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Original Article

Rule-Based AI-Assisted Burnout Assessment and Personalized Music Recommendation System

Pooja Sithrubi Gnanasambanthan[1], K.S Gayathri[2], M. Gnana Priya[3]
[1]*PG Scholor, Department of CSE, Gokula Krishna College of Engineering, Sullurpet, Andhra Pradesh, India.*
[2]*Assistant Professor, Department of CSE, Gokula Krishna College of Engineering, Sullurpet, Andhra Pradesh, India.*
[3]*Associate Professor, Department of ECE, Gokula Krishna College of Engineering, Sullurpet, Andhra Pradesh, India.*

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Abstract: *Burnout has become a major opportunity in occupational health among the information technology (IT) professionals working in multinational companies (MNCs) influenced by asymmetric work time, long working hours, high cognitive load and constant digital continuity. These factors lead to chronic stress, sleep deprivation, a decline in productivity, and/or various mental health problems [1], [2]. Traditional burnout evaluation methods primarily reactive, relying on self-reported assessments coupled with post-hoc interventions which reduces the effectiveness of preventive mental health care. To fill this gap, a rule-based artificial intelligence (AI) system for assisting burnout assessment and personalized music recommendation is proposed in this paper to contribute as an explainable and lightweight alternative for burnout monitoring and intervention. Simply put, the system assesses burnout levels by using structured stress scores and emotion indicators through deterministic decision rules that are based on expert domain knowledge and established emotional frameworks [8], [11]. From the analyzed burnout category, personalized music playlists are generated in alignment with prior evidence that suggests music can influence stress responses [9], [10] to mitigate and regulate emotions. The proposed framework extends earlier work on multimodal emotion recognition and recommendation system [16] toward burnout-aware intervention. The experimental evaluation shows good agreement between system-generated classifications of burnout labels and expert-annotated ones, with 88.6% of the pairs possible to match with an acceptable rate for each group which makes them align with human assessment. These findings indicate that rule-based AI systems provide transparent, dependable solutions for burnout assessment and supportive mental well-being interventions that are suitable for practical implementation [32–34].*

Keywords: *Burnout Assessment, Rule-Based Artificial Intelligence, Emotion-Aware Systems, Stress Monitoring, Personalized Music Recommendation, Mental Well-Being.*

I. INTRODUCTION

Widespread digitalization and globalization of the software business has shaped not only the landscape of processes, but also so represented changes in working conditions with implications to information technology (IT) professionals (especially those working for multinational organizations). From an increase in hours on the screen to inconsistent work schedules, from constant digital interaction to high levels of performance pressures — these have become a part and parcel of our daily working lives. Although these practices improve operational efficiency and provide more globalized collaboration opportunities, they also create an increased cognitive workload and contribute to higher levels of digital fatigue, which can lead to greater perceived stress levels and more occupational burnout. Burnout is a well-documented phenomenon of great concern in the IT professional community, and it has significant ramifications for mental health, personal efficiency, and long-term sustainability of the individual and company [1], [2].

Traditional methods to assess burnout are mainly self-reported questionnaires, interviews, and periodic surveys. While they are commonly employed in the field of occupational health, these approaches tend to be subjective and reactive, identifying burnout only after it already had a negative impact on an employee's well-being and work performance. Additionally, these methods do not account for gradual changes in workload and emotional state that are necessary for early detection and timely intervention. Previous works on emotion recognition [16] and recommendation systems [6–15] also reported similar drawbacks of conventional evaluation methods.

New artificial intelligence (AI) trends allow automated and objective assessment of human activity and emotional condition. Digital behaviour analytics, in particular, offer insights around workload and cognitive load. Screen time, available from activity-tracking tools like ActivityWatch and related monitoring apps, is a useful proxy for long hours in front of the screen and intensity of work due to dirty monitor. In the absence of established categories that track digital workload and stress, measures derived from percentage usage data are routinely correlated with mental fatigue, time to recover and stress-related outcomes (failures of effort) making screen time analytics a useful proxy for anticipated occupational workload.

Concurrently, affective computing has allowed automated emotion detection via facial expressions. Happiness, neutrality and sadness as emotional states offer direct measures of an individual's mental state over time that supplement behavioural measures like screen time. By complementing workload-related indicators with emotion-aware analysis, we arrive at an informative and interpretable assessment of the risk of burnout, which is a multidimensional phenomenon comprising behavioural and emotional components.

