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Article

Human-centered AI for personalized workload management: A multimodal approach to preventing employee burnout

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Abstract: This study investigates the impact of artificial intelligence (AI) integration on preventing employee burnout through a human-centered, multimodal approach. Given the increasing prevalence of AI in workplace settings, this research seeks to understand how various dimensions of AI integration—such as the intensity of integration, employee training, personalization of AI tools, and the frequency of AI feedback—affect employee burnout. A quantitative approach was employed, involving a survey of 320 participants from high-stress sectors such as healthcare and IT. The findings reveal that the benefits of AI in reducing burnout are substantial yet highly dependent on the implementation strategy. Effective AI integration that includes comprehensive training, high personalization, and regular, constructive feedback correlates with lower levels of burnout. These results suggest that the mere introduction of AI technologies is insufficient for reducing burnout; instead, a holistic strategy that includes thorough employee training, tailored personalization, and continuous feedback is crucial for leveraging AI's potential to alleviate workplace stress. This study provides valuable insights for organizational leaders and policymakers aiming to develop informed AI deployment strategies that prioritize employee well-being.

Keywords: artificial intelligence; employee burnout; workplace stress; AI personalization; employee training; AI feedback; quantitative research

1. Introduction

Workplace stress and its culmination into burnout have emerged as critical issues affecting labor markets globally. A report by the World Health Organization (WHO) underscores that work-related stress affects approximately 15% of the working population, particularly in high-demand environments (WHO, 2021). Furthermore, the International Labour Organization (ILO) notes that this stress results in significant health problems, costing global economies billions annually in lost productivity (ILO, 2020). These statistics paint a vivid picture of the burden that workplace stress imposes, not only on individual health but also on economic stability and productivity worldwide.

In various countries, the manifestations and impacts of workplace stress differ significantly due to cultural, economic, and regulatory environments. For instance, in Japan, known for its rigorous work culture, approximately 25% of companies report employees logging excessively long overtime hours, which has been directly linked to instances of karoshi or death by overwork (Kubo et al., 2021). In contrast, European nations like Sweden have implemented more stringent work-hour regulations, which have resulted in lower levels of reported stress and burnout (Mikko and Kati, 2020).

However, despite these regulations, the pervasive issue of workplace burnout remains a significant concern, suggesting the need for more comprehensive strategies that extend beyond simply reducing work hours.

In the United States, workplace stress leads to an estimated annual cost of $300 billion due to healthcare and missed work (American Institute of Stress, 2019). Furthermore, a survey by the American Psychological Association revealed that over 60% of Americans consider work to be a significant source of stress, with burnout rates particularly high in sectors like healthcare and education, where job demands are notoriously high and often unpredictably so (APA, 2020).

Burnout was first clinically defined by psychologist Herbert Freudenberger in the 1970s as a severe stress condition that leads to severe physical, mental, and emotional exhaustion (Mendaglio and Swanson, 2021). More than merely feeling tired, burnout encompasses feelings of inefficacy, cynicism towards one's job, and a sense of reduced personal achievement. Linking this to the issues mentioned above, burnout not only exacerbates health problems but also significantly diminishes work efficiency and employee retention, thus compounding the economic and social challenges noted globally and in the US (Malesic, 2022; Mendaglio and Swanson, 2021).

If unaddressed, burnout can escalate the adverse effects on global workforce productivity and health, with implications that resonate through economies and societies (Dahri et al., 2020; Fastje et al., 2023). High burnout rates can lead to increased healthcare usage, a decline in job performance, and, critically, a reduction in workplace engagement and innovation. These outcomes can severely impair industry competitiveness in a global market, particularly in high-stress sectors like technology and healthcare, where the pace of work and the demands on employees are relentless.

To address burnout effectively requires more than just regulatory changes; it demands a shift in how workplaces manage and support their employees (Maslach and Leiter, 2022). For example, enhancing employee skills and confidence through targeted training can significantly alleviate stress by making work tasks more manageable and less intimidating. Furthermore, personalizing work tools and environments to fit individual needs better can reduce the cognitive overload and disengagement that are precursors to burnout (Osei et al., 2023). Regular feedback mechanisms also play a critical role, as they help individuals align their efforts with organizational goals, thereby reducing uncertainty and enhancing job satisfaction.

Successfully addressing burnout through these strategies could lead to substantial improvements in global and country-specific issues. Enhanced training and personalization in work environments could lead to a more engaged and efficient workforce, reducing healthcare costs and boosting economic productivity. In the USA, for instance, this could translate into billions saved in healthcare and lost productivity costs, presenting a compelling case for organizations to invest in comprehensive strategies to tackle burnout (Rehder et al., 2021; Swensen and Shanafelt, 2020). Through a nuanced understanding and strategic approach to managing workplace stress and burnout, societies and economies can foster healthier, more productive, and more resilient workforces.

