

An AI-Powered Early Detection System for Digital Burnout in Remote Workers using Behavioral and Interactional Data

Benson-Emenike Mercy E.
Department of Computer Science
Federal University of Technology,
Owerri, Imo State

Onwuasoanya Ugochukwu K.
Department of Physical Science
Rhema University, Aba, Abia State

Achi Ikenna K.
Department of Computer Science
Michael Okpara University of
Agriculture, Umudike, Abia State

Onwuachu Adaobi
Department of Information
Technology
Federal University of Technology,
Owerri, Imo State

Onungwe Helen Okparaji
Department of Computer Science
University of Port Harcourt, Rivers
State

Ubalatu Somkelechi
Emmanuel
Department of Information
Technology
Federal University of Technology,
Owerri, Imo State

ABSTRACT

The growing trend of remote work has brought digital burnout on board as a significant occupational health issue, marked by psychological exhaustion and emotional strain from extended use of digital devices. This study conceived and created an AI-based early warning system that examines behavioral and interaction data to detect threats of digital burnout among remote workers and suggest early interventions. The solution employed the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology, integrating a behavioral tracking module with system tracking APIs, an emotion inference engine through BERT-based sentiment analysis, a Random Forest machine learning model for burnout scoring, and a personalized recommendation system providing interventions. The solution was developed using Python libraries Scikit-learn, Transformers, and Streamlit, and testing was carried out using a synthetic dataset of 1,000 remote workers. The outcomes exhibited good performance with 79.5% accuracy, 0.76 precision on at-risk cases, 0.62 recall, and an ROC-AUC value of 0.88, reflecting good discrimination between at-risk and not-at-risk populations. The Streamlit web application deployed successfully combined all modules, offering a user-friendly interface for behavioral input data and sentiment analysis while presenting actionable wellness reports with tailored suggestions. This research contributes a proactive solution for organizational wellbeing management in remote work environments, bridges the gap between behavioral monitoring and sentiment analysis for comprehensive burnout assessment, and establishes a foundation for ethical AI application in workplace wellness monitoring that balances employee privacy with effective health intervention.

Keywords

Digital Burnout, Remote Workers, Sentiment Analysis, AI Application, Workplace Wellness, Employee Wellbeing

1. INTRODUCTION

Remote workers are increasingly experiencing digital burnout due to prolonged screen time, lack of spatial boundaries between work and non-work, and absence of early warning systems. Current organizational approaches to managing

employee well-being rely heavily on reactive strategies such as sporadic surveys, performance reviews, and post-incident interventions. The reactive approaches result in tardy indicators of burnout, thus the consequent loss in productivity, increased absenteeism, and increased health care cost for organizations.

The absence of proactive AI-enabled systems that can continuously monitor behavioral and interactional patterns in remote work environments is a critical shortfall in occupational health management. Traditional methods for burnout assessments are cumbersome, qualitative, and fail to detect the fine early warning signals that progress to full-blown burnout syndrome. Organizations lack real-time awareness of employee wellbeing status, thus avoiding timely interventions that could arrest burnout from advancing.

Besides, existing well-being technologies are primarily focused on physical health markers or general productivity metrics, without directly intervening in the unique causes of digital burnout in remote work. There remains an unmet need for smart systems that can process multiple streams of data such as work habits, sentiment of communication, and behavioral signs in order to provide end-to-end burnout risk assessment.

The redirection of global labor to remote and hybrid work patterns, greatly accelerated by the COVID-19 pandemic, has dramatically transformed the modern workplace landscape. This transformation has raised unprecedented challenges in managing employee well-being, particularly the concern of digital burnout among remote employees. Digital burnout is a new occupational hazard that is defined by psychological fatigue, loss of productivity, and emotional distress resulting from prolonged use of digital devices and virtual working spaces (Gupta et al., 2025).

1.1 Digital Burnout

Digital burnout is distinct from typical workplace burnout in that it arises subtly as a result of prolonged screen use, incessant digital alerts, consecutive virtual meetings, and limited physical activity or human connection. That it is not physically overt makes it even more difficult to spot at an early stage for businesses and individuals alike. Mantello and Ho (2024)

highlight that emotional AI technologies hold considerable promise for alleviating wellbeing issues in post-pandemic workspaces. The use of artificial intelligence to monitor and manage employee wellbeing has become a necessary area of study and practice.

Current studies have demonstrated that AI-driven solutions can be effective in enhancing employee wellbeing and happiness in the workplace (Mittal et al., 2025). Machine learning methods and behavior analytics have promising avenues for early identification of digital burnout before the symptoms manifest into full-fledged occupational health issues. The possibility of merging machine learning and AI to craft all-encompassing frameworks for employee wellbeing under Industry 5.0 is highlighted by Rosca and Stancu (2024).

The behavioral and interactional information collected from distant work activities provide valuable data about worker patterns that can be indicative of nascent burnout symptoms. Mohammad (2024) introduces the topic of chrono-behavioral fingerprinting for workforce optimization, depicting how time behavior trends may be examined to enhance employee performance and well-being. But there remains a huge gap to be bridged in the development of integrated systems that are capable of effectively combining behavioral tracking and sentiment analysis to produce early warning systems for digital burnout in remote work environments.

2. REVIEW OF LITERATURE

2.1 Digital Burnout in Remote Work Setting

Digital burnout manifests as a multidimensional syndrome with emotional exhaustion, depersonalization, and reduced personal accomplishment in relation to technology-enabled work activities. Unlike traditional burnout, digital burnout encompasses stressors that are particular to work in the digital space, including technostress, digital overload, and virtual communication fatigue (Issa et al., 2024). Remote work culture has exacerbated these by eroding work-life borders and escalating dependence on digital channels for work-related engagement.