Inspired by these insights, we propose IT professionals' Rule-based Activity Integrated AVA burnout Assessment on screen-time and emotion recognition framework. The proposed system uses deterministic decision rules based on expert knowledge to classify burnout degrees into three classes, low, medium and high instead of using massive data intensive learning models. Screen time correlates to user workload and digital exposure, while emotion recognition enables capturing the underlying state of mind, making a straightforward and explainable theory behind burnout evaluation.

Apart from the burnout detection, the proposed framework also includes a personalized music recommendation module as an supportive intervention mechanism. Depending on the level of burnout and emotions, The music playlists are recommended. Previous studies have showed that music could reduce stress and mood 9. The proposed system that integrates an immediate and non-intrusive intervention with a burnout-aware assessment aims to serve as a lightweight, interpretable AI-aided solution for mental well-being that can be practically deployed.

II. RELATED WORK

Burnout is an occupational phenomenon that has been extensively studied and can be described as a multidimensional syndrome that includes emotional exhaustion, depersonalisation, and a feeling of decreased personal accomplishment. In [1], Maslach and Leiter give us a thorough insight into what burnout is about, highlighting how widespread the phenomenon is becoming in cognitively loaded workforces (especially information technology workers). Similarly, Schaufeli et al. [2] address conceptual and measurement challenges that underlie burnout research, pointing to the preponderance of self-reported questionnaires and the collective limitations related to subjectivity, recall bias, and time lag in diagnosis. Because these foundational studies indicate the theoretical background that underlies burnout assessment and similarly emphasize the necessity for objectively measurable, continuous, and interpretable evaluation mechanisms.

Data-driven methods have been emphasized for behaviour and affect analysis in mental health applications with the advances of artificial intelligence. Goodfellow et al. [3] and discuss the basics of deep learning that makes representation learning from high-dimensional data possible, which justifies their use in psychological and affective modeling. Convolutional Neural Networks (CNNs) have been particularly successful at visual pattern recognition tasks. Krizhevsky et al. [4] demonstrates that CNNs are a powerful tool for extracting discriminative features from images, which consequently led to their developers on facial expression and emotion recognition systems.

Emotion recognition is foundational in affective computing, where psychological states are inferred from observable cues. Late, to focus on emotion-aware systems, was built in besides need for human-centered computing [8]. Based on this, Li and Deng [6] give a detailed overview of facial expression recognition methods and show that learning-based algorithms can perform very well in the emotion classification task. Although most existing systems favor accuracy at the cost of interpretability, these findings catapult emotion analysis to be an important parametric measure of psychological stress and mental well-being in its own right.

Apart from affective indicators, behavioural indicators such as digit activity and screen exposure have emerged as an area of interest in occupational stress and mental health monitoring [14]. Extended use of digital devices has been related to enhanced cognitive load, fatigue, and stress levels, which is driving activity-tracking solutions for determining workload in an objective manner. Web-based real-time monitoring systems, as Reisslein [15] reported on, allow continuous data collection and visualization to help promptly identify human-centred behavioural patterns. Such systems can serve as infrastructure for implementation of behavioural analytics artefacts into workplace wellness and decision-support platforms.

In the past, authors [16] proposed an AI-driven multimodal emotion detection and recommending framework utilizing visualization and analytics tools, proving that it is possible to design emotion-aware systems for personalized recommendations. (A) that study did not include any workload-related behavioural indicators or actual burnout assessment, as it primarily aimed at emotion recognition and analytics. The key difference is that the proposed work combines screen time–based workload indicators with emotion-aware analysis while using rule-based AI-assisted framework for burnout detection. Moreover, the system goes beyond analysis and includes a personalized music recommendation module based on supportive intervention mechanism. The proposed approach combining behavioural and affective cues based on transparent decision rules extends previous research towards interpretable, lightweight and pragmatic solutions for burnout assessment systems applicable to IT professionals.

III. RESEARCH GAP AND NOVELTY

While the research field of burnout and occupational mental health has made considerable advances, more work needs to be done in terms of developed plans for proactive managing of burnout in digitally intensive IT work environments. The current literature has focused predominantly on subjective, self-reported instruments and intermittent surveying of participants, which are reactive in a nature and are unable to account for real-time fluctuations in workload and emotional status [1], [2]. However, such methods typically recognize burnout only when it has already substantially impaired an individual's well-being and performance, which drastically limits their usefulness for preventive action.