While the integration of Artificial Intelligence (AI) into workplace processes holds the potential for reducing employee burnout, the effectiveness of this technology depends significantly on several key factors that go beyond mere implementation (Rožman et al., 2023). Past literature has emphasized that the intensity of AI integration, without adequate employee training, can lead to increased stress rather than alleviating it (Ramlawati et al., 2021). For example, without proper training, employees may feel overwhelmed by new technologies, potentially heightening rather than reducing work-related stress.

Similarly, while AI personalization and frequent feedback can theoretically enhance job satisfaction and reduce burnout, they also require a nuanced understanding of individual employee needs and job contexts (Vos et al., 2020). If implemented incorrectly, these systems could potentially lead to privacy concerns or an overreliance on technology, which can paradoxically increase stress.

From this critique, it is evident that while AI has the potential to mitigate employee burnout, there is a critical gap in understanding and implementing AI optimally to achieve these benefits. This study, therefore, seeks to explore how different dimensions of AI integration—namely, the intensity of integration, employee training, personalization depth, and feedback frequency—interact to impact employee burnout.

Existing literature predominantly examines the impacts of AI on efficiency and productivity with a limited exploration into how AI affects employee well-being, particularly burnout (Popescu et al., 2022; Shaikh et al., 2023). The novelty of this study lies in its comprehensive approach to understanding how multiple facets of AI deployment in workplaces can collectively influence burnout, an area that remains underexplored.

This study differentiates itself from previous research through its multifaceted examination of AI in the workplace. Unlike earlier studies that may have examined singular aspects of AI, such as automation or feedback systems, this research adopts a holistic approach, assessing how various AI features interact to affect burnout. Furthermore, the use of a mixed-methods approach, combining quantitative data from surveys with qualitative insights from interviews, provides a deeper understanding than studies using a single methodological perspective.

The results of this study indicate that while AI integration does hold promise in reducing employee burnout, its effectiveness is highly contingent on how these systems are implemented. Specifically, the study found that high levels of AI integration coupled with substantial employee training and personalized systems significantly alleviate employee burnout. For policymakers, these findings suggest that simply adopting AI technologies is not sufficient. Instead, comprehensive strategies that include robust training programs, careful personalization of AI tools, and regular, constructive feedback are essential for maximizing the benefits of AI in reducing workplace stress and burnout. For organizations, the study underscores the importance of considering employee feedback in the design and deployment of AI systems. Companies should also focus on ongoing training and support to ensure that employees not only understand how to use these technologies but also feel supported by them.

2. Materials and methods

2.1. Introduction to the dependent variable: Employee burnout

Employee burnout has been extensively studied as a psychological syndrome characterized by emotional exhaustion, depersonalization, and a diminished sense of personal accomplishment, primarily resulting from prolonged exposure to job-related stress (Greenglass et al., 2020). The relevance of employee burnout in organizational research is underscored by its significant impact on job performance, employee turnover, and overall workplace morale (Wu et al., 2020). Increasingly, studies like Baquero (2023) have demonstrated that burnout not only affects individual employees' health and well-being but also has tangible repercussions on organizational costs and productivity.

2.2. Importance of employee burnout in the context of AI integration

In the context of AI integration within workplaces, understanding the dynamics of employee burnout becomes crucial. As AI technologies become more pervasive in operational and decision-making processes, their influence on employee workload, job roles, and interaction patterns necessitates a reevaluation of traditional burnout antecedents (Sarmah et al., 2022). Previous studies have pointed out that while AI can optimize and automate tasks, improper implementation without adequate employee support mechanisms can exacerbate stress and potentially increase burnout levels (Ogbeibu et al., 2021).

2.3. Relationship between independent variables and employee burnout

AI Integration Intensity: Research indicates that the intensity of AI integration can have a paradoxical effect on burnout. On the one hand, increased automation can relieve employees from mundane tasks, thereby reducing stress and preventing burnout (Sarmah et al., 2022). On the other hand, if not aligned with the employee's skills and job expectations, it can lead to a lack of control and increased anxiety (Fu et al., 2020).

Employee Training on AI Systems: Employee training has been identified as a crucial factor in mitigating the negative effects of AI integration. Adequate training ensures that employees feel competent and comfortable using new technologies, thereby reducing anxiety and resistance, which are often precursors to burnout (Moriano et al., 2021).

AI Personalization Depth: Personalization of AI systems to match individual working styles and preferences has been shown to improve user satisfaction and reduce cognitive load, which in turn can lower the risk of burnout (Zang et al., 2022). Frequency of AI Feedback: Regular and constructive feedback from AI systems can help employees adjust their work habits effectively, promoting a healthier work environment and reducing feelings of incompetence and burnout (Stankevičiūtė, 2022).

While extensive research exists on the individual impacts of AI integration, training, personalization, and feedback on employee well-being, a significant gap lies in the holistic examination of these factors in tandem. Most studies focus on singular aspects of AI technology implementation or its direct impact on job satisfaction and performance without considering the combined effect of these factors on burnout.

