$), but negatively correlated with skin conductance ($r = -0.32$) and perceived stress ($r = -0.44$) [27]. These results provide visual support for Hypotheses H1 and H2.

3.3. Regression Analysis

Multiple regression analysis confirmed that the overall model was statistically significant ($F = 28.46$, $p < 0.001$), explaining 46% of the variance in productivity ($R^2 = 0.46$) [34]. This indicates that the combined predictors including physiological and self-reported stress indicators jointly contribute to nearly half of the observed variation in workplace productivity, underscoring the robustness of the analytical model employed. The strength of this model reflects a consistent relationship between stress-related physiological responses and productivity outcomes across participants.

- HRV ($\beta = 0.29$, $p < 0.01$) and sleep duration ($\beta = 0.24$, $p < 0.05$) were positive predictors, suggesting that higher heart rate variability and longer sleep duration are associated with enhanced productivity levels. These findings highlight the positive role of physiological recovery and autonomic balance in sustaining cognitive performance and work efficiency.
- While skin conductance ($\beta = -0.18$, $p < 0.05$) and PSS-10 ($\beta = -0.31$, $p < 0.01$) were negative predictors, indicating that elevated sympathetic activation and perceived stress correspond with decreased productivity. This pattern is consistent with stress physiology theory, wherein heightened arousal levels and subjective strain impair concentration and task performance.

These results confirm H1 and H2, providing strong empirical support that both physiological and psychological stress indicators significantly influence workplace productivity. Furthermore, a comparison of standardized coefficients suggested that physiological stress measures (HRV and sleep duration) had stronger predictive power than self-reported stress, supporting H3 [35]. This finding implies that objective biometric data derived from wearables can serve as more stable and reliable predictors of performance outcomes compared to self-perceived measures, which are often influenced by cognitive bias and situational context [36].

In addition, the overall pattern of results reinforces the potential of integrating wearable-based monitoring systems into workplace wellness frameworks. By identifying early physiological signs of stress before subjective awareness emerges, organizations can implement timely interventions that maintain employee focus and performance [37, 38]. Hence, these regression results not only validate the study hypotheses but also provide a quantitative foundation for applying digital health analytics in enhancing occupational productivity and well-being [39].

3.4. Moderation Analysis

Work arrangement significantly moderated the relationship between stress and productivity (interaction $\beta = -0.15$, $p < 0.05$) [40]. The negative effect of stress on productivity was stronger for remote employees, while age and gender did not show significant moderating effects.

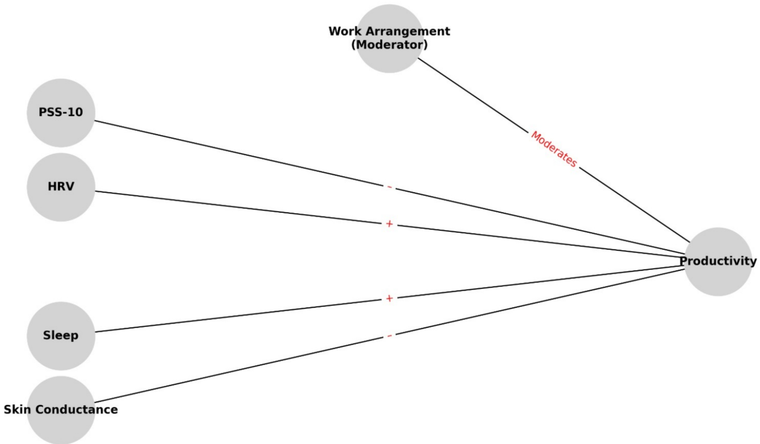

Figure 3. Regrission Model Diagram

This diagram illustrates the regression model tested in this study, including both predictors and the moderating variable. HRV and sleep duration positively predict productivity [41], while skin conductance and PSS-10 negatively predict productivity. Work arrangement acts as a moderator, strengthening the negative impact of stress on productivity for remote workers [42, 43]. As illustrated in Figure 3, physiological measures (HRV and sleep) exert stronger predictive power than self-reported stress, confirming H3. Furthermore, the moderating role of work arrangement supports H4, indicating that remote employees are more vulnerable to stress-induced productivity loss [44].