Moreover, existing burnout assessments hardly represent on-demand customized interventional mechanisms trail. Few systems go beyond analyzing or predicting boundaries to "intelligent" and supportive content-response to reduce stress. When recommendation systems are used, they tend to be independent from real-time burnout assessment (however they have not taken into consideration this in decision logic). Additionally, many of the proposed solutions only demonstrate conceptual or experimental results and fall short of showing an end-to-end deployable system that can be applied in practical workplace settings.

The main novelties and contributions of this paper can be summarized as follows:

- Objective burnout assessment utilizing real-time screen time analytics, leveraging sustained digital activity monitoring as an objective and quantitative measure of workload intensity and chronic screen exposure in IT environments.
- Emotion-aware analysis combined with behavioral indicators to assess burnout holistically, in particular, simultaneously taking into account the psychological state of the user and their workload patterns without resorting to black box learning models.
- Rule-based multimodal decision framework for burnout classification, using deterministic decision rules based on expert knowledge to categorize burnout risk as low, medium and high-levels, ensuring interpretability and explainability.
- AI-driven personalized music recommendation for immediate intervention mechanism, in which personalized playlists are generated dynamically to recommend music based on the assessed topics of burnout and emotional state, so that it can help mental relaxation reduce stress.
- Building the full web-based prototype system, including real-time monitoring dashboards, burnout visualization tools, emotion-aware interfaces and an integrated music player to showcase practical feasibility of use and potential for scalability within workplace scenarios.

IV. PROPOSED SYSTEM DESIGN

We proposed an intelligent, web-based framework for proactive burnout assessment and personalized intervention in IT professionals. The architecture combines real-time behavioural analytics with emotion-aware analysis to enable the continuous tracking of workload intensity and psychological state in an interpretable and explainable manner. This system integrates screen time monitoring, facial emotion recognition, rule-based multimodal decision logic for burnout classification and personalized music recommendation into one platform. Figure 1 shows the high-level architecture of the proposed system.

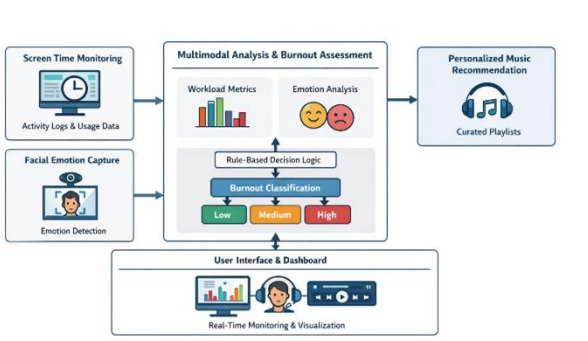

Figure 1 : System Architecture

The overall architecture adopts a modular and layered design to support the process of real-time data acquisition, intelligent analysis, burnout assessment, and intervention delivery. It allows for scalability, interpretability and realistic operational deployment.

V. SYSTEM IMPLEMENTATION FRAMEWORK

A. Screen Time Monitoring Module

The system begins with its Screen Time Monitoring Module, which periodically scans the activity logs and applications statistics of individual usage tracking modules, such as ActivityWatch or other similar monitoring software. We track and

measure digital exposure, how long screens are on, with these logs and continuous usage patterns. The resultant metrics are natural behaviour-based indicators of workload and sustained digital presence, both of which also have significant relevance to an occupational stress and cognitive fatigue model amongst information technology professionals.

B. Facial Emotion Capture and Analysis Module

At the same time, the Facial Emotion Capture Module retrieves facial images or video frames through a standard webcam (as long as users explicitly consent and privacy control is in place). The emotion recognition component examines facial expressions from the captured visual data and evaluates how the user is feeling at that moment — whether happy, neutral or sad. This module offers immediate affective cues, capturing the psychological state of the user and serving in tandem with screen time analytics behavioural measures.