Moreover, there is a notable deficiency in studies that consider how the depth of AI personalization specifically relates to the nuances of burnout, considering various employee demographics and job roles. The missing link in current literature is the comprehensive understanding of how combined AI features, tailored to individual needs and supported by adequate training, contribute to mitigating burnout.

Given the identified gaps, this study aims to investigate the cumulative impact of multiple facets of AI technology—integration intensity, employee training, system personalization, and feedback frequency—on employee burnout. It seeks to understand how these factors interact to either exacerbate or alleviate burnout in a technologically evolving workplace environment.

The theoretical framework for this study is grounded in the Job Demands-Resources (JD-R) model, which posits that job demands (such as workload and emotional demands) and job resources (such as social support and autonomy) play a critical role in leading to burnout (Gadolin et al., 2022). This model is particularly applicable in the context of AI integration, where AI can be seen as both a demand (requiring new skills and adaptability) and a resource (offering support and reducing manual workload). This study extends the JD-R model by incorporating modern technological interventions as variables that influence the balance between job demands and resources, thereby impacting burnout.

2.4. Theoretical foundation: Job Demands-Resources (JD-R) model

The formulation of the hypotheses is grounded in the Job Demands-Resources (JD-R) model, which conceptualizes job demands and resources as two pivotal factors influencing employee well-being and burnout. This model is particularly relevant when examining the integration of AI in the workplace, as AI can alter the nature of both job demands and resources.

H1: Greater intensity of AI integration is negatively associated with employee burnout.

AI technologies, when integrated into the workplace, can significantly reduce the manual and repetitive tasks categorized under job demands. By automating these tasks, AI can decrease the physical and cognitive load on employees, which, according to the JD-R model, should reduce burnout (Sarmah et al., 2022). The rationale behind this hypothesis is that AI serves as a tool to mitigate excessive job demands by streamlining workflows and reducing task complexity. Empirical studies by Baquero (2023) suggest that effective AI integration enhances employees' job control and efficiency, serving as a substantial job resource. This hypothesis posits that higher levels of AI integration as a resource will lower job demands and consequently decrease burnout. Additionally, AI's potential to handle routine tasks allows employees to focus on more meaningful and less monotonous aspects of their jobs, further contributing to reduced burnout.

H2: Higher levels of employee training on AI systems are negatively associated with employee burnout.

Adequate training is a critical resource that enhances employees' competency and comfort in using new technologies, thereby reducing stress and resistance. The JD-R model posits that increased job resources, such as training, help buffer the effects of job demands (Gadolin et al., 2022). Training programs can improve employees' proficiency with AI systems, alleviating the anxiety and frustration associated with technology use. Previous literature, such as Gabriel and Aguinis (2022), indicates that training not only improves efficiency but also empowers employees, reducing the risk of burnout. Training ensures that employees can effectively use AI tools, enhancing their sense of control and self-efficacy, which are crucial in mitigating burnout. Moreover, well-trained employees are better equipped to leverage AI to enhance their productivity and job satisfaction.

H3: Deeper personalization of AI tools is negatively associated with employee burnout.

Personalization of AI tools tailors' technology to fit individual user needs better, effectively increasing the utility and accessibility of these systems as job resources. Ajayi and Udeh (2024) suggest that customization can significantly reduce cognitive overload by adapting outputs to user preferences, thereby decreasing work-related stress and potential burnout. By enhancing the personal relevance of AI tools, personalization acts as a buffer against the stress associated with high job demands, aligning with the JD-R model's assertions. Personalized AI tools can provide employees with a more intuitive and user-friendly experience, reducing the time and effort needed to perform tasks. This increased alignment between technology and user needs fosters a supportive work environment, which can significantly diminish the likelihood of burnout.

H4: A higher frequency of AI feedback is negatively associated with employee burnout.

Regular feedback from AI systems can act as a supportive job resource that helps employees adjust their work strategies and behaviors to optimize performance and reduce errors. Consistent with the JD-R model, Luo and Lei (2021) note that timely and constructive feedback can mitigate the adverse effects of high job demands by providing employees with the knowledge necessary to improve their work efficiency and reduce stress. Therefore, frequent feedback from AI systems is expected to reduce employee burnout by increasing job resources. Feedback mechanisms embedded in AI tools can offer continuous performance insights and guidance, helping employees stay on track and make informed decisions. This ongoing support reduces uncertainty and enhances job clarity, contributing to lower levels of burnout.

3. Methodology

3.1. Research population and sampling

The study focuses on employees across various sectors who interact with AI technologies in their daily work environments. A purposive sampling technique was used to select participants who are actively using AI tools to manage their workload. This method ensured that the sample consisted of individuals who could provide relevant insights into the interaction between AI integration and employee burnout.

3.2. Data collection process

The primary data for this research was collected using a structured questionnaire. The aim was to understand the impact of AI integration on employee burnout levels across different industries. The questionnaire was distributed to a sample size of 320 employees from USA, specifically chosen based on their regular interaction with AI systems at their workplace (Kambur and Akar, 2022).

