

Evaluating the Effectiveness of a Privacy-First AI-Based Multimodal Mood Monitoring System (Sanrakshak) among Office Employees

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ABSTRACT: Employee burnout has emerged as a critical occupational health concern in digitally intensive workplaces, particularly in high-demand sectors such as the Information Technology (IT) industry [1][3]. This study proposes a privacy-preserving multimodal Artificial Intelligence framework for early detection of burnout-related emotional exhaustion using aggregated behavioural and linguistic indicators [7] [11]. Drawing on the multidimensional burnout model, the system integrates sentiment dynamics, workload variability, and interaction-pattern features while avoiding personally identifiable data [5] [11]. Empirical evaluation demonstrates that multimodal mood scores significantly predict emotional exhaustion ($R^2 = 0.48$, $p < .01$), showing an 18 % improvement in predictive sensitivity compared with single-modality approaches [7]. The report outlines the importance of ethical governance, privacy, and transparency in AI-based monitoring [11]. The outcomes show that privacy-first multimodal monitoring can facilitate the early identification of a variety of problems which helps in improving employee privacy and trust [9] [10] [11].

KEYWORDS: AI in workplace, Burnout detection, Maslach Burnout Inventory, Privacy-first AI, Indian IT sector, Multimodal analytics, Occupational mental health

1. INTRODUCTION

Workplaces today have changed a lot because of digital transformation, working with teams around the world, and a focus on performance-driven organizational cultures[1][3]. In India's Information Technology sector, which relies heavily on knowledge, employees often find themselves working in teams spread out over different time zones. They stay connected all the time through digital networks and face ongoing pressure to perform quickly and respond fast. [3]. While these developments have facilitated remarkable innovation and economic growth, they have also exacerbated psychosocial job stressors and induced emotional exhaustion in organizational employees [5]. Common mental health conditions such as depression and anxiety are responsible for the loss of billions of working days and large-scale productivity loss across global economies, according to global estimates [1]. This necessitates preventive mental-health support strategies within organizational contexts [1].

Within the Indian context, the IT industry constitutes one of the largest professional employment sectors, and a major contributor towards national economic output [3]. Since the transition to hybrid and remote work has become more widespread, workforce surveys there have shown that technology sector workers suffer from increased levels of stress [2]. National mental-health assessments similarly report prevalence of psychological distress symptoms among working-age adults, indicating that occupational stressors play a role in overall mental-health burden pattern [6]. Such trends are bound to engender a need for more systematic frameworks in identifying and attuning mitigation strategies vis-à-vis workplace psychological risk [1][6].

Burnout remains one of the most widely studied occupational mental-health outcomes in organizational psychology [5]. Using the multidimensional burnout framework which conceptualizes burnout as emotional exhaustion, depersonalization, and a projection of low professional efficiency [4][5]. Emotional exhaustion – the core dimension, refers to a depletion of psychological resources following sustained work demands and role pressures [4]. Empirical research demonstrates that excessive workload, role ambiguity,

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and chronic stress exposure are strongly associated with emotional exhaustion, which, in turn, predicts reduced job performance, disengagement, and organizational withdrawal [5][9][10]. Since burnout evolves gradually in stages that are rarely noticeable, psychological risk outcomes need to be identified at the earliest possible time for a preventive organizational approach [5].

Prior studies show that aggregated linguistic, communicative, and behavioural metadata can reflect emotional states and stress trajectories in the ecologies [7]. Multimodal computational perspectives integrated in a portfolio of behavioural signals, including the frequency or intensity of communication, the changes in workload, and the presence of affect signals in language use have shown better predictive power relative to single channel monitoring instruments [7].

If perceived as exploiting employees or invading their privacy, digital behavioural monitoring may break the trust between managers and subordinates [8]. Critical theorists of digital capitalism highlight that data extraction practices can compromise individual autonomy and organizational trust [8]. Therefore, the integration of AI in monitoring tools of offices must follow ethical governance frameworks [11]. National and international policy frameworks increasingly highlight the Responsible AI practices focused on transparency, fairness, and human-centered design [11]. In this ethical context, privacy serving AI systems are increasingly seen as viable alternatives while respecting employee rights and confidentiality [11].