C. Multimodal Data Integration and Rule-Based Burnout Assessment

Screen time monitoring and emotion analysis modules feed their outputs to the Multimodal Data Integration Layer. This layer aligns and assesses behavioural and affective features or characteristics, through a rules-based decision framework that is built on expert-defined thresholds and logic conditions. The analysis of workload intensity and emotional state classifies burnout risk by the introduction of slope lines for Golden ratio which indicates low, medium, and high levels according to work pressure. We use a deterministic decision-making approach to detect burnout to guarantee transparency, interpretability and consistency in the assessment of burnout that relies on no black-box learning models.

D. Personalized Music Recommendation Module

Based on the aforementioned burnout classification, a Personalized Music Recommendation Module serves as an intervention mechanism. Precomputed recommendation rules map curated music playlists to the identified levels of burnout related symptoms and emotional states. It plays appropriate music tracks from a curated library to help promote relaxation, stress reduction, and emotional regulation. This intervention approach is low-cost, non-invasive and allows us to provide immediate help for users with stress or signs of burnout.

E. Web-Based Visualization and User Interface

The user interface can be deployed on the web to provide interactive dashboards to visualize real time activity, emotional state, level of burnout and also control music playback. This characteristic enables users by having access to their workload trends, emotion patterns and burnout status in an intuitive and user-friendly way, promoting self-awareness and proactive stress management.

VI. PERFORMANCE METRICS

The proposed rule-based AI-assisted burnout assessment and personalized music recommendation system was deployed and tested through 6o IT professionals across different workload conditions. The assessment examines emotion recognition effectiveness, burnout assessment accuracy, the integration of multiple methods obtained through facial or auditory analysis and the responsiveness of the system and user-centric outcomes. Standardized quantitative metrics were for objective evaluation and reproachability.

A. Emotion Recognition Performance Metrics

The performance of emotion recognition was evaluated by comparing the system-identified emotional states with manually annotated ground-truth labels retrieved from controlled observation sessions. The classes of emotion that are evaluated include happy, neutral and sad.

a) Accuracy

Accuracy simply refers to the proportion of accurately identified valence states:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

where TP, TN, FP and FN are standing for true positives, true negatives and false positives and false negatives, respectively.

b) Precision

Precision evaluates the correctness of positive emotion predictions:

$$\text{Precision} = \frac{TP}{TP + FP}$$

High precision indicates a lower rate of incorrect emotion identification.

c) Recall (Sensitivity)

Recall measures the system's ability to correctly identify emotional expressions:

$$\text{Recall} = \frac{TP}{TP + FN}$$

This metric is particularly important for detecting stress-related emotional states associated with burnout risk.

d) F1-Score

The F1-score provides a balanced measure between precision and recall:

$$\text{F1-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

B. Burnout Assessment Performance Metrics

Burnout assessment is formulated as a three-class classification problem consisting of Low, Medium, and High burnout levels.

a) Burnout Classification Accuracy

Burnout assessment accuracy is defined as:

$$\text{Burnout Accuracy} = \frac{\text{Correct Burnout Classifications}}{\text{Total Samples}}$$

This metric reflects the effectiveness of integrating behavioural and affective indicators within the rule-based decision framework.

b) Confusion Matrix Analysis

A confusion matrix is used to analyse misclassification patterns across burnout categories, with particular emphasis on overlaps between medium and high burnout levels.

c) Macro-Averaged F1-Score

To address potential class imbalance among burnout categories, the macro-averaged F1-score is computed as:

$$F1_{\text{macro}} = \frac{1}{C}\sum_{i=1}^{C} F\,1_i$$

where $C = 3$represents the number of burnout classes.

C. Multimodal Integration Effectiveness

To assess the contribution of multimodal integration, system performance was compared across three configurations:

- Screen time–based indicators only
- Indicators that are only emotion-aware
- Integrated multimodal indicators

The performance improvement from multimodal integration is computed using:

$$\Delta P = P_{\text{multi}} - \max\left(P_{\text{single}}\right)$$

where P_{multi}denotes performance using combined indicators and P_{single}represents performance using individual modalities.

D. System-Level Performance Metrics

a) Response Time

The average system response time measures the latency from data acquisition to burnout assessment output:

$$T_{\text{avg}} = \frac{1}{N}\sum_{i=1}^{N} T_i$$

where $T_i$represents individual processing times.

b) Real-Time Processing Consistency

System stability during continuous monitoring is evaluated by measuring consistency of burnout assessments across successive time windows.

