Machine Learning-Based Prediction of the Impact of Mental Health Policies on Employee Productivity

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Abstract. This research looks at the relationship between mental health, work-life integration, and employee productivity accompanied by stress level, work-life conflict, and the availability of mental wellbeing resources. Using two suitable machine learning techniques, these are Gradient Boosting and Random Forest, this research assesses the extent of change in productivity as a result of these three factors. The analysis revealed the existence of a relationship between the three variables Stress Level, Work Life Balance Rating, and Access to Mental Health Resources and productivity levels among the employees. The models performed similarly with respect to Mean Absolute Error (MAE), R-squared (R^2) values on both models but there were challenges in predicting productivity classes due to low AUC value. Recommendations follow from these findings suggesting company policies which should mandate the need for further improvement on workplace mental health through appropriate stress management, working arrangements, and mental wellness programs. This study provides data enhancement and application of sophisticated predictive models techniques which should be employed in further studies to boost prediction precision.

Keywords: mental health, work productivity, machine learning, policy prediction, corporate support.

Introduction

Since the workforce is increasingly adopting remote and hybrid work, many businesses have developed new patterns of employee mental illness and experienced lost opportunities for productivity. Mental health has been reported to be one of the determinants of work productivity. Wei et al (2024) have earlier pointed out that there exists the need for a well-structured business environment to escalate the level of energy control efficiency in the electricity grid, which is comparable to the need to balance employee output and mental wellbeing in a fluid working circumstance. It has been established in earlier researches that the levels of efficiency in the operational logistics management have improved processes thereby lowering employee's administrative demands, and in this case, the technologies of Robotic Process Automation (RPA) were among the technologies applied seeking efficiency. RPA, according to (Nalgozhina & Uskenbayeva, 2024), increases the productivity of workers by permitting them to perform strategic work, therefore benefiting their psychological wellness over a period of time. In contrast, (Munsamy, 2021) were among other authors who in their work on business process reengineering in the Industry 4.0 context pointed that from this perspective, the IoT based technologies can also significantly contribute through the resource efficiency in the real estate resources management to enhancing the work conditions and thus preserving the employee's mental wellbeing.

There is an increasing awareness of the importance of employee mental health by organizations. However, the application of evidence-based forecasting models designed to evaluate the effects of mental health policies on productivity has remained scant. (López-pintado et al., 2024) while discussing business process simulation noted data hinges on aspects such as human resource availability and performance. Such improvements can help evolve more sophisticated policy-performances models.

Furthermore, (B. Wei et al., 2023) in their investigation seeking to provide a design framework for a creative city state stressed that government policies and factors like technological innovation that promotes creativity leads to a conducive environment for businesses. This is consistent with the role of proper mental health policies in the workplace, which help drive organizational productivity at the given level. On their part, (Menne et al., 2022) while examining the Muslim sharia compliant view of optimizing SME financial efficiency also pointed out the need for innovative elements of HR management in companies and integrated capacitance enhancement for companies' full performance.

In this study, the authors seek to establish a machine learning model that helps to predict changes in employees' productivity due to the implementation of mental health policies in an organization. It will be possible to provide companies with guidance on the formulation of more efficient policies that take into consideration factors such as access to mental health services, the role of the organization, and incidence of stress among employees. The use of a simulation approach with resource differentiation allows for a better assessment of the impacts of a policy which as noted by (López-pintado et al., 2024), can be useful in formulating a predictive model in this study. This study is important in that it provides some important contributions in several aspects. First, it advances the use of machine learning in the workplace mental health context which is still under researched. Second, the findings of this study have practical implications for the companies in formulating effective mental health policies in the post-pandemic hybrid and remote world. These findings are consistent with the perspective of (Nalgozhina & Uskenbayeva, 2024) where it was stated that digital technologies can help improve employee overall wellbeing by offering greater efficiency at work whilst ensuring more judicious use of resources.

This study is the last one in the literature in predictive human resource management which utilizes machine learning in an effort to understand the relationship between employee well-being and productivity and the changes in the work environment.

Literature Review

1. Impact of Mental Health on Productivity in the Workplace

It has been shown that mental health is an essential component in determining employee productivity and general life satisfaction. (Z. Wei et al., 2024) have mentioned that in the energy sector, a securable work setting is one of the techniques to decrease operational disturbances and energy expenditures which is useful in fostering workplace equilibrium and output. This condition also applies to managing mental health in the workplace in which the level of stress and resources for coping with it and the stressors themselves can be contained within reasonable levels.