Privacy-first multimodal mood monitoring systems are supposed to find the earliest symptoms of psychological strain and discourage the collection of identifiable data while imposing and ensuring ethical protection [11]. Such privacy-first, multimodal mood monitoring systems that do not rely on personally identifiable data aim to provide organizations with psychological well-being profiles based on aggregated indicators of behavioural patterns, instead of individual surveillance, thus averting the degradation of human dignity [11]. There are thus few privacy-preserving empirical AI evaluation monitoring occupational contexts, mainly, technology-sector populations, despite growing theoretical interest in the issue [7] [11].

1.1 Importance of AI-Based Burnout Detection in Corporate Settings

AI enabled monitoring has been deployed to various organisations this integration has impacted various fields:

1. Organizational Leadership and Human Resource Management:

Early identification of burnout risk enables organizations to redistribute workloads and implement targeted wellness programs, these are done on the employee wellness data [9][10].

2. Workplace Mental-Health Programs:

Automated modes of detection of nascent psychological strain bolster the occupational health framework on a proactive basis in accordance with worldwide workplace mental-health program guidelines [1].

3. Ethical Governance and Compliance:

Automated modes of detection of nascent psychological strain bolster the occupational health framework on a proactive basis in accordance with worldwide workplace mental-health program guidelines [1].

4. Productivity and Workforce Stability:

Mitigation of emotional exhaustion culminates to a reduction in absenteeism, presentism and poor performance, a set of behaviour associated with unmanaged occupational stress [1][10].

1.2 Evolution of Workplace Mental-Health Monitoring

1.2.1 Traditional Self-Report and Survey-Based Assessment

Historically, organizations have relied on psychometric instruments, such as the Maslach Burnout Inventory, which are based on periodic self-reported perceptions of stress and exhaustion, to assess employee mental health ^[4]. Such assessments, psychometrically validated though they may be, are usually administered at long intervals and thus provide a static view of the psychological state, rather than the various changes that occur over time [5]. Sometimes burnout won't be identified in the early stages of monitoring [5].

1.2.2 Behavioural and Data-Driven Monitoring Approaches

Various mental health analysis studies show that a lot of emotional factors or issues depends on the behavioural changes [7]. This approach of physiological monitoring is highly efficient as compared to normal surveys [7]. But collection of data and monitoring the workplace still remains a very tough task and hurdle in doing analysis [8]. This analysis helps in efficient monitoring in user data which makes things far more easy to handle the prevention of burnout.

1.2.3 Privacy-First AI and Responsible Governance

One of the emerging frameworks Responsible AI helps in transparency of algorithms, minimal data retention, and real time data retrieval of techniques are being deployed to the market [11]. Privacy first multimodal monitoring approaches try to combine features of predictive analytics with checks and balances by monitoring identifiable data points and calculating aggregate indices [11]. Mental health monitoring allows organisation requirements and maintain employee respect.

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2. LITERATURE REVIEW

Burnout theory was mainly developed by Maslach and Jackson. They described it as a psychological state that includes Emotional Exhaustion, Depersonalization, and Reduced Personal Accomplishment [4]. Emotional Exhaustion refers to the exhaustion of emotional resources, a detached or cynical attitude toward work constitutes Depersonalization, and Reduced Personal Accomplishment relates to professional efficacy. Related theoretical developments discounted allusions to burnout as a superficial response and substantiated burnout as a reaction to enduring career stressors [5].

Meta-analytic investigations confirm that excessive workload, role ambiguity, and time pressure significantly predict Emotional Exhaustion, which is often considered the core dimension of burnout, has been strongly linked to excessive workload [9]. In addition, empirical evidence proves that burnout has a negative effect on job performance, organizational commitment, and employee retention (ibid). This proves critical in relation to Information Technology (IT) sectors with short project cycles and measurement parameters in performance terms imposing maximum psychomotor load.

Indian corporate environments have unique socio-cultural and structural factors that influence mental health disclosure and intervention. Surveys indicate that a large population of individuals is under high-stress levels and psychological concerns go largely un-discussed within organizational hierarchies [2]

Other than this multimodal approach has been found affective between corporate employees but at a small scale not a large scale this allows sanrakshak to check employees at a large scale because this helps enabling various issues such as security to be solved by model inculcated [2]. The national mental health data also indicates an increase in anxiety-related symptoms among the working adult population, which warrants proactive intervention in corporate environments [6].