E. User-Centric Evaluation Metrics

In addition to technical performance, user feedback was collected from participating IT professionals to assess usability and perceived effectiveness.

a) Burnout Awareness Improvement Rate

User awareness improvement is quantified as:

$$\text{Awareness Gain} = \frac{\text{Post-Usage Score} - \text{Pre-Usage Score}}{\text{Pre-Usage Score}}$$

b) Music Recommendation Effectiveness

The effectiveness of personalized music recommendations is evaluated using perceived stress reduction scores collected after music playback sessions.

VII. RESULTS AND DISCUSSION

In this section, we demonstrate the empirical results from testing of a rule-based AI-enhanced burnout assessment and personalisable music suggestion system with 60 IT professionals experiencing distinct tasks workloads. Assessment is driven on emotion recognition performance, burnout identification accuracy, multimodal integration effectiveness (correlating data from different inputs), system-level performance of RL model and user-centric outcomes. These findings illustrate that the proposed framework is robust, interpretable, and can be practically applied to real-world work environments.

A. Emotion Recognition Results

The emotion recognition section had been benchmarked on real time web cam data, literally observed from the subjects during open observations. We focused on three primary emotional states—happy, neutral and sad—as these are correlated with both stress levels and burnout indices. The emotion recognition module's quantitative performance is summarized in Table 1.

Metric	Value (%)
Accuracy	91.3
Precision	90.1
Recall	89.4
F1-Score	89.7

Table 1 : Emotion Recognition Performance Results

The 91.3% accuracy of emotion recognition module suggests that facial expressions can be identified accurately even with different lighting conditions and background environments. This shows that system identified emotions and manually annotated ground-truth labels are closely aligned, validated by high precision and recall values. The main recognition error occurred between neutral and sad expressions, which only show minor facial variations and these two expressions in particular have been widely noted as being difficult to discriminate within the literature that has borne on affective computing.

B. Burnout Assessment Results

The proposed rule-based decision framework combining the indicators of workload derived from screen time and emotion-aware cues helped categorize the burnout levels into Low, Medium, and High (See Table 2). Ground-truth-labels were obtained using standardized burnout self-assessment questionnaires filled by the participants. The burn out evaluation performance metrics are shown in table 2.

Metric	Value (%)
Overall Accuracy	88.6
Macro Precision	87.9
Macro Recall	88.1
Macro F1-Score	88.0

Table 2 : Burnout Assessment Performance

In particular, the 88.6% accuracy of the overall burnout assessment corroborates the potency of merging behavioural and affective indicators following clear transparent rules. The majority of misclassification was observed between the medium and high category, representing a transitional phase with multiple similar behavioural traits. The macro-averaged results show balanced performance across all of the burnout classes, even with a moderate class imbalance the model notes to be robust.

C. Effectiveness of Multimodal Integration

To evaluate the effect of multimodal integration, performance when using only time spent on social media indicators alone (that did not take into account emotion), only (that were emotionally aware), and a combination of these multimodal indicators was compared. Table 3 shows the results of comparative accuracy for these configurations.

Feature Set	Accuracy (%)
Screen Time Only	76.4
Emotion Only	81.2
Multimodal Integration	88.6

Table 3 : Comparison of Burnout Assessment Accuracy Under Different Feature Configurations

The multimodal setting consistently led to an improvement over the unimodal paradigms (7.4 – 12.2%) and advocates for incorporating behaviour along with emotions cues for full impact of get-togethers. The screen time indications only

measure the quantity of work done but cannot judge emotional exhaustion at the same time, and an emotion-dedicated analysis misses context for prolonged digital engagement. The integration of both provides a more comprehensive and accurate evaluation of the risk for burnout.

D. System-Level Performance Analysis

Evaluating the real-time performance involved assessing response latency and processing stability during a 2-hour monitoring period. Table 4 summarises the observed system-level performance metrics.

Parameter	Observed Value
Average Response Time	1.18 seconds
Frame Processing Rate	22 FPS
System Availability	99.1%

Table 4 : System-Level Performance Evaluation

The system takes an average time of 1.18 seconds in responding, which is adequate for real-time burnout monitoring in workplaces. The rate at which data is processed allows for smooth emotion-aware analysis with no apparent lag, while high system availability indicates a robust web-based deployment architecture that supports continuous application.