4. DISCUSSION

The results provide empirical evidence that wearable based stress indicators can reliably predict workplace productivity. Consistent with prior studies in occupational health, this research confirms that elevated stress both physiological and perceived reduces employee performance. Notably, physiological measures such as HRV and sleep patterns demonstrated stronger predictive effects compared to self-reported stress, highlighting the advantage of wearable technologies for objective monitoring. The moderation effect of work arrangement underscores the importance of contextual factors. Remote employees, who often face blurred boundaries between work and personal life, appear more vulnerable to stress-induced productivity loss. This finding aligns with post-pandemic literature suggesting that remote work intensifies digital fatigue and work–life conflict.

Overall, these findings extend existing literature by demonstrating the direct link between physiological stress detection and productivity outcomes in organizational contexts a relationship that has been largely overlooked in prior research. The study also reinforces the potential of digital health technologies to serve as early warning systems for stress management and productivity optimization.

5. MANAGERIAL IMPLICATIONS

The results of this study carry important implications for managers and organizational leaders. First, the stronger predictive power of physiological indicators such as HRV and sleep duration compared to self-reported stress suggests that organizations should consider adopting wearable technologies as part of their employee well-being programs. These tools can function as early detection systems, enabling timely interventions before stress escalates into productivity loss. In addition, the findings highlight the need for stress-responsive work policies, particularly for remote employees who appear to be more vulnerable to stress-induced performance declines. Structured work hours, virtual wellness check-ins, and clearer boundaries between work and personal life could help mitigate these risks.

Furthermore, sleep and recovery should be recognized as strategic priorities in workforce management. Initiatives such as flexible scheduling, limiting after-hours communication, and offering wellness resources can help employees maintain healthier sleep patterns and, in turn, higher productivity. Importantly, managers should integrate both objective data from wearables and subjective insights from self-reported surveys to obtain a holistic understanding of employee well-being. Combining these approaches ensures that both physiological and psychological dimensions of stress are adequately addressed.

Finally, the adoption of wearable-based monitoring should be framed within a data-driven but supportive organizational culture. Transparency, respect for employee privacy, and clear communication are essential to ensure that these technologies are perceived as tools for support rather than surveillance. By doing so, organizations can transition from reactive to proactive stress management and foster a healthier, more productive workforce.

6. CONCLUSION

This study demonstrates that both physiological and self-reported stress indicators are significant predictors of workplace productivity. Wearable-based measures, particularly heart rate variability (HRV) and sleep duration, emerged as stronger predictors than self-reported stress, highlighting the advantages of objective monitoring technologies in organizational contexts. Furthermore, the moderating effect of work arrangement indicates that remote employees are more vulnerable to stress-induced performance declines, emphasizing the importance of tailored well-being strategies suited to diverse work environments.

Despite these findings, several limitations should be acknowledged. The cross-sectional design restricts causal interpretation, and the sample's focus on medium to large organizations may limit generalizability. Moreover, wearable devices can introduce technical issues such as measurement errors or varying accuracy across demographic groups. Future research should therefore consider longitudinal designs, include smaller and more diverse enterprises, and explore additional moderators such as leadership style, organizational culture, or digital workload. Advanced analytic methods like machine learning may also enhance predictive accuracy and enable more personalized stress management models.

In conclusion, this study provides empirical evidence linking wearable-based stress detection with workplace productivity, contributing to the growing field of digital health in organizational research. By integrating physiological and psychological perspectives, it encourages organizations to adopt wearable technologies as proactive tools for maintaining employee well-being and optimizing performance. Ultimately, the findings reinforce the potential of digital health innovation to build resilient, healthy, and high-performing workplaces.