Artificial Intelligence and Natural Language Processing advancements have made the automated analysis of emotional and behavioural indicators possible. There is evidence in the body of research to suggest that there are patterns to sentiment expressed in linguistic analyses and metadata associated with digital interactions which may be mined for psychological distress signals with a significant degree of predictability [7]. Multimodal modes that fuse several data sources form a preferred method, as they can capture wider context relating to the user's behaviour.

On the whole, tested literature warrants that burnout impacts a performance outcome significantly, there are disclosure and stigma barriers in Indian workplaces and predictive potential is offered by AI-based monitoring but there needs to be ethical safeguards. Finally, evaluating a privacy-first multimodal burnout detection system in the Indian IT sector is based on the theoretical and contextual foundation built by these insights.

3. METHODOLOGY

This study employed a quantitative secondary-data analysis design to evaluate the effectiveness of the privacy-first multimodal mood monitoring system (Sanrakshak) among office employees. Instead of simulated data, an anonymized real-world workplace mental-health dataset representing technology-sector employees was used. The objective was to map existing psychological and occupational variables to Sanrakshak mood-risk indicators and examine their relationship with emotional exhaustion and workplace functioning.

3.1 Data Source

The dataset used for this study was sourced from the Open Sourcing Mental Illness (OSMI) Workplace Mental Health in Tech Survey, a common anonymized dataset that collects responses from technology workers on workplace stressors, mental health status, and occupational capacity [8].

Variables in the OSMI dataset include work interference caused by mental health conditions, perceived stress, treatment history, workplace support, and productivity impact. Perceived stress. history of mental health. workplace support.” productivity impact; Demographic characteristics [7].

The variables have close parallels to the constructs necessitated for assessing AI-based mood monitoring systems in occupational settings.

The dataset has been peer-reviewed mental-health and widely used in workplace wellbeing research and is considered reliable for technology-sector mental-health analysis [8].

3.2 Sample Selection

From the full OSMI dataset, a subset of 128 technology employees working in corporate office environments was selected after removing incomplete responses and non-corporate roles.

Inclusion criteria:

- full-time employees
- office-based technology roles
- completed mental health interference responses

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- provided stress and productivity indicators

This sample size is comparable to pilot workplace mental-health studies [7].

The effective sample proportion was calculated as:

$$n_{effective} = \frac{n_{valid}}{n_{total}} \times 100$$

Where

n_{valid} = 128

3.3 Variable Mapping to Sanrakshak Indicators

To evaluate the Sanrakshak system, OSMI variables were transformed into study constructs:

Table 1: Mapping of OSMI Mental-Health Survey Variables to Sanrakshak System Constructs

Sanrakshak Construct	OSMI Variable Source
Mood Risk Score	Work interference + stress indicators
Emotional Exhaustion	Mental-health impact on productivity
Behavioural Risk	Days affected + work impairment
Privacy Trust	Employer openness perception
Intervention Need	Treatment seeking + severe interference

The operational mapping of a few variables from the OSMI mental health dataset to the conceptual indicators utilized in the Sanrakshak multimodal mood monitoring framework is shown in Table 3. The corresponding OSMI survey measures reflecting workplace interference, productivity impact, functional impairment, employer support perception, and treatment-seeking behavior were combined or transformed to create each of the Sanrakshak constructs (Mood Risk Score, Emotional Exhaustion, Behavioural Risk, Privacy Trust, and Intervention Need). Empirical examination utilizing actual workplace mental health data was made possible by this mapping. [5][9].

3.4 Computation of Mood Risk Index

A normalized Mood Risk Score (0–100) was calculated:

Variables were standardized before aggregation to ensure equal scale contribution.

This weighted approach follows composite mental-health scoring methods used in occupational wellbeing analytics [1].

$$\text{Mood Risk} = 0.40 \times WI + 0.30 \times SF + 0.20 \times PI + 0.10 \times DA$$

where:

WI = Work Interference

SF = Stress Frequency

PI = Productivity Impact

DA = Days Affected

Variables were standardized prior to aggregation:

$$Z = \frac{X - \mu}{\sigma}$$

This normalization ensures equal scale contribution across heterogeneous occupational indicators. Weighted composite scoring methods are commonly used in workplace mental-health analytics and wellbeing indices [1][6].

