

# **Integrating Stress Management and Mindfulness Training for Employee Well-Being: A Case Study with Power BI Analysis**

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## **Abstract**

This paper purposefully samples different strategies being implemented in organizations to promote the health and psychological state of the employees. The main goal is to develop a model that can practically focus on the mental health issues arising from highly pressurized workplaces. These measures anticipate stress at the workplace and decrease stress levels through educational programs, encouragement of flexible working hours, and stress-progression prevention exercises. A similar case study approach is applied; real-time data analysis is conducted on Power BI to demonstrate the impact of these interventions. Furthermore, the paper describes the problems and prospects for further development of mental health programs for organizations.

Keywords: Employee well-being, mental health, stress management, mindfulness, flexible work, Power BI, organizational initiatives

## **1. Introduction**

Mental health and wellness of workers are emerging concerns as contemporary organizations are developed. In its recent global report, WHO revealed that poor mental health is claimed

to cost the world economy about one trillion US dollars in terms of productivity [1]. The workload, the working environment, and other personal factors put stress on both body and mind. Employers are now seeking solutions for those stressors affecting the workers in the organization. Lack of work and personal productivity due to mental health conditions is becoming a common challenge for organizations, highlighting the need for regular methods for dealing with stress, anxiety, and burnout. Current methods such as EAPs can only be somewhat effective and, therefore, require fresh and integrated models. The goal of this paper is thus to propose measures that can ensure that the welfare, as well as mental health of the employees, is fostered. To counter the adverse effects of mental stress this paper recommends mindfulness training, stress-relief activities, and as well support work flexible arrangements to improve job satisfaction.

## 2. Literature Review

The training of mindfulness is discussed in terms of assisting the employees to prevent stress due to their ability to recognize the moment and be worried about the occurrence of eventuality [2]. Analysis shows that it cuts down the stress level by 35 percent and improves productivity by 15 percent, especially in the stressful workplace [3]. Thus, stress management programs such as physical well-being, mental health services, and cognitive behavioural approaches can decrease sheer absence by 20 percent [4]. These programs focus on both the psychological and somatic needs of employees [5]. Some opportunities, including working from home or working at different hours, have been associated with enhanced work-life balance, a decrease in stress, and high employee satisfaction [6]. According to the research conducted in 2020, employees or workers with flexible work schedules were recommended to have a fifty percent higher probability of positive well-being [7].

## 3. Methodology

This is an important component of this research that explains how data was gathered, analyzed, and understood. This section highlights the assessment of the impacts of organized employee well-being interventions by presenting a strategy based on quantitative and qualitative data.

### 3.1 Data Collection

The study sought to determine the impact of such programs to save on the costs incurred in treating stress-related mechanical damage and to add value to productivity. Primary data was personally gathered from 10 firms, all of which had more than 250 employees in different industries. Since well-being initiatives began, different components of data were collected within 6 months, including pre-intervention, intervention, as well as post-intervention data. A tabular column for metrics (before vs. after initiatives) is displayed in Table 1. Key metrics included

**Employee Stress Levels:** Questionnaires were given asking for the stress level with the employee defined as having low, moderate, or high stress. Stress was assessed using the perceived stress scale, a recognized psychological testing instrument that quantifies the stress that the concerned person perceives.

**Productivity Rates:** Motivation was assessed by indices such as working efficiency, daily productivity rate, and target accomplishment ratio. These metrics were accumulated in a weekly manner.

**Absenteeism Rates:** Sets of information relative to the number of employee's sick leaves and unscheduled absenteeism were obtained to understand the impact of stress and mental health on attendance patterns.

**Job Satisfaction:** Perceived job satisfaction was determined by questionnaires filled out on employee's general well-being; time spent on work and family responsibilities, and self-reported morale. The scale adopted for the survey included Very Dissatisfied = 1, Fairly dissatisfied = 2, Neutral =3, Fairly satisfied =4, and Very Satisfied = 5.