7. DECLARATIONS

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7.2. Author Contributions

Conceptualization: NS; Methodology: GK; Software: KD; Validation: MZ and AV; Formal Analysis: GK and KD; Investigation: NS; Resources: AV; Data Curation: MZ; Writing Original Draft Preparation: AV and KD; Writing Review and Editing: NS and GK; Visualization: AV; All authors, KD, MZ, GK, NS, and AV, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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7.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

REFERENCES

[1] M. Saxena, N. M. Avanesh, L. Niranjan, and P. Mohanty, “Wearable technologies leading to employee performance and productivity: Exploring the mediating role of mental health and wellbeing,” in *Technological Enhancements for Improving Employee Performance, Safety, and Well-Being*. IGI Global, 2025, pp. 111–130.

[2] M. N. Ayubi and A. Retnowardhani, “Optimizing learning experiences: A study of student satisfaction with lms in higher education,” *Aptisi Transactions on Technopreneurship (ATT)*, vol. 7, no. 2, pp. 527–541, 2025.

[3] J. E. Naranjo, C. A. Mora, D. F. Bustamante Villagómez, M. G. Mancheno Falconi, and M. V. Garcia, “Wearable sensors in industrial ergonomics: enhancing safety and productivity in industry 4.0,” *Sensors*, vol. 25, no. 5, p. 1526, 2025.

[4] M. H. R. Chakim, U. Rahardja, E. D. Astuti, E. Erika, and C. T. Hua, “The social empowerment role of the penta helix entrepreneurship ecosystem in driving the national economy,” *ADI Pengabdian Kepada Masyarakat*, vol. 6, no. 1, pp. 1–13, 2025.

[5] U. Yadav and S. Soni, “Adoption of wearable technology in the workplace: A study of employee perceptions and behavioral intentions,” in *Progressive Computational Intelligence, Information Technology and Networking*. CRC Press, 2025, pp. 462–468.

[6] T. S. Goh, D. Jonas, B. Tjahjono, V. Agarwal, and M. Abbas, “Impact of ai on air quality monitoring systems: A structural equation modeling approach using utaut,” *Sundara Advanced Research on Artificial Intelligence*, vol. 1, no. 1, pp. 9–19, 2025.

[7] M. Awada, B. B. Gerber, G. M. Lucas, and S. C. Roll, “Stress appraisal in the workplace and its associations with productivity and mood: Insights from a multimodal machine learning analysis,” *Plos one*, vol. 19, no. 1, p. e0296468, 2024.

[8] M. Awada, B. Becerik-Gerber, G. Lucas, and S. C. Roll, “Predicting office workers’ productivity: A machine learning approach integrating physiological, behavioral, and psychological indicators,” *Sensors*, vol. 23, no. 21, p. 8694, 2023.

[9] B. Kristianto, C. Dewi, H. D. Purnomo, K. D. Hartomo, and S. Z. M. Hashim, “Utilizing the yolov8 model for accurate hand recognition with complex background,” *PeerJ Computer Science*, vol. 11, p. e3244, 2025.

[10] G. Taskasaplidis, D. A. Fotiadis, and P. D. Bamidis, “Review of stress detection methods using wearable sensors,” *IEEe Access*, vol. 12, pp. 38 219–38 246, 2024.

[11] H. Hijry, S. M. R. Naqvi, K. Javed, O. H. Albalawi, R. Olawoyin, C. Varnier, and N. Zerhouni, “Real time worker stress prediction in a smart factory assembly line,” *IEEE Access*, 2024.

[12] J. Kallio, E. Vildjiounaite, J. Tervonen, and M. Bordallo López, “A survey on sensor-based techniques for continuous stress monitoring in knowledge work environments,” *ACM Transactions on Computing for Healthcare*, vol. 6, no. 3, pp. 1–31, 2025.

[13] P. H. P. Tan, M. Tukiran, and D. Wuisan, "Innovation practices and external support for msme performance and survival in indonesia," *International Journal of Cyber and IT Service Management (IJCITSM)*, vol. 5, no. 2, pp. 120–133, 2025.

[14] E. Lazarou and T. P. Exarchos, "Predicting stress levels using physiological data: Real-time stress prediction models utilizing wearable devices," *AIMS neuroscience*, vol. 11, no. 2, p. 76, 2024.

[15] B. M. Booth, H. Vrzakova, S. M. Mattingly, G. J. Martinez, L. Faust, and S. K. D'Mello, "Toward robust stress prediction in the age of wearables: Modeling perceived stress in a longitudinal study with information workers," *IEEE Transactions on Affective Computing*, vol. 13, no. 4, pp. 2201–2217, 2022.