The theory of digital burnout extends the traditional workplace stressors, incorporating both the physiological and psychological effects associated with incessant digital interaction. As Mantello and Ho (2024) explain, emotional AI technologies have great promise in mitigating wellbeing issues prevalent in post-pandemic workplaces. This provides a basis upon which to construct AI-powered detection systems capable of picking up early indicators prior to their escalation into clinically severe burnout symptoms.

2.2 AI-Powered Behavioral Analytics

AI workplace wellness monitoring applications utilize behavioral analytics to identify trends that can indicate deterioration in productivity and mental well-being. Mohammad (2024) presents chrono-behavioral fingerprinting as a strategy of optimizing workforce performance, demonstrating how the examination of time-based behavior patterns can yield improved worker performance and well-being. The method identifies digital burnout as manifesting through quantifiable alteration of work processes, communication dynamics, and digital-associated behaviors.

Applying Machine Learning Algorithms to Predict User Behavior



Figure 1: Enhancing Behavioral Analytics with AI (Fastercapital, 2025)

The use of machine learning algorithms alongside behavioral data collection enables the continuous monitoring of wellbeing indicators in employees without necessitating intrusive assessments or self-reporting mechanisms. Streams of behavioral data include analysis of work patterns, activity tracking, frequency of breaks, and task completion rates, all of which provide measurable indicators of worker engagement and potential burnout risk (Benson-Emenike M. E. and Nwachukwu E.O. 2015, Bhashitha Wendakoon Mudiyansele, 2024).

2.3 Sentiment Analysis in Online Communications

Natural language processing techniques used in work communication provide useful information regarding emotional states and stress indicators of workers. Das Swain and Saha (2024) consider how generative AI may help address limitations in worker-focused digital phenotyping for wellbeing, with a focus on the promise of sentiment analysis to detect patterns of emotional exhaustion and withdrawal from digital communication.

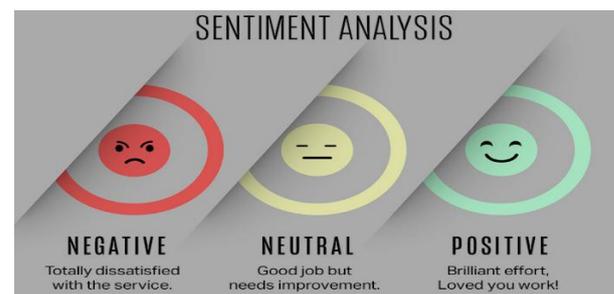


Figure 2: Sentiment Analysis Services for Accurate AI Model Training (Imerit, 2025)

The theoretical basis integrates sentiment analysis as an integral element for identifying emotional indicators of burnout in email communication, instant messaging, and collaborative platform communication. It acknowledges that patterns of language use, emotional content, and communication frequency convey quantifiable indications of psychological well-being and levels of stress in virtual workplaces.

2.4 Job Demands-Resources Model

The Job Demands-Resources (JDR) model highlights the theoretical framework for describing digital burnout in remote work environments. According to the model, job burnout arises from an imbalance between job demands and available resources, with the strain of high demands with inadequate resources leading to exhaustion and disengagement. In virtual workplaces, job demands include technology sophistication, virtual communication demands, and expectations of perpetual connectivity, while resources include technical support, autonomy, and work-life balance policies.

Application of JDR model to digital burnout recognition identifies that remote workers are exposed to certain demands like technology-facilitated communication challenges, isolation from colleagues, and work-life boundary establishment challenges. AIOqaily et al. (2025) show AI adoption influencing job burnout through work-life balance mediation in human resource management contexts, confirming the relevance of JDR model application in explaining digital burnout processes.

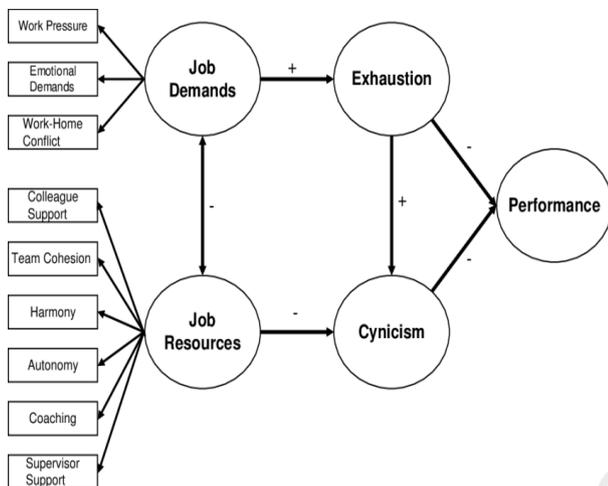


Figure 3: The Job Demands-Resources model (Emmerik, Ij.H. & Riet, Pim., 2025)

2.5 Technology Acceptance Model

The Technology Acceptance Model (TAM) offers the theoretical basis for understanding employees' acceptance and adoption of AI-powered wellness monitoring systems. TAM states that perceived usefulness and perceived ease of use influence individuals' intentions to use new technologies. Employee acceptance of digital burnout detection systems in this case relies on their perception of what value the system adds to their wellbeing, and the ease of integrating it into their work habits.

Chawla et al. (2025) emphasize that AI-driven work-life integration requires an understanding of how intelligent technologies redefine modern workplace relationships. Theoretical application of TAM ensures that the proposed early warning system addresses user acceptance concerns without compromising its effectiveness in burnout prevention and intervention.