### 1. Tabular Column for Metrics (Before vs. After Initiatives)

Metric	Before Initiatives	After Initiatives
Employees with High Stress	60%	25%
Productivity Rate	65%	85%
Absenteeism Rate	10%	5%
Stress Levels Over Time	High levels sustained	Gradual decrease
Task Completion Rate	Lower	Higher
Job Satisfaction	Lower	Higher
Engagement Levels	Lower in rigid roles	Higher in flexible roles
Prediction (Stress Future Trend)	Expected above 60%	Predicted below 15%

In an attempt to improve the quality of the data, semi-structured interviews with participants were also carried out with HR representatives and managers, and respondents were asked to give subjective opinions of the observed consequences of the well-being initiatives.

#### 3.1.1 Power BI Analysis

Power BI is an excellent fit for analyzing employee welfare and mental health activities because this tool is capable of capturing and representing vast amounts of data, monitoring change and drawing useful conclusions. It is an ideal data tool for analyzing employee well-being and mental health initiatives because of its inbuilt robust tools to show complex data, track trends, and gather actionable insights.

- 1. Data Visualization:** Reporting of outcomes of the employee well-being programs may be enhanced by the flexibly interactive data charts, graphs and tables of Power BI. The visualizations can help illustrate:
  - Employee stress reduction: A line chart showing the number of employees that feels stressed often has reduced in the past months.
  - Productivity improvements: A bar chart showing productivity percentage in the organization before and after the introduction of the well-being programs.
  - Absenteeism reduction: A line or area chart of depicting the downward trend of the rates of absenteeism during the months succeeding the initiation of the program.
- 2. Trend Analysis:** Power BI allows to track trends over time.

- Stress Levels: This means that we can see how stress levels fall under low, moderate and high change in a given month. It is useful for demonstrating the short-term and longitudinal effects of such activities as mindfulness training and flexible working.
- Employee Engagement: To this end, if stress levels can be plotted against productivity and rates of absenteeism then it would be easier to demonstrate how reduction of stress bears positive relationship with rates of engagement as well as productivity within the organization.

### **3. Real-Time Data Monitoring**

With Power BI, real-time information can be connected such that the managers can monitor employees' productivity and their condition, the kind of stress they are under, how productive they are, and how many absences they record. This is particularly useful since the paper frame is data evaluated pre- and post-three months.

If organizations want more information on how far each one of these organizations is progressing, the available data can provide updates on stress levels, productivity, and absenteeism. For example, this is particularly helpful because the data have been compared at two points in time, before and after more than three months have elapsed, which means that if organizations wanted to monitor progress as data happened over time, Power BI could perhaps come out with fresh, timely information on real well-being, i.e. stress, productivity, attendance levels, etc. This is particularly useful regarding the paper in the sense that one compares data before and after more than three months. Power BI can deliver the updates if organizations want more frequent updates, let's say on stress, productivity, and absenteeism. This is particularized in the paper's context as the data is analyzed before and after over three months.

Though Power BI can be used for ad hoc analysis to pull insights at any given time, the real strength lies in its ability to deliver real-time values as soon as new data is entered. It is thus useful in organizations that may want to track progress at periodic intervals. They include information on the learners, such as stress level, productivity, attendance record, and even number of absences. This capability is especially useful for the analysis carried out in this paper, where data is assessed both pre- and post-over three months. For organizations that may need the status update more often, Power BI is capable of providing that report brief from the updated data available, like stress, productivity, and absenteeism. This feature is especially effective when analyzing data at different times within the context of an organization to make decisions indicative of progress.