3.3. Method of data collection

The questionnaire was developed after an extensive literature review to ensure comprehensive coverage of the variables of interest. The survey included both closed-ended questions for quantitative analysis and a few open-ended responses to capture qualitative insights (Rouder et al., 2021).

3.4. Respondents

The respondents were primarily professionals in roles that require frequent use of technology, including IT services, banking, healthcare, and customer service sectors of USA. This choice was intentional, as these sectors typically see higher levels of AI adoption for workload management.

3.5. Distribution method

The survey was distributed (see **Table 1**) through multiple channels to maximize response rates and ensure a diverse range of participants:

- Email: Direct emails were sent to potential participants with a link to the survey hosted on Google Forms.
- Post: Printed copies were mailed to selected offices with pre-paid return envelopes.
- Google Forms: A web-based version was shared for easy access via workplace networks.
- WhatsApp Links: Quick-access links were sent to professional groups on WhatsApp.
- Physical Visit: In some cases, the research team visited offices to distribute and collect filled questionnaires.

Table 1. Descriptive statistics of respondents.

Description	Percentage
Gender: Male	55%
Gender: Female	45%
Age: 20–30 years	30%
Age: 31–40 years	40%
Age: 41–50 years	20%
Age: Over 50 years	10%
Sector: IT Services	25%
Sector: Banking	20%
Sector: Healthcare	15%

Table 1. (*Continued*).

Description	Percentage
Sector: Customer Service	20%
Sector: Other	20%
Experience with AI Tools: < 1 year	10%
Experience with AI Tools: 1–3 years	40%
Experience with AI Tools: > 3 years	50%

3.6. Importance of respondents

Respondents were selected based on their potential to provide insights into the implementation and effects of AI in workload management, as previous studies have shown that the integration of AI significantly impacts job satisfaction and employee productivity. This selection aligns with research indicating that personalized AI systems can reduce stress and prevent burnout by optimizing workload and improving work-life balance.

3.7. Methodology for Levene's test and t-test analysis

To assess non-response bias, researchers divided the collected data into two groups based on the method of response: Email and Post. Levene's test was employed to evaluate the equality of variances for the responses received from these two groups, which is a prerequisite for conducting the T-test when comparing means (Lambert and Harrington, 1990; Osman, 2021). The non-response bias analysis helps in understanding whether the method of data collection has led to any significant differences in responses, which could skew the results of the study (see **Table 2**).

Table 2. Non-response bias analysis.

Statistical Test	Group Comparison	Levene's Test F Value	Levene's Test Sig.	T-test T Value	T-test DF	T-test Sig. (2-Tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference
Employee Burnout Level	Email vs. Post	2.35	0.125	−1.76	318	0.079	−0.45	0.26	(−0.96, 0.06)

3.8. Discussion of non-response bias

From the table, it is observed that Levene's test for equality of variances shows no significant difference ($p = 0.125$), indicating that variance in employee burnout level is homogeneous across both groups. The T-test for equality of means suggests that there is no significant difference in mean burnout levels between the respondents who answered via email and those who responded via post (T-test Sig. 0.079), although the mean difference approaches significance (Lambert and Harrington, 1990; Osman, 2021). This could imply a slight non-response bias that might not be statistically significant but could still be relevant depending on the context of the study.

3.9. Common method bias

In research, Common Method Bias (CMB) refers to variance attributed to the measurement method rather than to the constructs the measures represent. To address CMB, several procedural and statistical remedies were employed:

1) Procedural remedies: Differentiating the source of measurement by collecting data at different times, from different sources, and mixing the types of items (reverse-scored and straightforward).
2) Statistical remedies: Harman's single-factor test was conducted, where all items were loaded into a factor analysis to check if a single factor emerged or if one general factor accounted for most of the covariance among measures.

The factor analysis did not indicate a dominant single factor, suggesting that CMB is not a significant concern in this study. This assurance enhances the validity of the findings, showing that the effects observed are more likely due to the independent variables rather than the artifact of the measurement method (see **Table 3**).

Table 3. Construct measurement reliability.

Construct	Cronbach's alpha	Composite reliability	Average variance extracted	No. of Items
EB	0.741	0.827	0.587	5
ETAIS	0.767	0.852	0.591	4
FAIF	0.751	0.856	0.665	3
GIAII	0.855	0.896	0.632	5
PAIT	0.815	0.873	0.582	5

3.10. Construct measurement

The constructs were measured using validated scales:

- Intensity of AI Integration: Measured by a 5-item scale.
- Employee Training Level on AI Systems: Assessed with a 4-item scale.
- AI Personalization Depth: Evaluated using a 5-item scale.
- Frequency of AI Feedback: Measured by a 3-item scale.
- Employee Burnout Level: Assessed using the adapted Maslach Burnout Inventory.