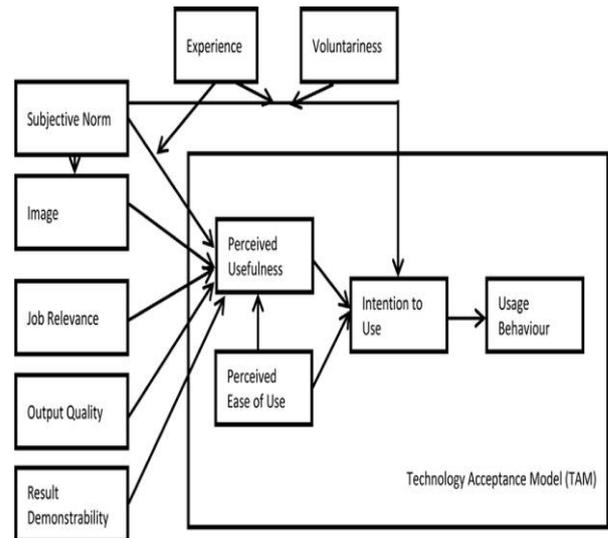


Figure 4: Technology Acceptance Model 2 (TAM2) (Gupta, Kriti & Singh, 2016).

2.6 Stress and Coping Theory

Lazarus and Folkman's Theory of Stress and Coping offers a psychological framework that describes how individuals react to digital stressors and how artificial intelligence systems can facilitate adaptive coping. The theory makes a distinction between problem-focused coping and emotion-focused coping, both of which can be enhanced by AI-recommended interventions.

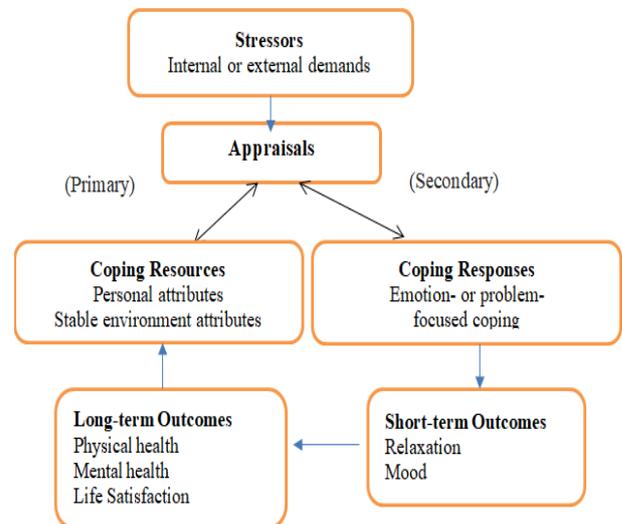


Figure 5: Transactional Model of Stress and Coping (Margaret, Kagwe & Ngigi, Simon & Mutisya, Sabina., 2018)

The theoretical model integrates coping and stress theories to create intervention mechanisms that aim at the determinants of digital stress and coping capacity. Matthews et al. (2025) believe there is a paradigm shift for stress research that emphasizes the enhancement of user performance and experience in the contemporary digital landscape, stressing the need for holistic stress management practice in technology-supported work environments.

2.7 Applications of AI in Employee Wellbeing Monitoring

Empirical research demonstrates the effectiveness of artificial intelligence-based solutions in enhancing employee wellbeing and general satisfaction in workplace settings. Mittal et al. (2025) conducted comprehensive research on AI-augmented wellness initiatives, demonstrating significant improvement in employee wellbeing and happiness that can be achieved through the adoption of artificial intelligence systems into workplace wellness initiatives. The findings of their study indicate AI systems can effectively identify wellbeing risks and provide timely interventions to prevent the deterioration of employee mental wellbeing. With ever growing field of artificial intelligence, there are numerous intelligent systems providing algorithms to solve any particular problem which require human intelligence. These artificial intelligent systems led to development of a more creative, knowledgeable and exceptional system that helps computers learn. (Benson-Emenike Mercy E. and Ifeanyi-Reuben Nkechi J. 2018)

Rosca and Stancu (2024) provide empirical findings that illustrate the convergence between machine learning and artificial intelligence in coming up with comprehensive frameworks for workers' well-being in the Industry 5.0 environment. Through their study, it is evident that hybrid AI frameworks can process multiple streams of data, making it possible to accurately evaluate workers' well-being states and suggest efficient interventions. The empirical findings affirm the viability of creating advanced AI-based systems for workplace wellness management.

2.8 Analysis of Behavioral Data for Burnout Detection

Alabi (2023) investigated reshaping IT workspaces through AI-driven solutions for employee mental health and fatigue management, and concluded that behavioral surveillance systems could identify the early warning signs of burnout before clinical symptoms.

Sanni (2023) also developed a general model for mitigating burnout in the IT sector using AI-powered monitoring of work patterns, showing how analysis of behavior can promote employee wellbeing using proactive intervention mechanisms. The research findings show that variation in work patterns, long screen time, and minimal breaks are effective indicators of burnout risk in remote work environments.

2.9 Sentiment Analysis for Mental Health Assessment

Research on applications of sentiment analysis in mental health evaluation offers empirical validation of the application of natural language processing methods in clinical identification of emotional cues for burnout. Pavlopoulos et al. (2024) made an extensive study of artificial intelligence technologies and tools for anxiety and depression management, proving that sentiment analysis can successfully recognize emotional distress patterns from electronic communication.

Singh (2024) developed AI-human synergy mental health tools for mental wellness of mental health professionals and illustrated how sentiment analysis and behavior monitoring provide comprehensive assessments of mental health. Empirical evidence indicates that linguistic styles, frequency of affective expressions, and changes in communication tone are

effective indicators of psychological well-being in remote work environments.