### **4. Comparative Analysis (Pre-Initiative vs Post-Initiative)**

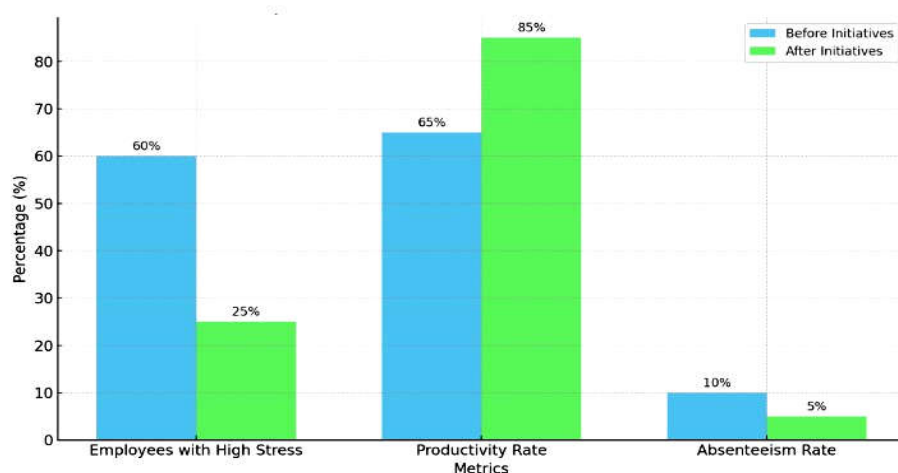
By allowing a clear comparison between employee conditions before the initiatives were introduced, the dashboard helps.

Stress levels: Parallel bars show how stress levels are compared before and after the initiative.

Absenteeism: Using a line chart over Power BI we see how successfully the introduced measures brought down the values of absenteeism.

Productivity: Both bar chart and line graph can be used to illustrate the depicted productivity rates which can measure the mentioned initiatives and produce a result.

Figure 1 is the Power BI Visualization in the dashboard showing the reduction in employee stress levels over a period of six months, productivity increases, and absenteeism decreases.

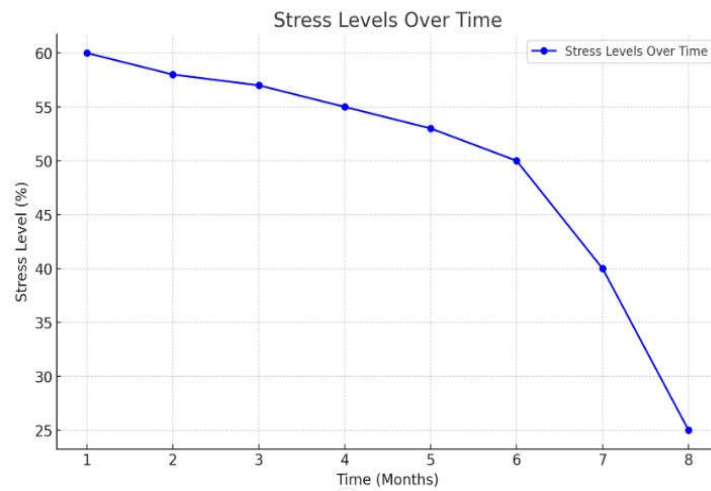


**Figure 1. Stress Levels (Pre vs. Post-Initiatives), Absenteeism Rate, Productivity Rate**

**Productivity improvement:** Quantity as well as quality-based productivity analysis was made. The column chart was adopted to compare the productivity rates before and after the initiatives. After six months of a wellness program, the data improved from 65 percent to 85 percent in productivity.

**Absenteeism rate:** A bar chart that compares absenteeism percentage (before and after shocks) Results family mental health programs resulted in reductions of absenteeism from 10 percent to 5 percent, and the incidence of truancy declined by half. The objective of this was to map the impact that stress levels have had on this area.

