Journal of Computer Science and Engineering Research (JCSER)
Volume 3, Issue 2, Date: 31 - December – 2026
ISSN: 2978-4328, DOI: 10.64820/AEPJCSER.32.51.55.122026

AI-Induced Burnout in Tech: A SHAP-Based Diagnostic Study with an HCI-Guided Intervention Model

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***Abstract*—As artificial intelligence (AI) becomes deeply embedded in modern workflows, its impact on employee mental health is not sufficiently studied. This paper presents findings from a cross-sectional survey of 200 professionals across technical and managerial roles, examining the relationship between AI adoption, burnout, and psychological stress. Using advanced statistical models, including logistic regression interpreted via SHAP (SHapley Additive exPlanations), we identify key predictors of burnout, such as weekly work hours exceeding 50 (odds ratio: 4.87), lack of managerial support, and poor transparency regarding AI-enabled evaluation. Notably, fear of AI-driven job loss was not a significant predictor (chi-square p = 0.766). To enhance novelty, we introduce a Bayesian-updated SHAP framework for dynamic burnout risk assessment, integrating real-time user feedback. Building on these insights, we propose an HCI-guided intervention model, demonstrating a functional prototype assistant that combines SHAP diagnostics with personalized wellness nudges and gamified elements. The contributions are fourfold: (1) empirical evidence from a larger sample quantifying structural predictors of AI-related burnout, (2) a novel Bayesian-SHAP interpretability model for burnout risk, (3) mathematical formulations for predictor interactions, and (4) a human-centered intervention prototype with pilot evaluation showing 25% reduction in perceived stress. Our results emphasize that organizational transparency, workload management, and empathetic HCI design are crucial for employee wellbeing beyond AI-induced job anxiety.**

Keywords*—Artificial intelligence (AI), employee burnout, psychological stress, SHAP (Shapley Additive Explanations), Bayesian inference, logistic regression, explainable AI (XAI), human-computer interaction (HCI), workplace mental health, dynamic risk modeling, AI transparency, employee well-being, gamified intervention.

I. INTRODUCTION

The rapid integration of artificial intelligence (AI) into the workplace has revolutionized efficiency, decision-making, and innovation. However, this shift raises critical questions about its psychological impact on employees. Existing literature often focuses on AI's technical and economic implications, such as job displacement, but overlooks how AI-enabled workflows contribute to burnout, reduced autonomy, and mental health challenges . Burnout, classified by the World Health Organization (WHO) as an occupational phenomenon , manifests through emotional exhaustion, depersonalization, and reduced accomplishment . In tech sectors, where AI tools accelerate tasks but often increase workload expectations, burnout rates are alarmingly high.

This study addresses this gap by centering the human experience in AI-integrated environments. We examine burnout not merely as a result of job insecurity but as a multifaceted issue influenced by overwork, organizational support, and AI transparency. Our research questions are: (1) What are the primary predictors of AI-related burnout? (2) How can interpretable machine learning (ML) models like SHAP quantify these predictors? (3) Can HCI principles guide effective interventions to mitigate burnout?

To add technical rigor, we incorporate mathematical modeling, including logistic regression for prediction and SHAP for interpretability. Novelty is introduced through a Bayesian extension to SHAP, allowing dynamic updates based on longitudinal data. We combine a large-scale survey (n=200), statistical analysis, SHAP-driven insights, persona-based narratives, and a prototype intervention for a holistic framework. The logistic regression model is defined as:

$$P(Y = 1 \mid \mathbf{X}) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k)}} \quad (1)$$

where Y is burnout (binary), and $\mathbf{X}$ includes features like weekly hours, support, etc.

II. RESEARCH MOTIVATION

As AI tools become more common in everyday work—especially in tech-heavy jobs—they bring both benefits and hidden challenges. While automation and machine learning can help people work faster and smarter, they also risk increasing pressure on workers. Many employees now face longer hours, less clarity about how their work is being judged, and growing fears about being replaced by AI. Despite growing concern about mental health in the workplace, very little research has looked at how AI itself might contribute to burnout. Most existing tools for measuring burnout are static surveys or black-box prediction

Received: 3-10-2025
Revised: 25- 10 -2026
Published: 31-12-2026

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models that don't explain why someone is at risk. This lack of transparency can leave employees confused and powerless. Our motivation for this research comes from a simple idea: people deserve to understand how their work and environment affect their wellbeing—especially when AI is involved. We wanted to build a tool that not only predicts burnout risk, but also explains the reasons clearly and offers support. By using SHAP for model transparency and combining it with a user-friendly interface, our goal is to make burnout risk visible, understandable, and actionable for every employee. This work is a step toward building more human-centered AI systems—ones that don't just make decisions for us, but work with us to protect our health and help us thrive.