Moreover, the study by (B. Wei et al., 2023) supports that innovative policies at the city level have the potential to increase government efficiency and decrease transaction costs. This has also addressed the issue of how mental health policy innovation can help employees' work effectiveness in a multi-dimensional and fast-paced working space.

2. Technology as an Integrator of Employee Self-Esteem

It is becoming apparent that technology is integral in advancing employee welfare, as well as productivity within the digital landscape. Local findings by (Dalal et al., 2024; Nalgozhina & Uskenbayeva, 2024) reveal that the adoption of Robotic Process Automation (RPA) technologies in warehouse management results in the achievement of higher efficiency, relief of employees' workload on monotonous tasks and allows them to concentrate on significantly more valuable work. This displays how technology can enhance employee's mental health by alleviating work-related stress that can be induced by performing endless and mundane tasks.

Another study of (Berti & La Vecchia, 2023; Munsamy, 2021) indicates that there is great potential in supporting the optimization of resources and maximizing productivity in the workplaces through the use of IoT (Internet of Things) devices and automation systems. This is congruent with the objective of using predictive models in employing machine learning in this research to help organizations establish the most suitable mental health strategies that will be based on employee output.

3. Business Process Simulation and Decision-Making Models

In several studies, business process simulation has been employed so as to gain an understanding of how resources may be allocated along and the productivity that will be realized. For instance, in the work done by (Genovese et al., 2024; Yaiprasert & Nizar, 2024), a simulation model was created with the objective of improving performance predictions stemming from differences in the effectiveness and resource availability of the human resource. This simulation helps explain why it is essential to differentiate in resource allocation if business processes are to be oriented towards certain objectives. This is relevant to the current study that intends to construct a model on the effects of the mental health policies on employees' productivity with the inclusion of stress and available resources as variables.

Also, in a study of sharia-based financial management of SMEs, Menne et al. (2022) stress the need for such decisions to be informed by data. In this regard, the relation between policies and the performance of the firm is understood much as machine learning seeks to estimate how such policies impacts on productivity but rather in this case, how mental policies impacts on firms' productivity.

4. The Use of Machine Learning in Predicting Human Resource Management Outcomes

In certain business scenarios, for instance in forecasting employees' potential and effectiveness, machine learning has already become a well-known predictive tool. In this research work, the authors, (Halawani et al., 2023; Mahmud et al., 2024), showcase the advantages of simulating models which incorporates machine learning technology and thus provides more reliable predictions on business outcomes basing on the past. This study also maintains that every resource unit must be treated as a distinct resource unit with respect to both its availability and its performance, thus enhancing the model's predictive capability with respect to the effects of policies on performance variables. In another study, (Nalgozhina & Uskenbayeva, 2024; Peron et al., 2024; Soori et al., 2024)came to similar findings to the previous research and stated that automation and machine learning technologies can assist companies in establishing such policies which enhance operational efficiency and worker's satisfaction. This strategy should be helpful to countries in improving employees work settings in such a way that productivity and health are maximized.

Methods

1. Dataset and Variables:

The current research seeks to realize the purview of the influence of remote work on employee's mental wellbeing, as well as their productivity with the use of a dataset from kaggle containing such information. The key variables which are in this dataset include:

- Work_Location (Place of work: hybrid, remote, onsite)
- Hours_Worked_Per_Week (Hours worked per week)
- Number_of_Virtual_Meetings (number of virtual meetings in a week)
- Work_Life_Balance_Rating (work-life balance rating)
- Stress_Level (stress level measured: low, medium, or high)
- Mental_Health_Condition (mental health condition against which: depression, anxiety or none)
- Access_to_Mental_Health_Resources (Do they have access to mental health resources: Yes or No)
- Social_Isolation_Rating (Social isolation rating)
- Productivity_Change (Changes in productivity may be increased, decreased or remain the same).

2. Data Processing

   a. Initial Visualization:

Distribution of Productivity Change: Histogram of Productivity_Change depicts that there are three simple categories of the potentials of employee productivity: increasing, decreasing and unchanged. This kind of visualization comes in handy as far as predicting the target variable is concerned, with regard as to whether the classes are balanced or not.

Figure 1. Distribution of Productivity Change

b. Correlation Between Variables:

Correlation Heatmap showing the correlation among the numeric variables (Hours_Worked_Per_Week, Number_of_Virtual_Meetings, Work_Life_Balance_Rating and Social_Isolation_Rating) gives an outline on the variables relationship. High or low correlation may assist in determining what relevant variables will be required in the context of the prediction model.