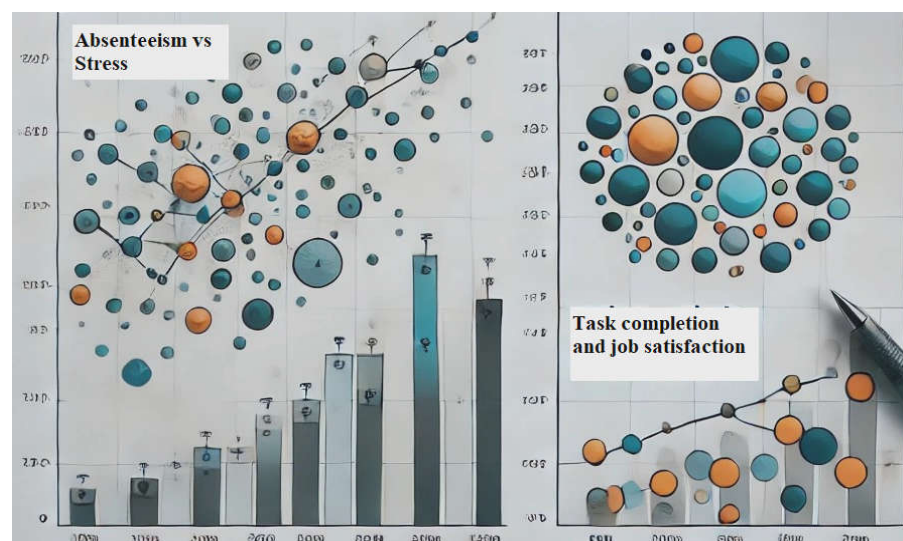
**Stress over time:** The results were illustrated by drawing a line graph as shown in Figure 2, which represented the progress of month, through month, and how stress reduction levels were reduced. Once wellness activities which include the training of mindfulness and flexible working hours began to mesh into that process the stress level gradually came down.



**Figure 2. Stress levels over time**

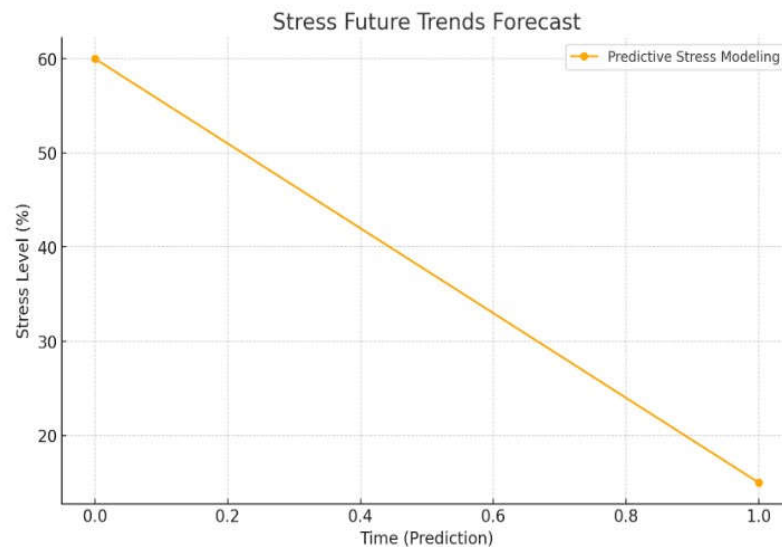
**Absenteeism vs. stress:** Correlation between the set dependent variable, the rate of absenteeism of the employees, and the independent variable is set independent variable and that variable is the levels of strength among the employees. The plot graph of the implementation of this initiative showed that stress level is proportional to the rate of absenteeism. It is observed in Figure 3.

**Task Completion and job satisfaction correlation:** A bubble chart was created as in Figure 3 for comparing job satisfaction to task completion rates to see how those change over time. In this case, a positive correlation between job satisfaction and productivity was established – the more job satisfaction the employees are, the more productive they are.