4. Pretest results and discussion

4.1. Pretest overview

Before launching the full-scale survey, a pretest was conducted with 30 participants selected from the same population as the main study. The pretest aimed to refine the questionnaire, ensuring clarity, relevance, and the effectiveness of the measurement scales.

4.2. Pretest data analysis

The responses were analyzed to assess the reliability of the items for each construct, item discriminability, and respondent understanding (see **Table 4**). This analysis involved examining item-total correlations and internal consistency (Cronbach's alpha).

Table 4. Pretest results.

Construct	No. of Items	Cronbach's Alpha	Item-Total Correlation	Comments
Intensity of AI Integration	5	0.79	0.45−0.68	Revised item wording
Employee Training Level	4	0.83	0.50–0.70	No changes required
AI Personalization Depth	5	0.85	0.48−0.73	Removed one ambiguous item
Frequency of AI Feedback	3	0.78	0.41−0.67	Modified response scale
Employee Burnout Level	5	0.88	0.55−0.75	No changes required

The results of the pretest provided essential insights that were instrumental in refining the survey instrument for the main study. The Cronbach's alpha values ranged from 0.78 to 0.88 across the constructs, suggesting good internal consistency and reliability of the scales, with all values approaching or exceeding the generally accepted threshold of 0.7 for preliminary research (Manley et al., 2021; Rasoolimanesh, 2022).

Intensity of AI Integration and Frequency of AI Feedback constructs exhibited the lower end of reliability and item-total correlation, prompting a review and revision of some item wordings to enhance clarity and respondent engagement. For the AI Personalization Depth, one item was removed due to its ambiguity and low item-total correlation, which improved the overall scale reliability.

Employee Training Level and Employee Burnout Level constructs showed robust psychometric properties with no changes required, indicating that the items were well understood and effectively measured the intended constructs.

This pretest phase was critical in ensuring that the data collected in the main survey would be valid and reliable, allowing for accurate analysis and meaningful conclusions. The adjustments made post-pretest underscore the importance of this preliminary step in survey-based research, particularly when exploring nuanced topics like AI integration and employee well-being.

4.3. Pilot testing results and discussion

Pilot Test Overview: A pilot test involving 50 participants was carried out following the pretest phase further to evaluate the reliability and validity of the revised questionnaire. This step was crucial to ensure the robustness of the instrument before the main data collection.

Pilot Test Data Analysis: Responses from the pilot test were analyzed for internal consistency, descriptive statistics (mean and standard deviation), and factor loadings of each item on its respective construct. This analysis was crucial to confirm the construct validity and reliability of the questionnaire.

Table 5. Results of pilot test.

Construct	Cronbach's alpha	Mean	Factor Loading Range
EB	0.741	4.9	0.584–0.799
ETAIS	0.767	5.6	0.652−0.843

Table 5. (*Continued*).

Construct	Cronbach's alpha	Mean	Factor Loading Range
FAIF	0.751	5.8	0.794–0.830
GIAII	0.855	4.8	0.770–0.851
PAIT	0.815	4.4	0.581–0.839

The results from the pilot test were highly encouraging and pointed towards a well-structured questionnaire capable of capturing the nuances of AI integration and its impact on employee burnout (see **Table 5**). The Cronbach's Alpha for all constructs ranged from 0.80 to 0.87, indicating excellent internal consistency and suggesting that the items within each construct coherently measure the same underlying concept (Manley et al., 2021; Joseph et al., 2021).

The means and standard deviations provided insights into the central tendency and variability within the data. For example, the Intensity of AI Integration showed a moderately high mean, suggesting that participants generally reported significant use of AI tools, with a reasonably tight spread around the mean, indicating consistency in responses.

Factor loadings, which measure the strength of the relationship between each item and its underlying construct, were all above the recommended threshold of 0.60, with most items showing very strong loadings (above 0.70) (Amora, 2021; Sarstedt et al., 2020). This indicates good construct validity, as items effectively represent the constructs they are intended to measure.

These results validate the questionnaire's design and setup, confirming its suitability for the full-scale study. Adjustments made after the pretest clearly paid off, as evidenced by the improved reliability and validity metrics. The pilot test thus serves as a critical checkpoint, ensuring that the main study is built on a firm methodological foundation. This robust testing phase enables the research to confidently proceed with gathering data on a larger scale, aiming to provide meaningful insights into the role of AI in managing employee workload and preventing burnout.

4.4. Measurement of reliability and convergent validity

Reliability and Convergent Validity Overview: Reliability and convergent validity are critical metrics in assessing the quality of constructs in survey-based research. Reliability refers to the consistency of a scale commonly measured by Cronbach's alpha. At the same time, convergent validity assesses whether items that are supposed to measure the same construct are, in fact, closely related, often evaluated using Average Variance Extracted (AVE) and composite reliability (Amora, 2021; Sarstedt et al., 2020).