[16] A. Kadim, I. Yusnita, A. Sutarman, R. Lesmana, and F. A. Ramahdan, "Assessing the impact of corporate governance and strategic leadership on economic growth and market stability," *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 6, no. 2, pp. 177–187, 2025.

[17] T. Pujiati, H. Setiyowati, B. Rawat, N. P. L. Santoso, and M. G. Ilham, "Exploring the role of artificial intelligence in enhancing environmental health: Utaut2 analysis," *Sundara Advanced Research on Artificial Intelligence*, vol. 1, no. 1, pp. 37–46, 2025.

[18] K. Srinivasan, F. Currim, C. M. Lindberg, J. Razjouyan, B. Gilligan, H. Lee, K. J. Canada, N. Goebel, M. R. Mehl, M. M. Lunden *et al.*, "Discovery of associative patterns between workplace sound level and physiological wellbeing using wearable devices and empirical bayes modeling," *npj Digital Medicine*, vol. 6, no. 1, p. 5, 2023.

[19] C. Belletier, M. Charkhabi, G. Pires de Andrade Silva, K. Ametepe, M. Lutz, and M. Izaute, "Wearable cognitive assistants in a factory setting: a critical review of a promising way of enhancing cognitive performance and well-being," *Cognition, Technology & Work*, vol. 23, no. 1, pp. 103–116, 2021.

[20] F. G. Antonaci, E. C. Olivetti, F. Marcolin, I. A. Castiblanco Jimenez, B. Eynard, E. Vezzetti, and S. Moos, "Workplace well-being in industry 5.0: a worker-centered systematic review," *Sensors*, vol. 24, no. 17, p. 5473, 2024.

[21] S. Purnama, C. S. Bangun, and E. P. Mahadewi, "Predicting consumer purchase intention in personal shopper services using big data analytics and sem," *International Journal of Cyber and IT Service Management (IJCITSM)*, vol. 5, no. 1, pp. 105–119, 2025.

[22] S. A. Khowaja, A. G. Prabono, F. Setiawan, B. N. Yahya, and S.-L. Lee, "Toward soft real-time stress detection using wrist-worn devices for human workspaces." *Soft Computing-A Fusion of Foundations, Methodologies & Applications*, vol. 25, no. 4, 2021.

[23] P. Traunmuller, A. Jahanjoo, S. Khooyooz, A. Aminifar, and N. TaheriNejad, "Wearable healthcare devices for monitoring stress and attention level in workplace environments," *arXiv preprint arXiv:2406.05813*, 2024.

[24] M. A. Setiawan, H. Hartoyo, K. B. Seminar, B. Sartono, R. Fitriati, and V. Ginting, "Improving e-service quality of indonesian toll road application with entrepreneurship insights," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 7, no. 2, pp. 503–515, 2025.

[25] F. Sutisna, N. Lutfiani, E. Anderson, D. Danang, and M. O. Syaidina, "E-commerce and digital marketing strategies: Their impact on startupreneur performance using pls-sem," *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 6, no. 2, pp. 215–223, 2025.

[26] B. B. Van Acker, P. D. Conradie, P. Vlerick, and J. Saldien, "Employee acceptability of wearable mental workload monitoring: exploring effects of framing the goal and context in corporate communication," *Cognition, Technology & Work*, vol. 23, no. 3, pp. 537–552, 2021.

[27] R. Aprianto, R. Haris, A. Williams, H. Agustian, and N. Aptwell, "Social influence on ai-driven air quality monitoring adoption: Smartpls analysis," *Sundara Advanced Research on Artificial Intelligence*, vol. 1, no. 1, pp. 28–36, 2025.

[28] M. De Choudhury, "Toward improved workplace measurement with passive sensing technologies," *Technology and Measurement around the Globe*, p. 46, 2023.

[29] I. Okpala, C. Nnaji, I. Awolusi, and A. Akanmu, "Developing a success model for assessing the impact of wearable sensing devices in the construction industry," *Journal of Construction Engineering and Management*, vol. 147, no. 7, p. 04021060, 2021.