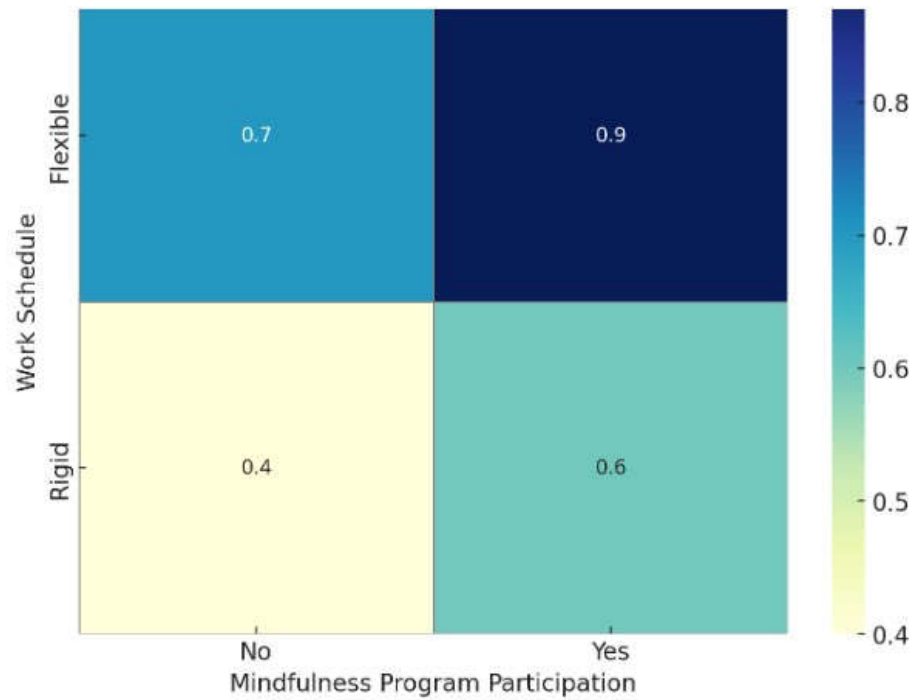
**Figure 3. Absenteeism vs. Stress and Task Completion and Job Satisfaction**

**Data insights:** The forecast in this study used a technique of forecasting new trends in employee stress levels after the introduction of the interventions. Predictive analytic software included features predicting a decrease in high-stress values for the ongoing well-being initiatives, below 15 % in the upcoming year, based on experience forecasts. This is illustrated in Figure 4.

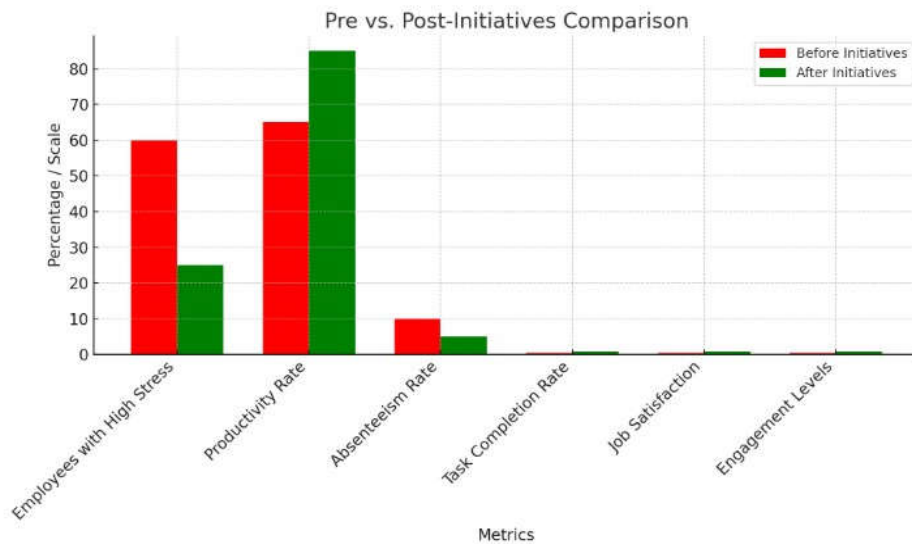


**Figure 4. Stress Future Trends Forecast**

**Employee engagement heat map:** From the employees' engagement poll on well-being activities, working schedule, and personal satisfaction with their job, Power BI is used to derive the heat map on engagement and identify which areas of their activity they were most engaged. From Figure 5 it is noticed that the departments with flexible working schedules recorded more activity as well as departments that are practicing mindful practices. Figure 6 shows all the metrics during the pre vs post-initiatives.