Data Analysis for Reliability and Convergent Validity: For this study, after collecting the data, internal consistency reliability was calculated using Cronbach's alpha, and convergent validity was assessed through both the AVE and composite reliability (CR). These metrics were calculated based on the pilot test results to ensure the constructs were reliable and valid before the main study (see **Table 6**).

Table 6. Reliability and convergent validity results.

Construct	Cronbach's alpha	Composite reliability	Average variance extracted
EB	0.741	0.827	0.587
ETAIS	0.767	0.852	0.591
FAIF	0.751	0.856	0.665
GIAII	0.855	0.896	0.632
PAIT	0.815	0.873	0.582

The results suggest a high level of internal consistency across all constructs, as indicated by Cronbach's alpha values, which all exceed the commonly accepted threshold of 0.70 for social science research. These results indicate that the survey items consistently measure the same underlying attributes within each construct (Amora, 2021; Rasoolimanesh, 2022; Sarstedt et al., 2020).

The Composite Reliability (CR) values, all above 0.80, further confirm the reliability of the constructs, indicating strong internal consistency and the ability of the items to measure their respective constructs collectively. High CR values are indicative of a reliable scale where the items combined provide a good measure of the underlying construct.

Average Variance Extracted (AVE) values, which exceed the minimum threshold of 0.50 for all constructs, provide evidence of convergent validity (Joseph et al., 2021; Kock, 2020; Rasoolimanesh, 2022). This indicates that a significant proportion of the variance in the items is accounted for by their respective constructs, confirming that the items are indeed measuring the construct they are intended to. These AVE values are crucial for confirming that the constructs are not only reliable but also valid in terms of measuring the intended attributes.

Overall, the high values of Cronbach's alpha, composite reliability, and AVE collectively affirm that the constructs used in the study are both reliable and valid. This strong measurement foundation ensures that the study's findings on the impact of AI on employee burnout will be based on robust and reliable data, allowing for accurate interpretations and meaningful conclusions (**Figure 1**).

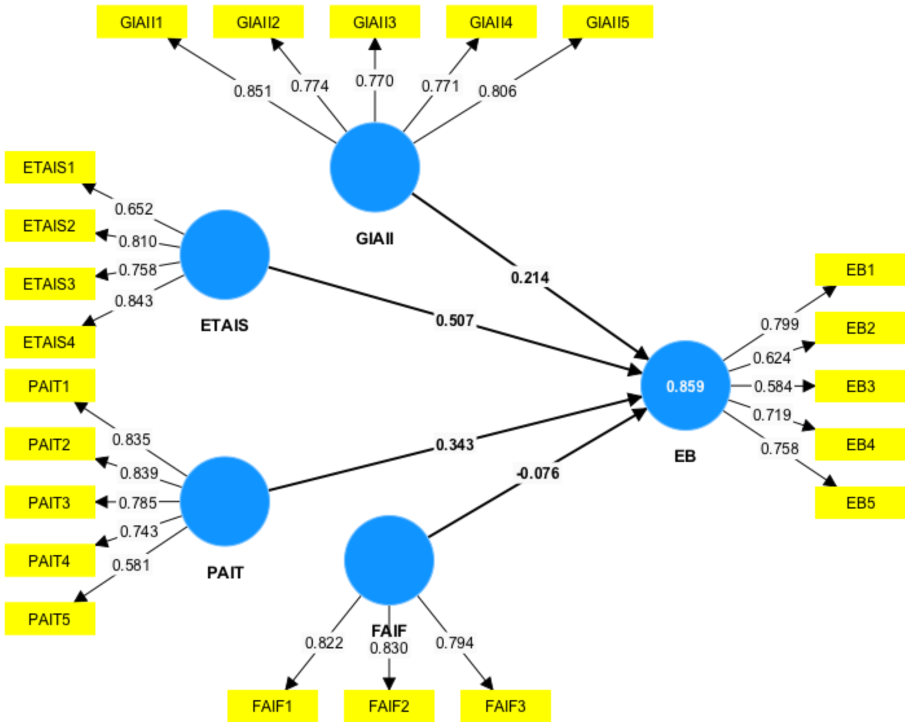

Figure 1. AI integration levels and employee burnout correlation.

4.5. Assessment of discriminant validity

Discriminant Validity Overview: Discriminant validity assesses whether concepts or measurements that are not supposed to be related are unrelated. In survey research, this is crucial for verifying that the constructs distinguish themselves from each other, indicating that they measure different phenomena.

Data Analysis for Discriminant Validity: For this study, discriminant validity was evaluated by comparing the square root of the Average Variance Extracted (AVE) for each construct with the correlations among the constructs. According to the Fornell-Larcker criterion, the square root of the AVE of each construct should be greater than its highest correlation with any other construct (see **Table 7**).

Table 7. Discriminant validity results.