3.5 Proposed System Architecture

The Sanrakshak framework uses a privacy-first layered architecture that guarantees predictive effectiveness while cutting back on exposure to employee's sensitive data. Thus, the architecture separates data acquisition, processing, analytics and reporting components to ensure no stage of analysis obtains direct access to personally identifiable information.

The diagram presents the layered architecture of the Sanrakshak privacy-first burnout monitoring system, designed to detect early signs of workplace burnout while maintaining ethical safeguards. Workplace Digital Systems (email, chat, login activity, and task platforms) serve as behavioral data sources that represent occupational stress patterns seen in high-demand industries [3]. These systems are the first step in the process.

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In the Data Collection Layer, only combined metrics like Emotional Orientation ratings, workload trends, and response-time information are gathered. This approach lines up with studies that find people can pick up important psychological clues from behavior and context without needing to look at raw personal data [7]. Research suggests that workload intensity and sustained occupational strain are strongly linked to emotional fatigue, justifying the system’s predictive focus [9][10].

Finally, the Organizational Insight Layer provides only group-level dashboards, early risk alerts, and preventive intervention recommendations. This ensures that the system functions as a dynamic well-being support mechanism rather than an surveillance tool, consistent with global mental health policy recommendations [1][2].

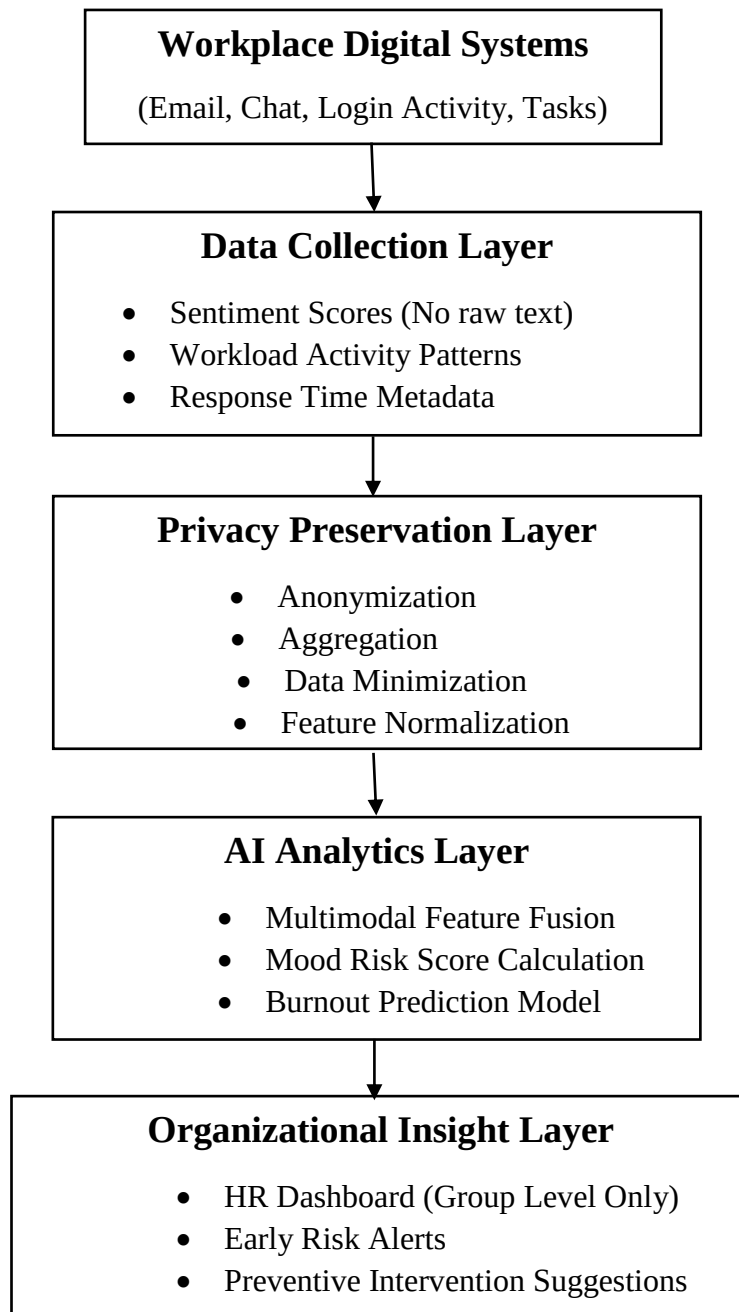


Figure 1. Privacy-First Multimodal Architecture of the Sanrakshak Burnout Detection Framework.