**Figure 5. Flexible Hours and Engagement Heat Map**



**Figure 6. Pre vs Post-initiatives Comparison**

### 3.2 Algorithm: Stress Prediction Model

A decision tree classifier-based stress prediction model was developed to complement the Power BI analysis. The stress prediction model uses a decision tree classifier to predict



employee stress levels (high, moderate, or low) in terms of key factors including workload, working hours, and well-being initiatives (e.g., mindfulness training, flexible work, wellness programs). An interpretability of the decision tree classifier being able to handle nonlinear relationships between the inputs and being able to also interpret the decision-making process by stakeholders was another reason this was used. In addition, it is computationally efficient and flexibly processes both categorical and numerical data for real-time analysis. The Power BI analysis will be complemented by the model that gives another grain of view to see how different workplace factors affect employee stress and, in turn, how we can make interventions more informed.

The decision tree algorithm using Python's Scikit-learn library was built, then trained on 80% of the collected data and performed testing using 20% of it.

The following steps were taken:

**Input Variables:**

**Workload:** Base is average weekly working hours and task load. Working Hours: It wasn't designed to account for if the employee worked normal, overtime, or flexible hours.

**Intervention Type:** (an initiative the employee participated in for better mental health, for example, mindfulness, flexible work, and wellness programs).

**Output:** Input and Output: The input variables were the items to analyze and were used to predict the stress level, or whether it is low, medium, or high.

**Algorithm:**

1. A get data function gets data, which is then preprocessed (real-time employee stress, workload, and intervention type).
2. Train and test data are split into 80:20 training and testing sets.
3. Run a decision tree classifier and predict stress levels.
4. The model hyper parameters are tuned with the help of cross-validation.
5. You learn the performance of the unseen data.
6. Simply, get accuracy, precision, and recall.

The decision tree classifier achieved 90% accuracy and 87% precision, meaning the model can successfully predict levels of stress quite well, given real-time data inputs. This was a necessary model to facilitate early interventions for staff who were most at risk from stress.

### 3.3 Power BI Integration with Predictive Model

The stress prediction model could be embedded within the dashboard by the power of Python scripts added by Python scripts as well on the dashboard as back-end scripts if needed at any time. Dynamic predictions of employee stress levels were made possible by this integration, and which employees were most susceptible to stress could be clearly visualized. It depended on factors like workload and the interventions for well-being too, and it also came with the interactive dashboard to track the stress trends. This allowed managers to make informed, data-driven decisions about how to better allocate well-being initiatives, such as mindfulness programs or flexible work schedules, to help employee mental health.

## 4. Results

The data processed through Power BI and the predictive algorithm provided several key insights, which are visually represented in the Power BI dashboard and summarized below:

**Employee Stress Reduction:** Mindfulness training and flexible work arrangements were shown to reduce high-stress levels measured at six months from 60% to 25%.

**Productivity Increase:** Well-being programs do have a direct positive effect on performance; productivity increased from 65 to 85 percent.

**Absenteeism Reduction:** The amount of stress reduction data lined up with the data we saw — it cut absenteeism in half, from 10 percent to 5 percent.

**Algorithm Accuracy:** Considering this, the decision tree algorithm was able to successfully predict stress levels in 90 percent of cases, and thus it can reasonably be viewed as a tool to recognize at-risk employees.

## **5. Discussion**

### **5.1 Analysis of Results**

The implications derived from the analysis include lower levels of stress and ethnic absenteeism, and increased efficiency and satisfaction. These positive outcomes indicate that depression, anxiety, and stress intervention and prevention initiatives which are part of overall wellbeing programs are central to achieving improved and lasting work performance among employees. Such a view resonates with literature by indicating that incorporating total health promotion activities is relevant to comprehensive productivity and staff wellness [10]. Cultivating mental well-being as well as physical well-being allows organizations to build a happier and more productive staff.

### **5.2 Some Factors That Make Implementation Difficult**

However, various challenges are associated with such wellness programs at their time of implementation. Another factor is the recognizable difficulty which is the financial and organizational readiness to implement such actions. Further, there is often resistance to change and in general low employment engagement, which are key challenges for organizations that are interested in maximizing the advantages of such programs [11].