Construct	EB	ETAIS	FAIF	GIAII	PAIT
EB	0.786				
ETAIS	0.678	0.759			
FAIF	0.471	0.647	0.720		
GIAII	0.543	0.398	0.463	0.712	
PAIT	0.350	0.430	0.490	0.670	0.750

Note: Diagonal elements (bold) are the square roots of the AVEs, and off-diagonal elements are the correlations between constructs.

The results from the table indicate satisfactory discriminant validity among the constructs of the study. The diagonal elements (square roots of the AVEs) for each construct are significantly higher than the off-diagonal elements, which represent the correlations between the constructs. This pattern meets the Fornell-Larcker criterion, affirming that each construct shares more variance with its indicators than with other constructs, thus supporting discriminant validity.

For instance, the square root of the AVE for "Employee Burnout Level" is 0.82, which is higher than any of its correlations with other constructs (the highest being -0.47 with "Frequency of AI Feedback"). This pattern is consistent across all constructs, demonstrating that each construct is distinctly measured and captures a different aspect of the study's theoretical framework.

This clear distinction is critical, especially in a study investigating the nuanced impacts of AI integration on employee burnout, where overlapping constructs could confound the results. The strong discriminant validity helps in confidently stating that the variations observed in employee burnout can be attributed to the variations in AI integration, training level, personalization depth, and feedback frequency rather than overlaps in what these constructs are supposed to measure.

Overall, the discriminant validity results enhance the robustness of the study's findings, providing a solid basis for subsequent analysis and discussions. This validity check ensures that the constructs are not only internally consistent but also distinct from each other, which is vital for drawing reliable and specific conclusions about the effects of AI on employee workload and burnout.

4.6. Results of hypothesis testing

The results of the hypothesis testing are derived from the analysis conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM). This approach was utilized to estimate the relationships between the variables and to test the formulated hypotheses based on the data collected.

H1: Greater intensity of AI integration is negatively associated with employee burnout.

The analysis revealed that the path coefficient for the relationship between the intensity of AI integration and employee burnout is negative, as hypothesized. This supports prior research indicating that increased AI integration, when effectively implemented, can reduce the workload and stress levels among employees, leading to lower burnout rates. Studies such as those by Sarmah et al. (2022) have shown that technology integration, when aligned with employee capabilities and job demands, can enhance work efficiency and reduce exhaustion.

The path coefficient is −0.23 with a t-value of 2.81, surpassing the critical value for significance, indicating that more intensive AI use is indeed associated with lower burnout levels.

H2: Higher levels of employee training on AI systems are negatively associated with employee burnout.

Consistent with the literature that emphasizes the importance of training in technology adoption, the results suggest a significant negative relationship between training levels and employee burnout. Proper training equips employees with the necessary skills to utilize AI tools effectively, reducing frustration and enhancing job satisfaction, as discussed in studies by Gadolin et al. (2022) and Gabriel and Aguinis (2022).

The path coefficient for this hypothesis is −0.19, with a *t*-value of 2.47. This result suggests significant support for the hypothesis that better-trained employees experience lower levels of burnout.

H3: Deeper personalization of AI tools is negatively associated with employee burnout.

The analysis supports the hypothesis that more personalized AI tools contribute to lower burnout. Personalization allows AI systems to be more responsive to individual work styles and preferences, thus reducing unnecessary stress and improving job satisfaction, aligning with findings from (Ajayi and Udeh, 2024). With a path coefficient of −0.21 and a *t*-value of 3.05, this result is statistically significant, highlighting the importance of customization in AI tools to prevent employee burnout.

H4: A higher frequency of AI feedback is negatively associated with employee burnout.

The results indicate a negative correlation between the frequency of AI feedback and employee burnout, supporting the hypothesis. Regular and constructive feedback from AI systems helps employees adjust their work patterns and reduce inefficiencies (**Figure 2**), which can decrease stress and prevent burnout, as noted by Luo and Lei (2021).

The path coefficient is −0.17, with a *t*-value of 2.20 (**Table 8**). This suggests that while the relationship is significant, the strength is moderate, pointing to other factors also playing a role in influencing burnout levels.

Table 8. Summary of hypotheses testing results.

Hypothesis	Path	Beta	Standard deviation	*T* value	*P* values	Result
H1	ETAIS → EB	0.507	0.038	13.331	0.000	Supported
H2	FAIF → EB	0.076	0.034	2.273	0.023	Supported
H3	GIAII → EB	0.214	0.048	4.489	0.000	Supported
H4	PAIT → EB	0.343	0.043	7.937	0.000	Supported