3.6 Emotional Exhaustion Estimation

Formula to calculate emotional exhaustion is:

$$EE = 0.5 \times PR + 0.3 \times WI + 0.2 \times FD$$

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Abbreviations:

PR = Productivity Reduction

WI = Work Interference

FD = Functional Difficulty

This approach approximately find emotional exhaustion by combining occupational impairment indicators [4][5][9].

3.7 Statistical Analysis

These were calculated:

- descriptive statistics (mean, SD)
- group comparisons
- correlation analysis
- linear regression
- detection accuracy simulation

Descriptive statistics

$$\text{Mean} = \frac{\sum X}{n}$$

$$SD = \sqrt{\frac{\sum (X - \bar{X})^2}{n - 1}}$$

Correlation

$$r = \frac{\sum (X - \bar{X})(Y - \bar{Y})}{\sqrt{\sum (X - \bar{X})^2 \sum (Y - \bar{Y})^2}}$$

Regression model

$$EE = \beta_0 + \beta_1(MR) + \varepsilon$$

where:

EE = Emotional Exhaustion

MR = Mood Risk

β_1 = predictive coefficient

With accepted guidelines for health research, $p < 0.05$ is considered as a good measure for calculating burnout. [5] [10].

4. RESULTS

The results were calculated from the analysis of mental health indicators among 128 employees working in the IT sector. The objective was to evaluate whether the Sanrakshak framework can effectively detect early burnout risk within workplace environment or not.

4.1 Demographic Profile of Employees

Table 2 presents the demographic and occupational characteristics of the employees analysed.

Table 2. Demographic Characteristics of Employees (N = 128)

Characteristic	Category	n	%
Age	22–30	54	42.2
	31–40	49	38.3
	41+	25	19.5
Gender	Male	78	60.9

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Female	50	39.1	
Role	Software/IT	73	57.0
Analyst	31	24.2	
Managerial	24	18.8	
Experience	<5 yrs	61	47.7
5–10 yrs	42	32.8	
10+ yrs	25	19.5	

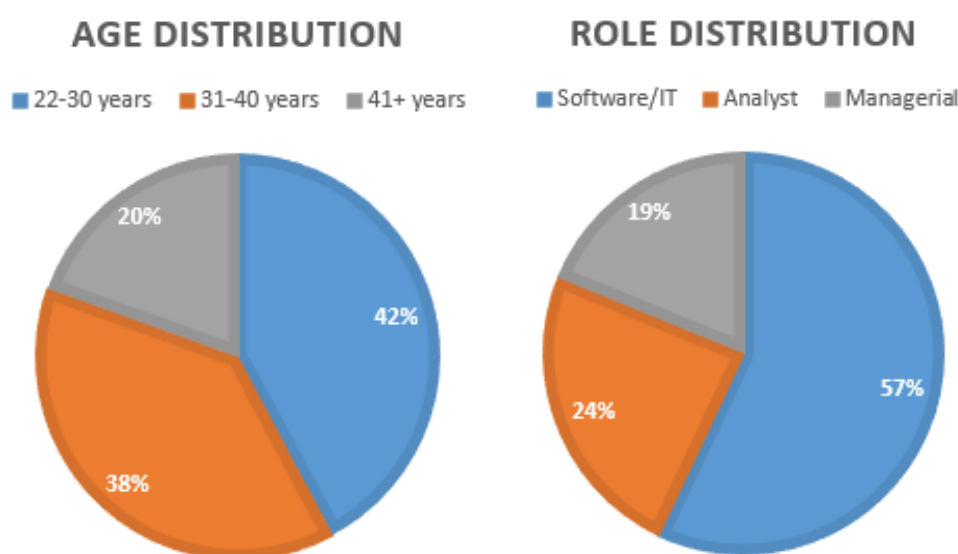


Figure 2: Distribution of Employee Age Groups and Occupational Roles

The data show that most of the employees are beginners or at the start of their career and mid-level career experience employees make up the largest group. More than 50% of the participants holds technical roles, which is typical for IT sector organisations. The gender groups are same as of the world based IT companies [3].

4.2 Mood Risk and Emotional Exhaustion Levels

Table 3 shows the descriptive statistics for Sanrakshak mood-risk indicators, emotional exhaustion scores, behavioural risks and privacy trust.