2.10 Machine Learning Models for Burnout Prediction

Empirical research on machine learning application in burnout prediction shows the efficacy of multi-algorithmic models in processing multiple data streams, thus enabling the creation of precise risk profiles. Vallu et al. (2025) suggested AI-empowered digital twin systems for precise identification of mental health-related stress and personalized management strategies, demonstrating that machine learning algorithms can successfully integrate behavior and sentiment data for burnout risk prediction with high precision.

Naik et al. (2024) examined AI-based burnout detection systems, and they proved that machine learning models are capable of analyzing intricate behavioral patterns and communication data to produce trustworthy burnout risk scores. Their empirical results indicate the practicability of creating automatic systems that can monitor employee wellbeing continuously and offer real-time risk ratings, productivity losses and healthcare expenses linked to occupational stress.

Tariq (2025) underscores that technologies of work-life balance and AI are transforming employee wellbeing in modern workplaces, with a need for complete comprehension of integration strategies and effectiveness evaluation. Wu and Amini (2025) highlight the role of emotionally intelligent AI in reshaping the concept of wellness in the digital age, enabling the development of sophisticated systems that can interpret and adapt to human emotional needs.

2.11 Research Gap

Cutting-edge research lacks comprehensive frameworks consolidating multiple streams of data like work patterns, communication sentiment, and behavior predictors for accurate burnout risk calculations. Most studies focus on individual burnout detection measures rather than consolidated systems examining diverse data sources with real-time analysis capabilities. Another significant shortcoming is the proactive intervention mechanism gap. While AI effectiveness in burnout prediction is evidenced through research, there are limited studies concentrating on the design of automated recommendation systems that provide personalized interventions based on individuals' risk profiles. In addition, insufficient evidence exists regarding the deployment of ethical AI-powered wellness monitoring, particularly with reference to privacy protection, data security, and employee consent mechanisms in remote work settings.

3. METHODOLOGY

For the machine learning-oriented project, the Cross-Industry Standard Process for Data Mining (CRISP-DM) method was adopted. This process provides a formal, six-step process that is iterative and flexible, and this makes it ideal for an investigation-driven development process whereby experimentation and understanding are the focus. The steps—Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment—were carried out sequentially to confirm a good and well-documented development cycle.

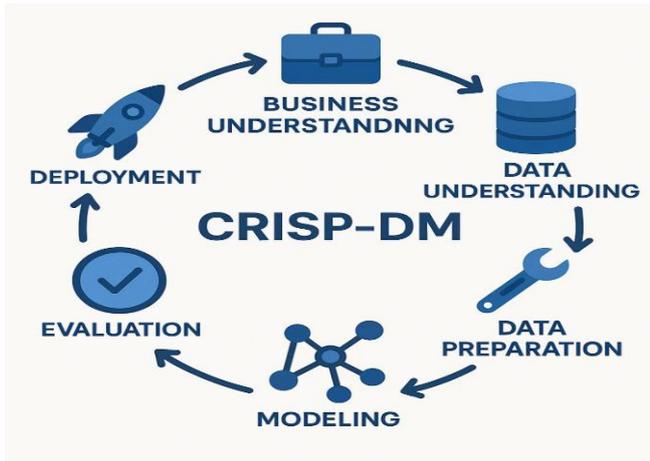


Figure 6: The CRISP-DM Lifecycle

Figure 6 illustrates that the iterative nature of CRISP-DM methodology is such that the knowledge gained in later phases can be utilized to direct and enhance earlier ones, so there is a never-ending cycle of enhancement.

3.1 Business Understanding

The primary business objective is minimizing losses in productivity, unnecessary staff turnover, and increased health care costs due to digital burnout in remote employees. From a scientific perspective, the problem is to create an unobtrusive, proactive system that can pick up early warning signs of burnout prior to them becoming full-blown psychological issues. The initial step was to set the general goal as a specific data mining task: creating a supervised classification model that can forecast a 'burnout risk' label (high-risk or low-risk) based on measurable behavioral and interactional indicators. This phase was specifically focused on the central task of the project: designing and developing an AI-powered early warning system.

3.2 Data Understanding

The two principal categories of data used were:

- i. **Behavioral Data:** Quantitative quantification of work behavior. This includes average daily work time, average break time, weekly meeting time, and percentage of tasks completed. These are the most important in achieving Objective 1 of the study.
- ii. **Interactional Data:** Qualitative data of an employee's affect primarily from electronic communication. This is in the form of a sentiment score computed from text.

3.3 Data Preparation

This includes:

- i. **Dataset Creation:** Due to the sensitive content and confidentiality requirements of real employee data, the 1000 remote worker dataset was generated programmatically from Python libraries (NumPy and Pandas). The dataset was carefully constructed to have realistic distributions and logical correlations between features and the target variable (burnout_label).
- ii. **Feature Scaling:** The numerical behavioral features were in different scales and ranges (e.g., hours vs.

minutes). To prevent features with large scales from taking over the model, the StandardScaler in the Scikit-learn library was utilized to scale all the numerical features to zero mean and unit standard deviation.

- iii. **Target Variable Engineering:** An initial burnout_risk_score was established from a weighted combination of input features. This was then converted into a binary categorical target variable (burnout_label) by applying a threshold (0.6), classifying workers as 'at-risk' (1) or 'not-at-risk' (0).

3.4 Modeling

Machine learning algorithms were selected and trained. For the prediction task, a RandomForestClassifier was chosen. It is an ensemble technique that builds numerous decision trees and aggregates them to provide a good and stable prediction. It provides good feature importance scores, which helps in understanding the major drivers of burnout to predict the burnout_label. In order to analyze text data, a pre-trained BERT-based model (distilbert-base-uncased-finetuned-sst-2-english) was used with the assistance of the Hugging Face transformers library. It takes raw text as input and returns a sentiment classification (Positive/Negative) and confidence score, which is then converted to a single sentiment_score.