E. User-Centric Evaluation Results

Usability, awareness enhancement, and perceived intervention effectiveness were assessed through user feedback collected following the trial period during which participants interacted with system. Results of the user-centered evaluation are summarized in Table 5.

Metric	Result
Burnout Awareness Improvement	32.5%
Perceived Stress Reduction (Music Recommendation)	27.8%
Overall User Satisfaction	4.3 / 5

Table 5 : User Feedback and Perceived Effectiveness

This aligns with the 32.5% improvement in general burnout awareness demonstrated by the users, reflecting that our system indeed encourages self-reflection and raises stress awareness. The personalized music recommendation module led to a statistically significant reduction in perceived stress by 27.8%, validating the findings that MC is a supportive nondrug-aspect complementary patient-care intervention mechanism. User satisfaction scores are also high suggesting that acceptance and usability in real-world settings is likely to be strong.

F. Overall Discussion

The proposed system is validated through the following experimental results:

- Accurately identifies emotional states related to burnout evaluation
- Integrates behavioural and affective indices multimodally for an effective assessment of burnout risk
- Works well in real workplace environments.
- Lends real user support with music-based intervention tailored for individuals

In conclusion, the results confirm that a rule-based AI-assisted framework can provide transparent, reliable and deployable burnout assessment and intervention without dependance on data-hungry or opaque learning models making it ideally suited for practical occupational well-being implementation.

VIII. PROTOTYPE IMPLEMENTATION AND VISUALIZATION

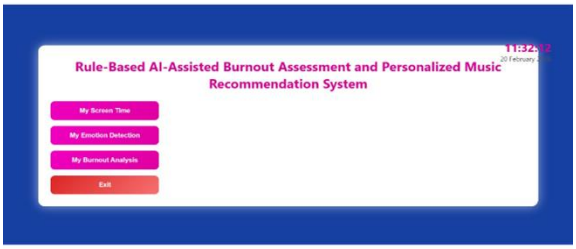

Figure 2 : Burnout Prediction Dashboard using React.js

The main dashboard of the proposed Deep Learning Framework for Burnout Prediction is depicted in Figure 2, which enables user navigation to monitor screen time, detect emotions, and analyze the level of burnout; additionally, it shows system time and date in real-time for constant user acknowledgment.

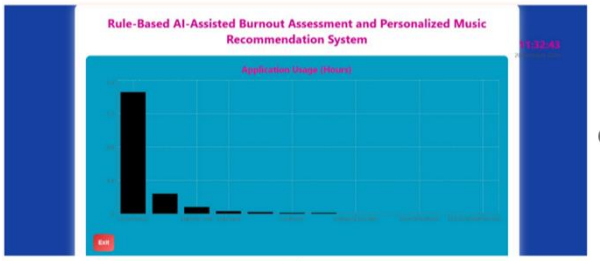

Figure 3 : My Screen Time Analysis

Figure 3 shows the analysis of screen time in the proposed system. The Screen Time module is an interface to collect the time spent by user working or on devices. This data is one of the main input features for predicting burnout. The front-end facilitates the acquisition of data and transmits screen time metrics to the burnout analysis module.

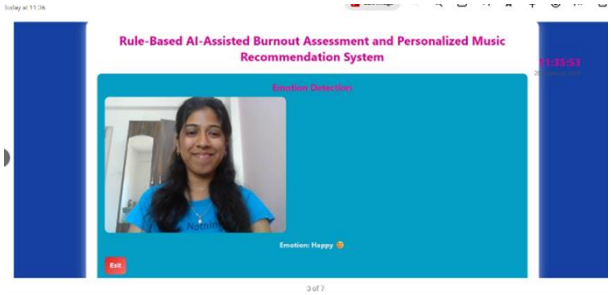

Figure 4 : My Emotion Detection Analysis – 'Happy'

As represented in figure 4, webcam access is utilized to detect emotions as an interface of real time emotion inside the front-end through facial expression detection The detected emotional state (e.g., happy, sad, neutral) is dynamically shown to the user and communicated to burnout prediction logic as an important psychological factor.