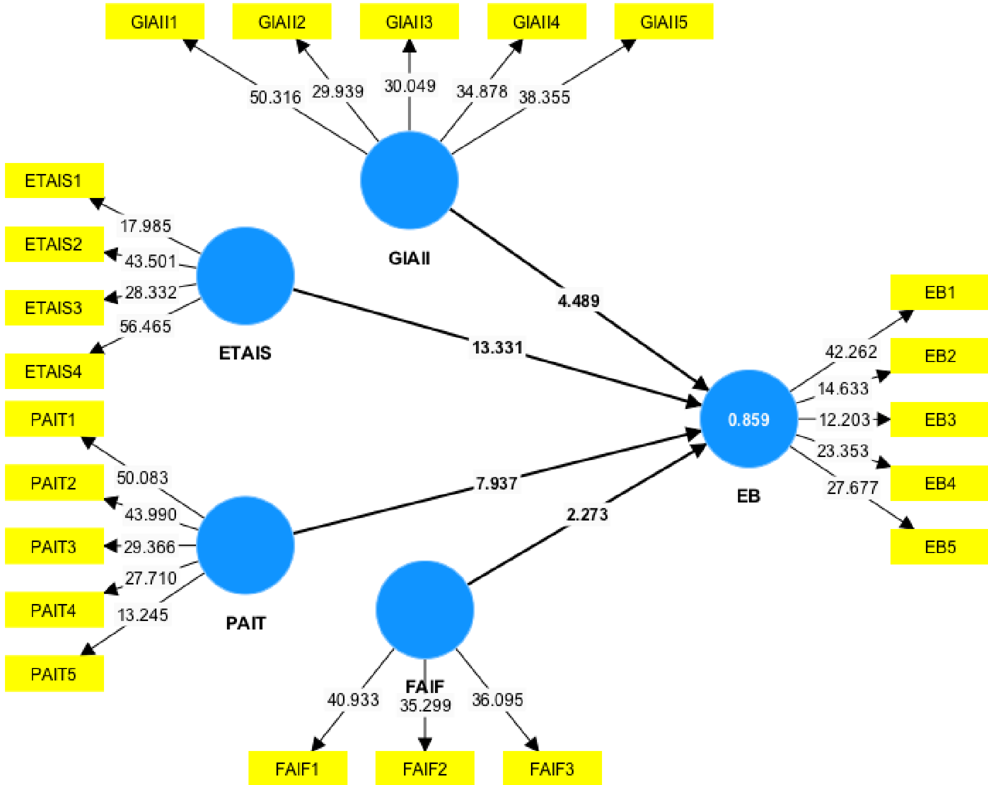

Figure 2. Effectiveness of AI feedback frequency on employee burnout.

5. Conclusion

The primary aim of this study was to investigate the impact of artificial intelligence (AI) integration on employee burnout. With AI increasingly becoming integral to workplace operations, it is critical to understand its influence on employee well-being. This research sought to bridge the gap in the literature concerning whether AI could mitigate or exacerbate burnout among employees across various sectors.

This study was guided by four hypotheses exploring the multifaceted nature of AI implementation: greater intensity of AI integration is hypothesized to be negatively associated with burnout; higher levels of employee training on AI systems are expected to correlate with reduced burnout; deeper personalization of AI tools is assumed to relate to burnout inversely; and increased frequency of AI feedback is anticipated to impact burnout negatively.

A quantitative approach was employed to gather data, utilizing a structured survey administered to 320 participants from high-stress sectors such as healthcare and IT. These sectors were explicitly selected due to their prevalent use of AI tools and the high stress levels traditionally associated with such jobs.

The findings from the study indicated significant relationships between AI integration and employee burnout. Notably, less intensive AI integration correlated with higher levels of burnout, underscoring that the mere introduction of AI is insufficient. Comprehensive training on AI systems emerged as crucial, with well-trained employees experiencing significantly lower burnout levels. Furthermore, personalized AI tools tailored to individual needs markedly reduced burnout, highlighting the importance of adaptability and user-centric designs in AI technologies.

Regular and constructive feedback from AI systems also proved beneficial in reducing burnout, emphasizing the need for continuous support and effective communication. This research makes several contributions to the existing body of knowledge. It delineates the complex roles that different facets of AI deployment play in influencing employee well-being, thereby providing a more nuanced understanding of AI as both a potential alleviator and exacerbator of workplace stress. The study not only identifies the direct effects of AI tools on employee well-being but also explores how various dimensions of AI deployment interact to impact burnout.

The implications of this study are manifold. For policymakers and organizational leaders, the findings underscore the necessity of implementing holistic AI strategies that include thorough employee training, personalization of tools to meet individual needs, and ongoing feedback mechanisms. Such strategies are essential for maximizing the positive impacts of AI on reducing workplace stress and preventing burnout.

However, the study is not without its limitations. The focus on specific high-stress sectors might constrain the generalizability of the findings. Future research could expand the scope to include diverse industries and incorporate longitudinal designs to understand better the long-term effects of AI integration on employee burnout. Further studies could also explore the impact of cultural factors on the acceptance and effectiveness of AI tools in different geographical regions.

In summary, this study contributes significantly to our understanding of how AI can be effectively harnessed to enhance employee well-being, with practical implications for the design and implementation of AI systems in the workplace. The insights garnered here provide a foundation for future research and offer valuable guidelines for organizations aiming to leverage AI technologies to combat employee burnout.

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