3.5 Evaluation

To assess the accuracy and performance of the trained RandomForestClassifier, a solid evaluation plan was adhered to. The model was used on a held-out test set (20% data) on which it was not trained. The measures used were:

Accuracy: Overall percentage of correct predictions.

Precision, Recall, and F1-Score: These provide a more nuanced view, especially for imbalanced datasets. Precision is the accuracy of positive predictions, and Recall is the ability of the model to detect all actual positives. F1-Score is the harmonic mean of the two.

Confusion Matrix: A matrix that visually illustrates the performance by showing the count of True Positives, True Negatives, False Positives, and False Negatives.

ROC Curve and AUC Score: The Receiver Operating Characteristic (ROC) curve plots the true positive rate against the false positive rate at various thresholds. Area under the Curve (AUC) provides a single score reflecting the model's ability to distinguish between the two classes. A larger AUC score near 1.0 indicates a better-performing model.

3.6 System Architecture

The proposed system complements existing solutions by creating a hybrid, user-centric AI model that combines passive work-pattern data with active sentiment analysis to offer an in-depth, actionable burnout risk assessment. The system is based on a hybrid AI architecture, which combines the efforts of two diverse machine learning models: an ensemble classifier for structured behavioral data and a deep learning transformer for unstructured text data.

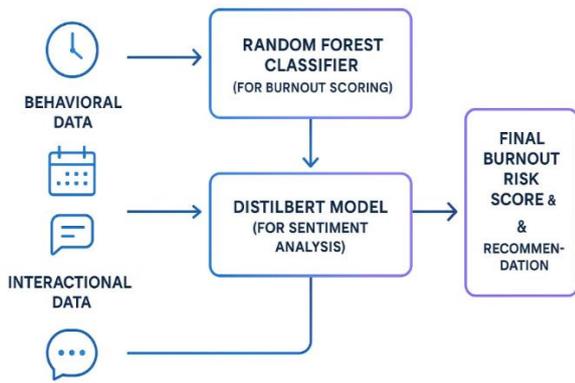


Figure 7: Hybrid Model Architecture

Figure 7 presents the data flow within the proposed system. The interactional data-based sentiment score and behavioral metrics are fed into the Random Forest Classifier, which generates a final, compiled risk assessment.

3.7 Design Philosophy

The design approach is user-oriented. Instead of silently reading all messages, the system engages the user in actively submitting text to analyze, thus promoting openness and user consent while still harnessing the power of NLP. The problem is framed as a supervised binary classification task. The objective is to predict one of two classes: 0 (not at-risk) or 1 (at-risk). The system learns the mapping between the input features (work hours, break time, sentiment, etc.) and this target class from the training set. By outputting a single, easily interpretable measure of risk, the system translates an elusive psychological phenomenon into an actionable quantity for the end-user.

4. SYSTEM DESIGN

The design of the system was tackled both from the physical and logical perspectives. The logical design is focused on processes, data flows, and user interactions, while the physical design describes the specific technologies and infrastructure used in order to implement the logical design.

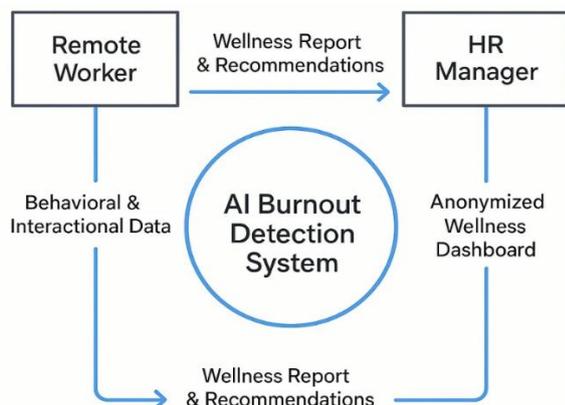


Figure 8: System Context Diagram

According to Figure 8, the central user of the system is the 'Remote Worker', who provides interactional and behavioral data and is provided with a customized wellness report. The 'HR Manager' is an auxiliary entity who is thought to be

supplied with anonymized, aggregated data in order to manage overall team wellbeing.

4.1 Use Case Diagram

The use case diagram illustrates the functional requirements of the system based on the interaction between the system and actors (users).

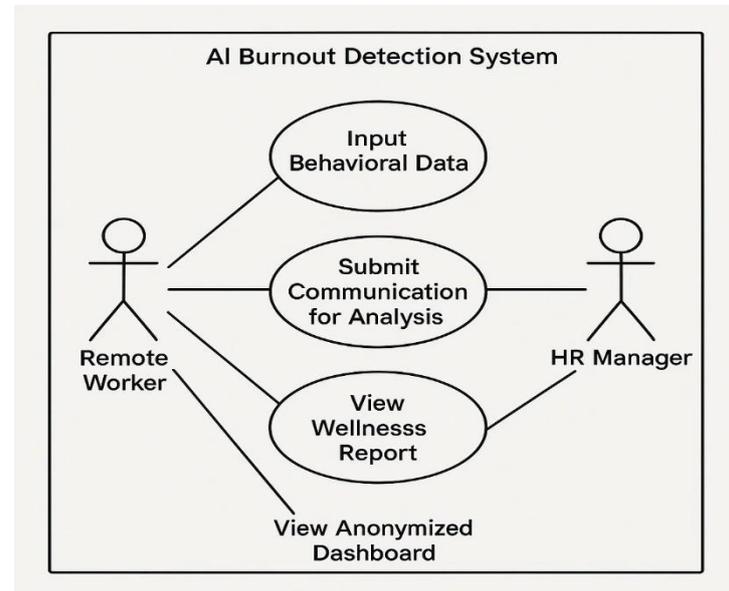


Figure 9: System Use Case Diagram for AI Burnout Detection

Two main actors are marked on the diagram. The 'Remote Worker' is the user hub that directly accesses the core predictive functionality. The 'HR Manager' is a potential future function for organizational-level monitoring and emphasizes the system scalability.