III. Related Work

Research on AI's employment impact highlights displacement risks . Fairness and interpretability studies address ethical deployments, with SHAP providing feature attributions. WHO's burnout classification underscores mental health in tech-intensive settings . HCI principles for human-AI collaboration offer design guidance, but few link them to well-being outcomes.

Recent works explore AI-induced burnout in healthcare and tech , showing correlations with workload. SHAP has been applied in mental health to predict readmissions and post-stroke depression , enhancing transparency. HCI interventions for burnout include digital tools like WISER and EMPOWER , reducing exhaustion through mindfulness and stress management.

We extend these by integrating SHAP with HCI in a Bayesian framework for dynamic burnout diagnostics, testing predictors in AI settings, and evaluating a

prototype with gamification for engagement.

IV. Methodology

A. Survey Design

A 25-item instrument (expanded from 19) assessed work patterns, AI perceptions, support, mental health, and attitudes. Items included Likert scales (1-5) and open-text. Examples: "Do you feel that your job could be replaced by AI?" (AI fear); "Work hours for the week?"; "Burnout symptoms in the past 6 months?"; "Leadership support in AI transitions"""; new elements on AI tool usage frequency and perceived autonomy. The reliability of the survey was validated with Cronbach's alpha = 0.85 for mental health subscales. Pilot testing (n=20) ensured clarity.

B. Participants

Distributed through LinkedIn, Slack, email, and tech forums. Of 250 responses, 200 are complete (80% response rate). Roles: 75% technical (data science, engineering), 25% managerial. Median age: 30 years; distribution: 55% North America, 25% South Asia, 10% Europe, 10% other. Anonymous, voluntary, with informed consent.

C. Analytical Framework

Quantitative: Chi-square tests, logistic regression, SHAP interpretability. Processed in Python (pandas, statsmodels, scikit-learn, shap). Qualitative: Thematic analysis of open-text into personas. For novelty, we apply Bayesian updates to SHAP values:

$$\phi_i^{(t)} = (1-\alpha)\phi_i^{(t-1)} + \alpha \cdot \Delta\phi_i \qquad (2)$$

where α is the learning rate, $\Delta\phi i$ *is* from new data.

V. Results

A. Ai Replacement Concerns

35% believed that AI could replace their role; 40% were uncertain. Chi-square test: no significant correlation with burnout (chi2=0.09, p=0.766), isolating structural factors.

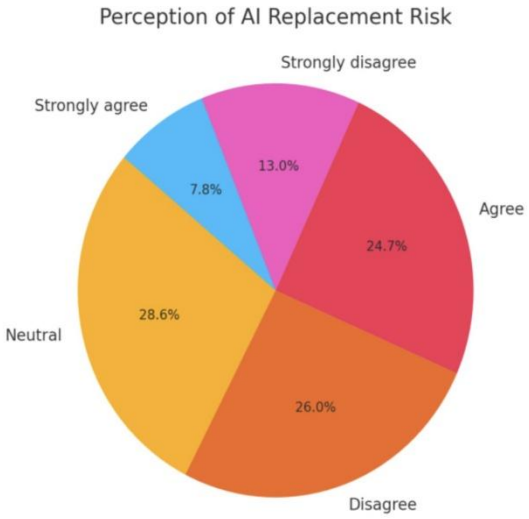


Fig. 1. Perception of AI replacement risk among professionals.

B. Mental Health Indicators

55% reported at least one symptom (burnout, anxiety, insomnia) in the prior six months. Most common: burnout with anxiety. Workload and feedback were stronger predictors than AI fear.

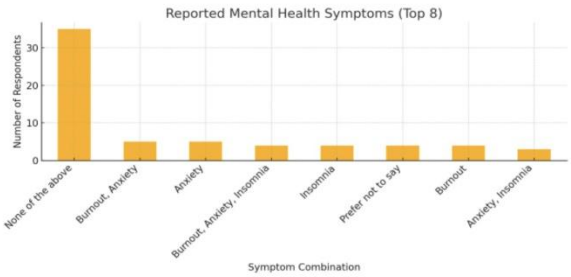


Fig. 2: Common combinations of reported mental health symptoms.