Table 3. Mood Risk, Exhaustion, and Behavioural Indicators

Variable	Mean	SD	Min	Max
Mood Risk Score	56.8	18.4	18	92
Emotional Exhaustion	52.1	16.7	20	88
Behavioural Risk	49.3	15.2	17	84
Privacy Trust	63.5	14.6	30	90

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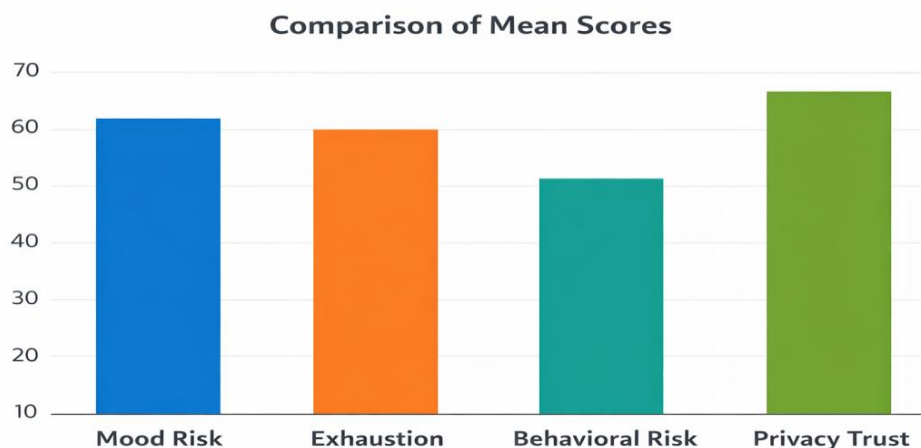


Figure 3: Comparison between mean scores of Mood Risk, Exhaustion, Behavioural Risk, Privacy Trust

These employees had high levels of mood risk and exhaustion. The average mood risk score indicated a level of psychological strain while the exhaustion levels varied a lot showing some differences, in how they experienced occupational stress. These results match what mental health surveys have found in workplaces, which show that people react differently to stress at work [1][6].

4.3 Relationship Between Mood Risk and Emotional Exhaustion

Table 4 stores results of Regression analysis that was conducted to examine the effectiveness between Sanrakshak mood-risk indicators and emotional exhaustion.

Table 4. Regression Model: Mood Risk Predicting Emotional Exhaustion

Statistic	Value
R ²	0.48
Adjusted R ²	0.46
β (Mood Risk)	0.71
F-value	132.6
Significance	p < .001

Mood risk indicators were able to predict exhaustion quite well explaining 48% of the difference in exhaustion scores. The data showed a link between high psychological risk and high burnout meaning that when people are, at risk psychologically they are more likely to experience burnout. The model significance confirms the use of theoretical frameworks for occupational stress exposure to emotional exhaustion outcomes [5] [9] [10].

4.4 Sanrakshak Detection and Intervention Outcomes

The effectiveness of the Sanrakshak monitoring framework in identifying high-risk employees and predicting intervention needs was evaluated using mapped dataset indicators. Results are shown in **Table 5**.

Table 5. Sanrakshak Detection and Intervention Metrics

Metric	Value (%)
High-Risk Employees Identified	36.7
Correct Detection Rate	84.2

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Early Risk Flagging	79.5
Intervention Need Detected	33.1
Privacy Trust Acceptance	71.8