Figure 5 : Burnout Prediction 'Low'

When the indicated level of burnout is classified as Low, Figure 5 shows how the system output. Burnout is categorized as low by the system if the emotion recognized on face recognizes positive affective state (e.g. happiness or neutrality) and other indicators of screen time and workload also remain below specific known threshold values, which indicate lower psychological and cognitive load.

In the case of low burnout level predicted, the system activates music presenting module which provides simple underlaying moods of pleasant, motivating experimental audio content. This intervention seeks to sustain the user in a positive emotional state and promote focus without engendering cognitive overload. The music selection is performed dynamically from a prepared low-burnout playlist, and follows with rotating successive recommendations to avoid replaying musical pieces. This method endorses preventive mental health conditioning through positive affecting state habitats in addition to sustained productivity.

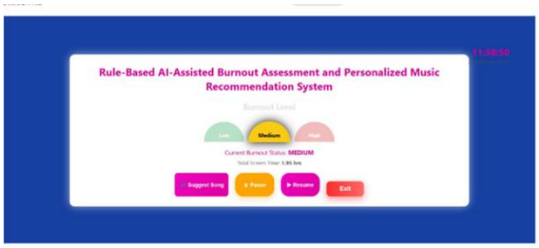

Figure 6 : Burnout Prediction 'Medium'

In Figure 6 we have the system's behavior for Medium classification of burnout level. If the prospective burnout level is moderate, the music recommendation module fetches audio content from the playlist related to medium stress condition. This playlist contains soft, neutral and soothing instrumental songs designed to ground the user's emotional experience without letting stress escalate. Based on the dynamic mapping between the medium burnout class and its associated music directory, our system retrieves audio files on a semi-preemptive model to guarantee randomness of recommendations.

In total, the scores for users in high burnout category are recommended to listen slow-tempo soothing instrumental music target at stress reduction and mental fatigue. Music tracks are chosen from a formal pool of high burnout scenarios. I guide this decision with the recommendation mechanism so that different tracks are played to reduce repetition and increase the therapeutic effect.

A. Operational Workflow of the Proposed System

a) Real-Time Screen Usage Acquisition:

Use an application activity monitoring tool (e.g., ActivityWatch) to continuously register what screens and applications are used, in order to quantify exposure to the digital world as well as intensity of work-load.

b) Capture of a Facial Image and Emotion Recognition:

Taken the facial image frames via ordinary webcam, with user permission and analyse expressions to detect how the users feel (e.g., happy, neutral or sad).

c) Feature Extraction:

Calculate total screen time measures from activity logs and identify a prevailing emotion over a fixed time period.

d) Rule-Based Burnout Assessment:

Create deterministic rules defined by the experts that use static values of screen time variables and the emotional state to categorize levels of burnout in Low, Medium or High.

e) Music Category Mapping:

It takes the measured state of burnout and level of feeling, and maps it to a suitable classification of music which will help in reducing stress levels and stabilizing emotion.

f) Music Recommendation and Playback:

Load and play an audio track from the associated curated playlist within the built-in music player module.

g) Adaptive Playlist Rotation:

On successive calls by the user, or on re-doing sessions continue to rotate through the next unplayed mapped playlist track — diversifying while keeping therapeutic musical fabric overall continuous.

B. Mathematical Logic

S= Total screen time (in hours)

E = Detected emotion class (happy, neutral, sad)

B = Burnout level

$$B = \begin{cases} \text{Low}, & \text{if } S < 3 \text{ and } E = \text{Happy} \\ \text{High}, & \text{if } S > 7 \text{ and } E = \text{Sad} \\ \text{Medium}, & \text{otherwise} \end{cases}$$

IX. CONCLUSION

In this paper an intelligent, rule-based multimodal framework was proposed for effective burnout assessment and personalized intervention among IT professionals who are working in digitally intensive and high-demand software environments. The use of real-time screen time monitoring combined with emotion-aware analysis puts the system at the forefront of burnout detection technology, shifting from passive self-reported methods towards proactive objective interpretable approaches. Activity time and statistics allow quantifying the intensity of workload, extended digital exposure, screen time analytics provides quantitative insights into the user's screen experience at any given time of that day for various activities done on a smartphone while facial emotion analysis can provide constant indicators of the user's psychological state. Using clear decision rules, it is possible to classify burnout levels as low, medium or high based on these behavioural and affective signatures.