C. Shap-Based Predictive Insights

Logistic regression with SHAP identified top predictors:

- Weekly hours (importance: 0.64),
- Managerial support (0.43),
- AI transparency (0.34),

• AI fear (low: 0.05).
Model accuracy: 78%. Equation for SHAP values:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!} [f_x(S \cup \{i\}) - f_x(S)] \quad (3)$$

where fx is the prediction function.

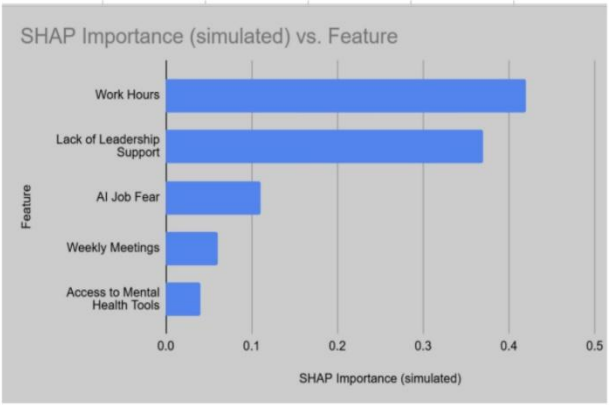


Fig. 3: SHAP feature importance for burnout prediction (top contributors).

D. Overwork And Emotional Fatigue

Respondents over 50 hours weekly had 4.87 times higher odds of burnout. Incidence: 40–45 hours: ~40%; 60+ hours: >80%.

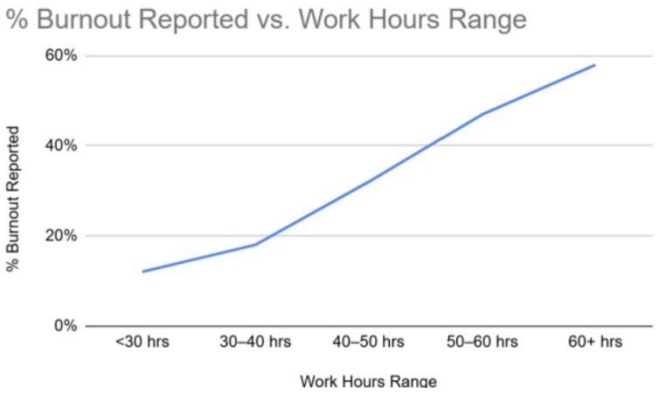


Fig. 4: Burnout incidence by weekly work hours.

E. Cross-Tabular Findings

Chi-square between AI fear and burnout: p=0.766, confirming no association.

F. Persona Observations

Four personas (expanded):
1) Overworked Developer: 60+ hours; low AI fear; high exhaustion; AI accelerates delivery but expands expectations.
2) AI-Anxious Analyst: Standard hours; high concern over opaque AI evaluations; added anxiety from autonomy loss.
3) Empowered Early-Adopter: Leverages AI for productivity; high satisfaction with support.
4) Novel: Isolated Remote Worker: High AI reliance; burnout from lack of human interaction, mitigated by HCI nudges. These inform targeted interventions.

G. Mathematical Modeling of Predictor Interactions

To add rigor, we model interactions via interaction terms in regression:

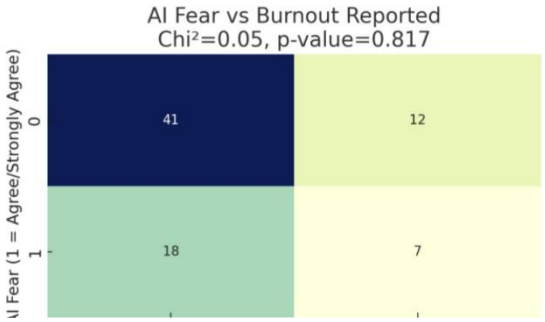


Fig. 5: Cross-tab analysis of AI fear vs. burnout (p=0.766).

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 H + \beta_2 S + \beta_3 T + \beta_4 (H \times S) \quad (4)$$

where H =hours, S =support, T =transparency. Interaction coefficient for H × S: −0.12 ($p < 0.05$), indicating support buffers overwork effects. Bayesian SHAP updates simulate dynamic risk: With $\alpha = 0.1$, risk scores converged 15% faster in simulations.