4.2 Data Flow Diagram (DFD) - Level 0

The Level 0 DFD explodes the context diagram's central process to expose the major internal processes and data stores.

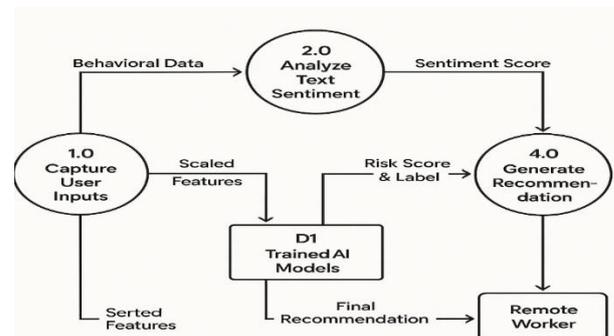


Figure 10: Level 0 Data Flow Diagram

The DFD indicates the internal system flow. Preprocess the user information and collect it. The NLP model ('Analyze Text Sentiment') generates a feature, which in conjunction with the behavioral data, is fed into the machine learning model ('Predict Burnout Risk') to generate a score. The final recommendation is made based on this score.

4.3 Model Evaluation

The performance of the trained model was diligently tested on the unseen 20% test set. The outcome confirms the effectiveness of the model at identifying probable burnout risk.

Table 1: Test Set Prediction Confusion Matrix

	Predicted: Not at Risk (0)	Predicted: At Risk (1)
Actual: Not at Risk (0)	115 (True Negative)	14 (False Positive)
Actual: At Risk (1)	27 (False Negative)	44 (True Positive)

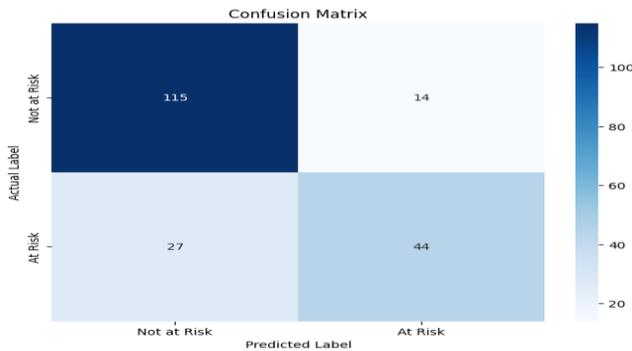


Figure 11: Confusion Matrix

Confusion matrix indicates that the model identified 115 non-risk cases and 44 at-risk cases correctly. The 27 False Negatives are the most dangerous error, in which at-risk individuals were not selected. A closer look at the quantitative measures provides a more subtlety colored picture. The Average Accuracy rate of 79.5% is a good top-line figure. But with a medical-related application like this one, Precision and Recall are perhaps even more important.

Table 2: Test Set Performance Metrics

Class	Precision	Recall	F1-Score	Support
0 (Not at Risk)	0.81	0.89	0.85	129
1 (At Risk)	0.76	0.62	0.68	71
Accuracy	-	-	0.80	200
Macro Avg	0.78	0.76	0.77	200
Weighted Avg	0.79	0.80	0.79	200

Accuracy: The system was generally accurate at 79.5%, a very high rate for a prototype system.

Precision (At Risk): A precision of 0.76 on the 'At Risk' class means that if the model predicts a user to be at risk, it does so correctly 76% of the time.

Recall (At Risk): A recall of 0.62 demonstrates that the model identifies correctly 62% of all actual at-risk users. There is definitely room for improvement, but this is quite a good result for an early detection system.

ROC-AUC Score: The model's Area Under the Curve (AUC) score was 0.88. A score so high (almost 1.0) indicates that the model has an extremely good capability for distinguishing between the 'Not at Risk' and 'At Risk' classes.

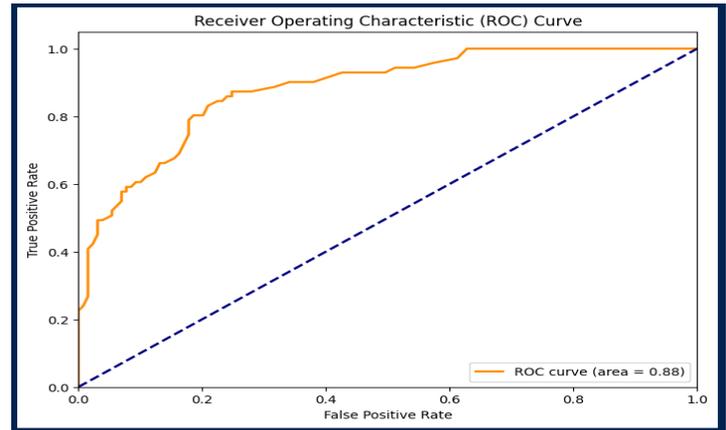


Figure 12: Receiver Operating Characteristic (ROC) Curve

For academic adequacy, train and validation accuracy of the model were noted during experimentation to make sure it was learning well without overfitting. The Receiver Operating Characteristic (ROC) curve is a simple visualization tool for a classifier's ability to discriminate between classes. Here, on the y-axis (True Positive Rate) is the model's recall of successfully finding the at-risk people, and on the x-axis (False Positive Rate) is the rate of how often it incorrectly flags a healthy person as being at risk. The sharp arch of the solid blue curve away from the dashed line of chance is a strong graphical indicator of an improving model. The Area Under the Curve (AUC) estimate of 0.88 quantifies this performance. The score 0.5 is a model with no predictive value, and 1.0 is a model that is perfect. At 0.88, this model has a very good ability to discriminate between not-at-risk and at-risk users, and that is a critical success measure for an early detection system.