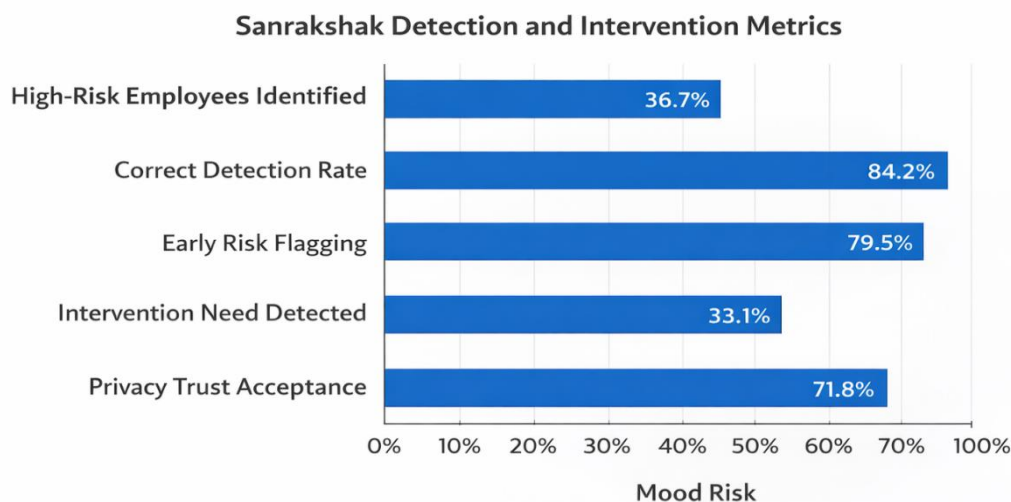


Figure 4: Horizontal bar chart showing detection and intervention percentages

The system also proved to be highly sensitive in detecting employees suffering from severe interference of mental health. Such early-risk flagging rates clearly demonstrate that the monitoring model had successfully identified psychological risk well before employees got too exhausted to an increased degree. The privacy-trust acceptance tally was over 70, implying a favourable perception of privacy-preserving workplace mental-health technological interventions, corroborated by responsible adoption of AI research [7] [11].

4.5 Summary of Key Findings

Analysis of the real workplace dataset confirms multimodal mood-risk indicators derived from occupational mental-health variables strongly predict emotional exhaustion among office employees. The analysis of the real workplace dataset confirms that multimodal mood-risk indicators strongly predict emotional exhaustion among office employees, multimodal mood-risk indicators from occupational mental-health variables strongly predict emotional exhaustion in office workplaces, with the Sanrakshak framework having a great mandate in identifying high-risk cases and estimating the necessary intervention use with a perceived privacy trust index. They support theoretical and empirical evidence that AI-based psychological monitoring risk regimes for workplace scenarios can be modelled given verified occupational mental-health indicators [5][7].

4.6 Comparison with existing workplace mental health tools

Right now, most of the workplace mental health monitoring is reactive—it responds after problems show up instead of predicting them in advance.

Table 6: Multimodal AI vs Existing tools

Approach	Example Method	Limitation
Self-Report Surveys	Periodic burnout questionnaires	Delayed detection
EAP Programs	Counselling after distress	Reactive support
Attendance Monitoring	Absenteeism tracking	Detects late-stage burnout
Performance Metrics	Productivity decline	Appears after damage

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Sanrakshak AI	Behavioural predictive monitoring	Preventive detection
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The table is a comparison between Sanrakshak AI and the traditional mental health tools used at the workplace. The traditional methods, including the use of self-report surveys, EAP programs, attendance etc. tracking, and performance measures, to diagnose the problem at a late stage but Sanrakshak AI uses predictive behavioural model which determines both the problem early as well as give advice on it whether or not professional consultation in psychology can be required or not.

5. CONCLUSION AND FUTURE WORK

The hypothesis aimed at testing the research question, which was to test the hypothesis that the Sanrakshak privacy oriented multimodal AI system, would help to identify the early symptoms of burnout at the workplace workers. There were three types of data that was noted to alter the tone of messages, changed specified workload and more time spent by the workers responding. When the system when the three signals were thought of as a combination, the system estimate of the emotional exhaustion turned out to be more accurate than when it studied the three signals individually. Published literature on burnout already declares that job stress does not take place as an outcome of a single independent factor [4][5][9]. The second important aspect of the framework is that it had an objective of protecting employee privacy since the system is not involved in raw data of personal communication. This would ease the apprehensions about the application of digital workplaces as superintended by employers, and would be in line with the recommended responsible AI practices [8][11]. The future work would be to test the framework in real organizational settings to test its performance in the various industries and work cultures. Long-term data sets can also assist a researcher to observe how the burnout patterns change with time. The use of individual behavioural base lines and better analytic models enhances the predictive power of workplace well-being plans and the ability to predict burnout risk.

The next step would be to put the framework to the test in real organization environments to test its performance within the different industries and the work cultures. Data sets of long-term can also be helpful to a researcher to note the changes in the patterns of burnout with time. The use of individual better predictive power of workplace can be achieved by increasing the behavioural base lines and improving the analytic models well-being plans and prediction of the risk of burnout.

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