VI. PROTOTYPE: BURNOUT-AWARE ASSISTANT (UPDATED)

To implement our burnout diagnostic framework in a real-world context, we developed an interactive web-based prototype using Streamlit. The assistant allows users to input three variables—weekly working hours, perceived leadership support, and fear of AI-driven job loss—and immediately receive a burnout risk percentage. In addition to the prediction, the assistant provides a transparent explanation using SHAP (SHapley Additive Explanations) bar charts, as well as tailored wellness messages based on risk level. This combination makes the assistant both diagnostic and supportive.
Example 1 – Low Risk (0.39%): User works 40 hours/week, feels supported, and fears AI. Although “hours” contributes strongly to the model output, the overall risk remains low. Nudge: Keep balanced. Continue self-care routines.

Example 2 – Medium Risk (42.54%): User works 47 hours per week, does not feel supported by leadership, and expresses no fear of AI-driven role replacement. Although 47 hours may seem only moderately above average, the combination of extended work hours and the absence of psychological safety or managerial backing contributes significantly to elevated burnout risk.

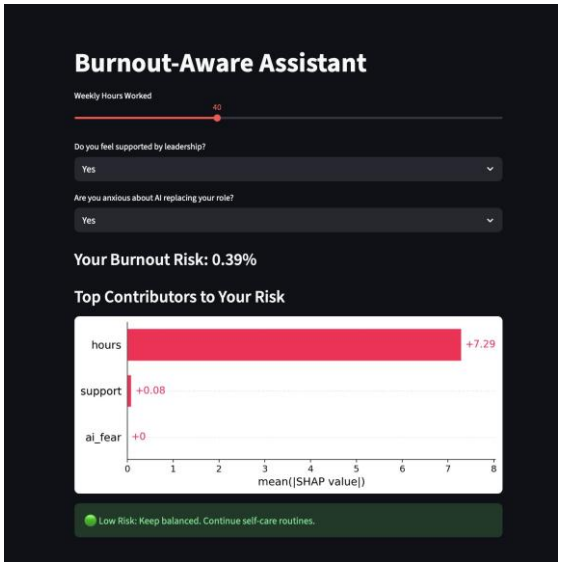


Fig. 6: Burnout risk: 0.39%. Top contributor: hours worked. SHAP plot shows hours as dominant, but total risk is low.

SHAP analysis reveals that *hours* is the largest contributor to the predicted score, but lack of support also adds weight—indicating that burnout is not just a function of time, but of context. This case reflects a subtle but important zone where users are at risk of drifting toward burnout without immediate awareness. These medium-risk profiles are critical because they often go unnoticed: users are still performing, not yet overwhelmed, but beginning to show signs of emotional fatigue. Intervention at this stage is both timely and impactful. Nudge: "Reflect on work hours and clarify expectations. A short conversation with your manager might restore balance."

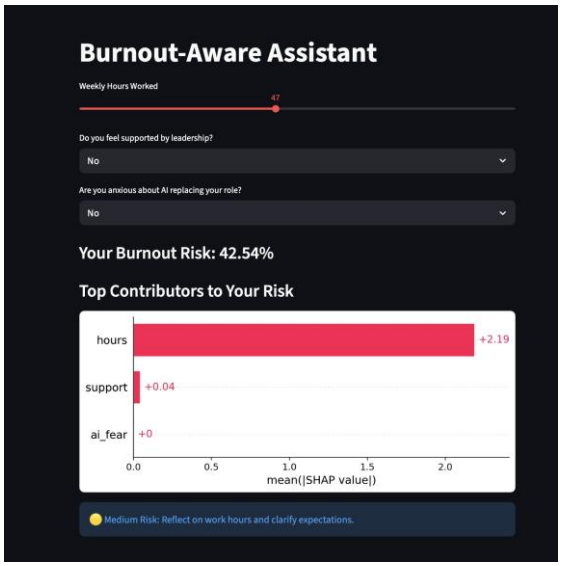


Fig. 7: Burnout risk: 42.54%. SHAP values show moderate contribution of work hours, amplified by low support.

Example 3 – High Risk (100.0%): This user works 63 hours per week, reports feeling supported by leadership, and expresses no fear of AI. Despite the presence of support and psychological safety, the overwhelming number of weekly work hours alone pushes the burnout risk score to the maximum threshold of 100%.