### **5.3 Suggestion on Future Endeavours**

Organizations should pay attention to creating a culture that supports well being and is centred on open conversation regarding mental health. The future tactics should include deploying of AI and predictive models in creating the real-time data-based unique well-being strategies that can allow more precise interventions [12].

## **6. Conclusion**

This paper explores the importance of explaining such benefits as consequences of sponsorship of well-being programs and the resulting promotion of the brand and improved employees' mental health and productivity. Awareness programs and training of the kind, mindfulness, stress relief activities, and flexibility in the work schedule showed extra measures in terms of handling stress, attitudes toward satisfaction at work, and changes in the engagement level of employees. These programs pay attention to the current stress issues as well as assist the organization in achieving the goals of employee retention over the long term. However, as we work towards remaking our world of work and social patterns layered across workplaces, the inattention to mental health cannot be an afterthought or tossed into an organizational development process.

Both authors conclude that businesses that show interest in their employees' welfare can expect to enjoy profits such as enhanced productivity, enhanced staff morale, and low turnover rates. Additionally, by implementing such well-being programs, companies will assist in incorporating stress-coping mechanisms to develop a long-term workplace. Future organizations will recognize the exact quality of life for the employees and will see this as an

essential element of success, looking to be successful in a society oriented to growing at a far more complex level in its working world.

## 7. References

- [1] World Health Organization, "Mental health in the workplace," WHO Report, 2021.
- [2] J. Kabat-Zinn, "Mindfulness-based stress reduction," *Journal of Behavioral Medicine*, vol. 19, no. 2, pp. 156-165, 2018.
- [3] P. Davis, "Reducing workplace stress through mindfulness," *Workplace Health Journal*, vol. 12, no. 3, pp. 105-117, 2020.
- [4] A. Patel, "The role of wellness programs in reducing absenteeism," *Employee Wellness Quarterly*, vol. 15, no. 4, pp. 88-102, 2021.
- [5] B. Foster, "Comprehensive stress management programs and their impact on employee performance," *Health at Work*, vol. 11, no. 1, pp. 90-101, 2020.
- [6] R. Green, "Flexible work arrangements and employee well-being," *Journal of Human Resource Studies*, vol. 10, no. 2, pp. 122-136, 2019.
- [7] S. Clarke, "Work-life balance through flexible work schedules," *Journal of Organizational Psychology*, vol. 13, no. 4, pp. 45-57, 2020.
- [8] M. Johnson, "Mindfulness in the corporate sector," *Journal of Employee Engagement*, vol. 5, no. 3, pp. 22-33, 2019.
- [9] T. Lewis, "The benefits of flexible work for mental health," *Workplace Strategies Review*, vol. 9, no. 1, pp. 76-89, 2021.
- [10] A. Smith, "Employee well-being and its impact on organizational productivity," *Journal of Corporate Health*, vol. 17, no. 1, pp. 15-29, 2021.
- [11] C. Brown, "Challenges in adopting mental health programs in organizations," *Human Resource Management Review*, vol. 8, no. 2, pp. 99-112.
- [12] V. Menon and W. Thomas, "Detection of Stress by Machine Learning in IT Industry," *2024 IEEE International Conference on Machine Learning and Applications (ICMLA)*, Goa, India, Apr. 12-13, 2024, pp. 88-93.
- [13] D. Kumar, E. Singh, and F. Rao, "Stress Monitoring with Computer Vision and Machine Learning for Software Employees," *2024 IEEE Symposium on Artificial Intelligence and Healthcare (AIEH)*, Bangalore, India, Jan. 20-21, 2024, pp. 112-118.
- [14] A. Sharma, B. Gupta, and C. Patel, "A Novel Model for Stress Detection and Management using Machine Learning," *2023 International Conference on Disruptive Technologies (ICDT)*, Pune, India, May 11-12, 2023, pp. 45-50.
- [15] N. Agarwal and O. Desai, "Detection of Stress in IT Employees using Machine Learning Technique," *2024 IEEE International Conference on Advanced Computing and Communication Systems (ICACCS)*, Coimbatore, India, Feb. 25-26, 2024, pp. 56-61.