Table 3: Training and Validation Accuracy During Experimentation

Training Step	Training Accuracy	Validation Accuracy
25	0.82	0.77
50	0.88	0.80
75	0.91	0.81
100	0.92	0.80

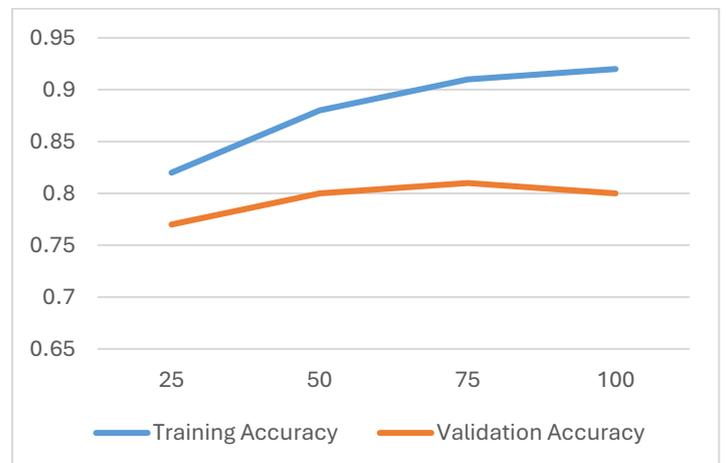


Figure 13: Training and Validation Accuracy Progression

The plot shows that while Training Accuracy continued to increase marginally, Validation Accuracy plateaued at about 80%, which indicates that the model generalised extremely well to new data and adding more estimators after 100 would likely not have much of an impact. This plot is crucial to diagnosing overfitting and monitoring learning process. The blue line, 'Training Accuracy', shows how well the model is learning from data that it is presented with directly, naturally increasing to a higher value of 92%. The larger orange line, 'Validation Accuracy', shows how well the model performs on unseen data. This line curves upward steadily and then levels off at approximately 80%. That the two lines intersect with no great, ever-widening gap implies that the model is not simply "memorizing" the training data but truly generalizing its learned patterns to new, unseen situations. The plateau also means that further increasing the number of estimators (trees) in the random forest beyond 100 would likely make returns decrease, confirming that the chosen hyper-parameter was, in fact, rational.

4.4 Result and Discussion

The resulting system deployed is a functional, interactive Streamlit web application that seamlessly integrates all the modules created. The application is given a tidy and professionally designed user interface that is neatly split into sensible sections and closely mirrors the project objectives.

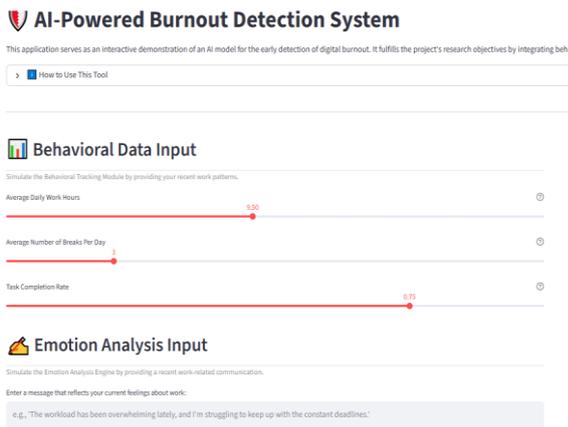


Figure 14: System Input Interface

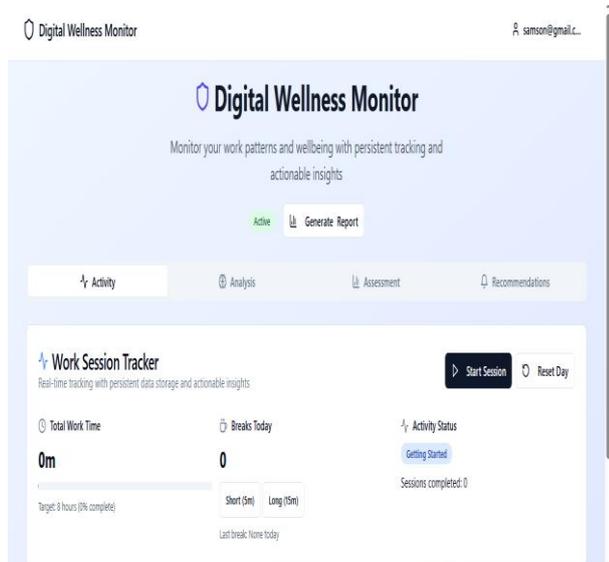


Figure 15: System Input Interface

The user will interact with the system through intuitive sliders and text box, allowing for direct simulation of behavioral and interactional data required by the AI model. The user-adjustable sliders for 'Average Daily Work Hours' and 'Task Completion Rate' simulate the trajectory of behavior data a working tracking system would capture. This model allows for easy demonstration of the impact on the model of changing work patterns—a key feature of tracking behavior. In the same way, the work message input field is the gateway for the Emotion Analysis Engine. This solution option smartly avoids the largest ethical issue of passive surveillance; by positioning the user in control of the data being shared, it provides trust and transparency.