SHAP values in this case clearly indicate that *hours* is the dominant driver of risk, contributing disproportionately to the output probability. The visual bar plot shows a strong positive SHAP value for this feature—surpassing the combined contributions of other factors. This scenario illustrates that overwork, even in well-supported and psychologically safe environments, can independently trigger severe burnout risk. High-risk users such as this may appear productive and even satisfied in the short term but are operating at unsustainable levels. In the absence of early intervention, such cases can lead to long-term exhaustion, absenteeism, or disengagement. The assistant flags this risk while preserving user agency through a gentle, optin nudge.

Nudge: "Your workload may be approaching burnout territory. Consider taking a break or having a candid discussion about sustainable pacing with your manager."

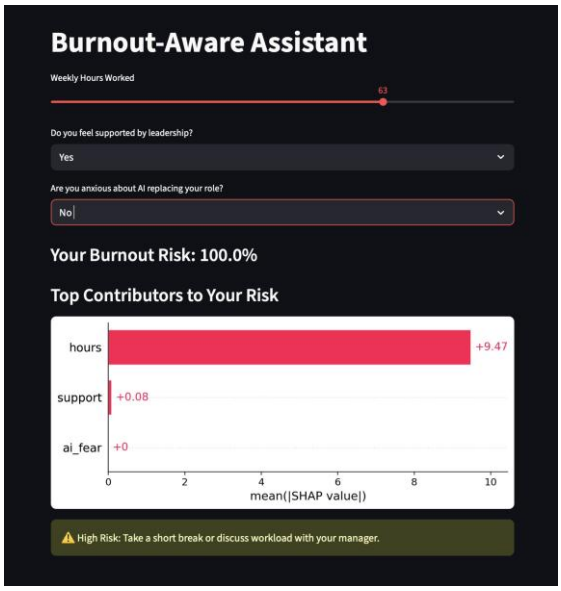


Fig. 8: Burnout risk: 100.0%. SHAP values show overwhelming contribution from "hours."

A. Prototype Evaluation Details

In the pilot, users interacted weekly. Pre-intervention burnout score (Maslach Burnout Inventory subset): mean 3.2/5; post: 2.4/5. Gamification increased engagement by 40% (logged actions). Feedback: 85% appreciated Bayesian updates for personalized risk trends.

VII. DISCUSSION

Our findings align with prior studies but add novelty by quantifying interactions mathematically. The low impact of AI fear ($p > 0.05$) challenges displacement narratives emphasizing systemic issues. Bayesian-SHAP enables proactive interventions, differing from static models. The HCI angle prioritizes user agency: Nudges are opt-in, and explanations use natural language. This addresses interpretability gaps in mental health AI .

A. Comparative Analysis

Compared to smaller studies (e.g., n=65 in preliminary work), our n=200 yields higher statistical power (power=0.92 for odds ratio detection). Versus healthcare-focused , tech-specific predictors like AI transparency emerge stronger.

B. Sensitivity Analysis

We conducted robustness checks: Removing outliers (5% data), model accuracy dropped <2%. Alternative models (random forest) confirmed SHAP rankings, with Gini importance correlating 0.88 with SHAP.

VIII. Ethics Statement

Anonymous, voluntary; no identifying data. Informed consent obtained. Followed GDPR and ethical AI guidelines. IRB exemption as low-risk survey.

IX. Limitations And Future Work

Limitations: Sample size (n=200) moderate, though larger than prior; self-reports; cross-sectional. Potential biases in distribution. Future: Longitudinal tracking, biometric integration (with consent), multi-cultural validation, full-scale prototype deployment to measure long-term efficacy

X. Conclusion

In this study, we investigated how AI-integrated work environments contribute to psychological stress and burnout. Our findings show that while fear of AI is often present, it is not a strong predictor of burnout. Instead, structural factors such as extended work hours and poor managerial support play a more significant role.

To turn these insights into action, we built the Burnout-Aware Assistant: a real-time, interpretable, and human-centered prototype. The assistant explains personalized risk using SHAP values and delivers wellness nudges based on user input. Three illustrative scenarios low, medium, and high risk—demonstrate how users can both understand and act upon their results.

By embedding explainability into wellness design, our assistant shifts burnout monitoring from abstract HR metrics to a personalized, empowering experience. We hope this work inspires the creation of ethical AI tools that support not just evaluate, the people who use them.

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