[30] D. Gathmyr, U. Suhud, H. Herlitah, H. Hamidah, R. T. H. Safariningsih, and J. Wilson, "Technological advancements in perceived organizational support enhancing healthcare systems towards sustainable development goals," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 7, no. 2, pp. 516–526, 2025.

[31] M. Herold, S. Simbula, and M. Gallucci, "Can smartphone applications and wearable technologies im-

prove workplace well-being and help manage stress? a systematic review," *Current Psychology*, vol. 43, no. 36, pp. 28 650–28 673, 2024.

[32] C. Dewi, D. Manongga, Hendry, E. Mailoa, and K. D. Hartomo, "Deep learning and yolov8 utilized in an accurate face mask detection system," *Big Data and Cognitive Computing*, vol. 8, no. 1, p. 9, 2024.

[33] W. Szewczyk, I. Mongelli, and J.-C. Ciscar, "Heat stress, labour productivity and adaptation in europe—a regional and occupational analysis," *Environmental Research Letters*, vol. 16, no. 10, p. 105002, 2021.

[34] J. Oh, G. Y. Cho, and H. Kim, "Performance analysis of wearable robotic exoskeleton in construction tasks: Productivity and motion stability assessment," *Applied Sciences*, vol. 15, no. 7, p. 3808, 2025.

[35] C.-M. Rosca and A. Stancu, "Fusing machine learning and ai to create a framework for employee well-being in the era of industry 5.0." *Applied Sciences (2076-3417)*, vol. 14, no. 23, 2024.

[36] S. Canali, B. De Marchi, and A. Aliverti, "Wearable technologies and stress: toward an ethically grounded approach," *International journal of environmental research and public health*, vol. 20, no. 18, p. 6737, 2023.

[37] N. Lutfiani, U. Rahardja, S. Wijono, K. D. Hartomo, and H. Purnomo, "Unlocking the potential of ai-enabled startup through digital talent in higher education," in *2024 3rd International Conference on Creative Communication and Innovative Technology (ICCIT)*. IEEE, 2024, pp. 1–6.

[38] M. Bolpagni, S. Pardini, M. Dianti, and S. Gabrielli, "Personalized stress detection using biosignals from wearables: A scoping review," *Sensors*, vol. 24, no. 10, p. 3221, 2024.

[39] S. Purnama, B. L. Pradana, G. Khanna, S. Suhandi, A. Rizky, I. N. Hikam, and M. F. Kamil, "The impact of war on the cryptocurrency economy from a management perspective," *International Journal of Cyber and IT Service Management*, vol. 4, no. 2, pp. 143–154, 2024.

[40] S. N. Kodithuwakku Arachchige, R. F. Burch V, H. Chander, A. J. Turner, and A. C. Knight, "The use of wearable devices in cognitive fatigue: current trends and future intentions," *Theoretical Issues in Ergonomics Science*, vol. 23, no. 3, pp. 374–386, 2022.

[41] L. Kask, N. Bloom, and R. Porta, "Health informatics: Utilization of information technology in health care and patient management," *International Journal of Cyber and IT Service Management*, vol. 4, no. 1, pp. 53–58, 2024.

[42] S. Nepal, G. J. Martinez, S. Mirjafari, S. Mattingly, V. D. Swain, A. Striegel, P. G. Audia, and A. T. Campbell, "Assessing the impact of commuting on workplace performance using mobile sensing," *IEEE Pervasive Computing*, vol. 20, no. 4, pp. 52–60, 2021.

[43] D. Wuisan, J. W. Manurung, C. Wantah, and M. E. Yuliana, "Entrepreneurial self-employment and work engagement in msmes through autonomy and rewards," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 7, no. 1, pp. 264–281, 2025.

[44] E. Svertoka, S. Saafi, A. Rusu-Casandra, R. Burget, I. Marghescu, J. Hosek, and A. Ometov, "Wearables for industrial work safety: A survey," *Sensors*, vol. 21, no. 11, p. 3844, 2021.