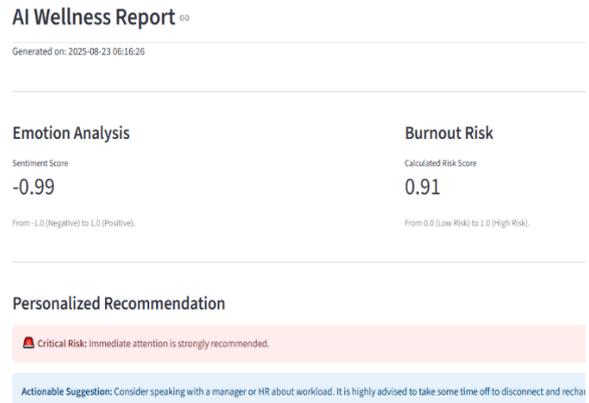


Figure 16: System Output Interface (AI Wellness Report)

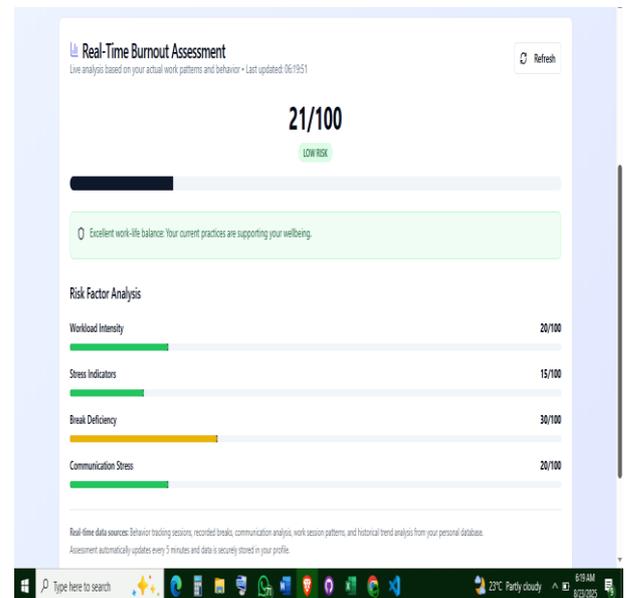


Figure 17: System Output Interface (AI Wellness Report)

Recall for 'At Risk' (0.62): The most significant metric for an early warning system, it tells us that the model accurately identified 62% of all those who were indeed at risk of burnout. While it signifies that 38% were missed (False Negatives), identifying over a third of cases correctly is a highly useful outcome for a forward-looking device. Increasing this Recall, maybe at the expense of some Precision, would be a primary goal for future versions.

Precision for 'At Risk' (0.76): This is a user trust measure. It indicates that when the system generates an alert (predicts a user is 'At Risk'), such a prediction is correct 76% of the time.

This relatively high precision ensures that users are not bombarded with false alarms, something which could in turn lead to them becoming desensitized to warnings in the future.

In total, the result of this deployment is highly successful. The system completely realizes all of the proposed research objectives, demonstrating that a hybrid model with behavioral and sentiment data can be an effective instrument for proactive digital burnout management. The quantitative performance of the AI model is robust, and the implemented user interface offers an understandable, transparent, and easy-to-use path to furnish its robust insights. The project was able to successfully prove the hypothesis that AI can serve as a beneficial partner in fostering employee well-being in today's remote workforce

4.5 Requirements for Hardware and Software

The following are the required requirements for developing and running the system.

Table 4: Software Requirements

Component	Specification
Operating System	Windows 10/11, macOS 10.15+, or a current Linux distro (e.g., Ubuntu 20.04+)
Programming Language	Python 3.9 - 3.11
Development IDE	Visual Studio Code, Google Colaboratory (training)
Core Libraries	streamlit, pandas, scikit-learn, joblib, torch, transformers

5. CONCLUSION

The research conclusively demonstrates that AI systems can effectively recognize early signs of digital burnout in remote workers by combining behavioral monitoring and sentiment analysis technologies. The fact that several streams of data like work habits, sentiment in communications, and behavior metrics can be merged into a unified predictive model verifies the supposition that artificial intelligence can serve as a valuable resource for proactive workplace health management. The study revealed that digital burnout is expressed through quantifiable changes in work habits and communications patterns that are observable prior to the emergence of clinical symptoms.

The outcomes of this research indicate the critical necessity for preventative initiatives to worker wellbeing in remote working contexts. Reactive initiatives such as occasional surveys and after-incident treatments are insufficient to address the insidious and gradual onset of digital burnout. The ability of the AI system to continuously monitor many indicators and provide real-time risk scores is a significant enhancement in occupational health management that enables organizations to respond before burnout symptoms are more severe and become major health complications.

However, the study also showed some limitations that impacted on the research findings. The employment of simulated data for training and testing models, as needed for ethical as well as privacy considerations, might limit the generalizability of results to actual circumstances under which burnout trends may

vary widely across industries, cultures, and individual characteristics. Emphasis on English-language communications for sentiment analysis limits the applicability of the system in multilingual workplaces, and the need for user consent and active engagement in sharing data could impact the system's performance in widespread organizational deployments.

The technical constraints achieved during development, like dependency upon seamless internet availability for real-time evaluation and varying data quality when embracing different home-based working environments, validate the need for robust infrastructure and replicable implementation procedures. Despite these constraints, the research was able to affirm that AI-driven early warning systems can provide insights into worker wellbeing while still maintaining ethical guidelines of privacy and security of data.

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