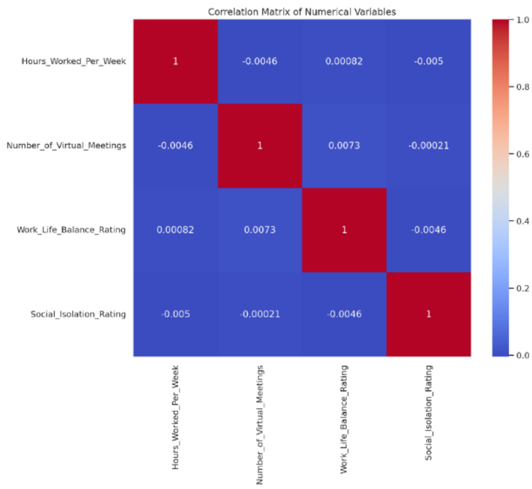

Figure 2. Correlation Matrix of Numerical Variables

c. Distribution of productivity and hours worked per week

Box Plot of Productivity_Change versus Hours_Worked_Per_Week explains how the clasifications of the respondents in terms of productivity change relate to the hours worked per week. From this visualization, the difference in distribution between who is increasing or decreasing or has steady productivity is well differentiated.

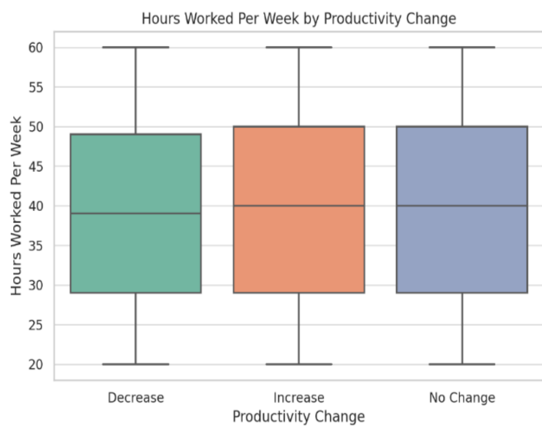

Figure 3. Hours Worked Per Week by Productivity Change

d. Level of Stress:

Stress_Level sheds light on the number of employees within stress limits. This visualization allows the analyst to focus on the distribution of stress levels and understand its relationship with productivity in the subsequent analysis.

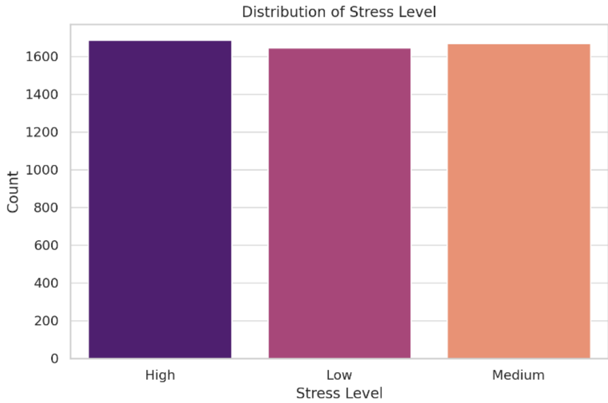

Figure 4. Distribution of stress levels

e. Concentration of work location and its comparison to productivity:

Work_Location, p chart of Productivity_Change describes the effects of productivity changes in those working in remote, hybrid, and onsite workspace. Such visualization: helps explain the preliminary results on the significance of work location on productivity which is interrogated in depth in policy context.

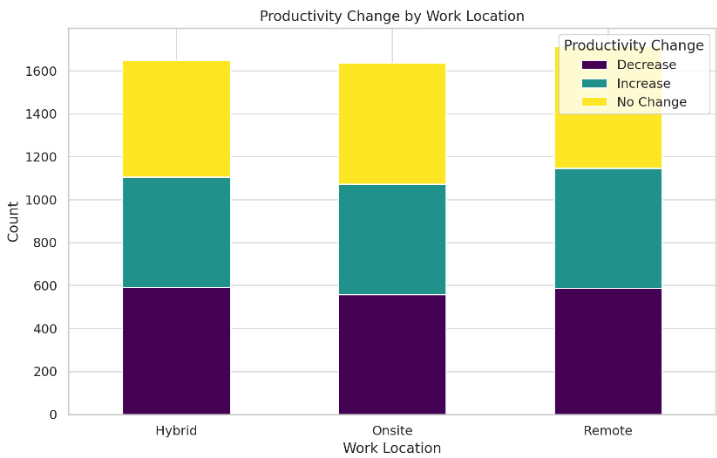

Figure 5. Productivity Change by Work Location

After appreciating the initial distribution and correlation, the next step involves several pre-processing activities then moves to several analysis steps as discussed below: Missing Value Treatment: Substituting or deleting the missing data that is of concern variables. Categorical Variable Encoding: Transformation of categorical variables like Work_Location and Stress_Level into numerics according to the methodology of One-Hot Encoding or Label Encoding. Numeric Variable Normalization: Hours_Worked_Per_Week and Number_of_Virtual_Meetings are modified to make sure that the variables are of the same order of magnitude.