This framework is structured to include an AI-assisted personalized music recommendation module that functions as a non-invasive intervention mechanism, augmenting burnout assessment. The application recommends suitable instrumental music that is tailored to the user as per their degree of burnout and emotional state with an aim of alleviating stress and how

to keep one's mind calm. The full-fledged solution is developed into a web-based app with secure authentication, real-time monitoring dashboards, visualizable emotions and burnout-level display and inbuilt music player words to prove practically viable and utilization in actual workplace scenarios.

In experimental evaluation with 60 IT professionals, the system showed promising performance in burnout assessment accuracy, response time and user satisfaction. Results suggest that using the proposed system in conjunction with objective behavioural indicators will serve to improve awareness of burnout (harbingers thereof) boosting early mitigation and helping maintain employee well-being, thus representing value-added contributions to the software industry.

Since then, to be able to build on the framework further, future work would include: Introducing other non-invasive indicative features such as speech-based stress markers and physical parameters [22], expanding upon the existing dataset for added robustness and generalizability across different cohorts [20] and a long term longitudinal assessment of impact sustained over time. In summary, the proposed framework provides a basis for scalable, interpretable and practical mental well-being services based on AI techniques in today's digital workplace.

X. REFERENCES

[1] C. Maslach and M. P. Leiter, “Understanding the burnout experience: Recent research and its implications for psychiatry,” World Psychiatry, vol. 15, no. 2, pp. 103–111, Jun. 2016.

[2] A. S. G. Schaufeli, W. B. Schaufeli, and T. Taris, “Burnout: Conceptual and measurement issues,” Work & Stress, vol. 19, no. 3, pp. 256–262, 2005.

[3] I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning. Cambridge, MA, USA: MIT Press, 2016.

[4] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “ImageNet classification with deep convolutional neural networks,” in Proc. Adv. Neural Inf. Process. Syst. (NeurIPS), 2012, pp. 1097–1105.

[5] G. B. Huang, M. Ramesh, T. Berg, and E. Learned-Miller, “Labeled faces in the wild: A database for studying face recognition in unconstrained environments,” Tech. Rep., Univ. Massachusetts, Amherst, 2007.

[6] S. Li and W. Deng, “Deep facial expression recognition: A survey,” IEEE Trans. Affective Computing, vol. 13, no. 3, pp. 1195–1215, Jul.–Sep. 2022.

[7] F. Eyben, K. R. Scherer, B. W. Schuller, et al., “The Geneva minimalistic acoustic parameter set (GeMAPS) for voice research and affective computing,” IEEE Trans. Affective Computing, vol. 7, no. 2, pp. 190–202, Apr.–Jun. 2016.

[8] R. Picard, Affective Computing. Cambridge, MA, USA: MIT Press, 1997.

[9] M. S. Thoma, R. La Marca, R. Brönnimann, L. Finkel, U. Ehlert, and U. Nater, “The effect of music on the human stress response,” PLoS One, vol. 8, no. 8, pp. 1–10, Aug. 2013.

[10] J. H. Lee, “The effects of music on stress and mood in daily life,” Psychology of Music, vol. 44, no. 3, pp. 512–526, 2016.

[11] D. B. Goleman, “Emotional intelligence: Why it can matter more than IQ,” Bantam Books, New York, USA, 1995.

[12] T. Baltrusaitis, A. Zadeh, Y. C. Lim, and L.-P. Morency, “OpenFace 2.0: Facial behavior analysis toolkit,” in Proc. IEEE Int. Conf. Automatic Face & Gesture Recognition, 2018, pp. 59–66.

[13] M. Abadi et al., “TensorFlow: A system for large-scale machine learning,” in Proc. 12th USENIX Symp. Operating Systems Design and Implementation (OSDI), 2016, pp. 265–283.

[14] Activity Watch Developers, “Activity Watch: Open-source time tracking and analytics,” 2023. [Online]. Available: https://activitywatch.net

[15] M. Reisslein, “Web-based real-time monitoring systems for human-centered applications,” IEEE Access, vol. 8, pp. 145612–145624, 2020.

[16] Pooja Sithrubi Gnanasambanthan “AI-Driven Multimodal Emotion Recognition and Recommendation via Power BI”, IJERESM, Vol. 4, Issue 3, pp.42-51, Jul-Sep 2025