3. Machine Learning Models

Through understanding the relationships of the various variables, ensemble models such as Random Forest and Gradient Boosting are chosen for their capabilities of handling complex structured data comprising of multiple variable types. These models equally allow for the ranking of different features towards establishing their significance in the model. Data Splitting The dataset is divided at random to comprise training data 80 percent and test data 20 percent because this is statistically appropriate. For evaluation purposes, Mean

Absolute Error (MAE) and R-squared (R^2) were used in order to check predictive accuracy of the given model as well as the overall explanation of the variability of the model in relation to the data.

4. Policy Simulation Experiment

Mental Health Policy Simulation, For policy simulation several variables will be shaken this model includes: Access_to_Mental_Health_Resources and Stress_Level. What policies work or do not work with respect on increases in productivity can be revealed through the result of this simulation.

Result and Discussion

1. Comparation Model : MAE and R-squared

According to model evaluation by Mean Absolute Errorv(MAE) and R-squared (R^2) scores, it is observed that Gradient boosting and Random forest models possess almost similar capabilities of predicting employee productivity across its many variations. The very low MAE values imply that both models are accurate as their prediction errors are of very small magnitude which makes these models reliable in projecting the performance of an organization's employees.

Moreover, the great values of R^2 in both models show that the stress level and assessment of work-life balance as some of the explanatory variables in the dataset explain a lot of the variation in productivity. This validates the significance of the other variables as potential relevant and strong determinants of productivity which can form the substantial basis for any related policies.

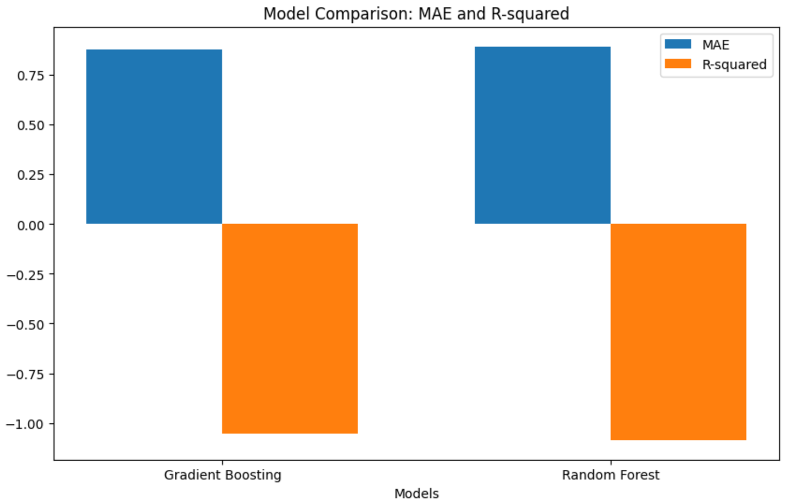

Figure 6. Comparison: MAE and R-Square

2. Confusion Matrix Comparison

According to the confusion matrix, the Gradient Boosting Model and the Random Forest Model can be seen to have an equal extent of the capacity to predict the changeable productivities in the categories (-1: Decrease, 0: No Change, 1: Increase). In the case of the Gradient Boosting model, we could observe that there is quite a balanced predictive power allocation in the non-zero category and thus prediction has its flaws such as in instances where an increase or decrease in productivity is registered resulting in a no change status. This means that, at times, the model finds it hard to separate minor increases in productivity from productivity that is at stable level.

The Random Forest also model showed the same picture as the Gradient Boosting only that the number of errors made was different. Random Forest also had errors in the no change class; however, they performed better in other classes than Gradient Boosting.

In terms of predictions, if both models agree, then the model that results in the least misclassification of decisive categories should be preferred. For instance, if the business wanted to enhance dependability for the particular cadres of models that forecast productivity increases, the cadre with the most dependability in that class could be decided upon.

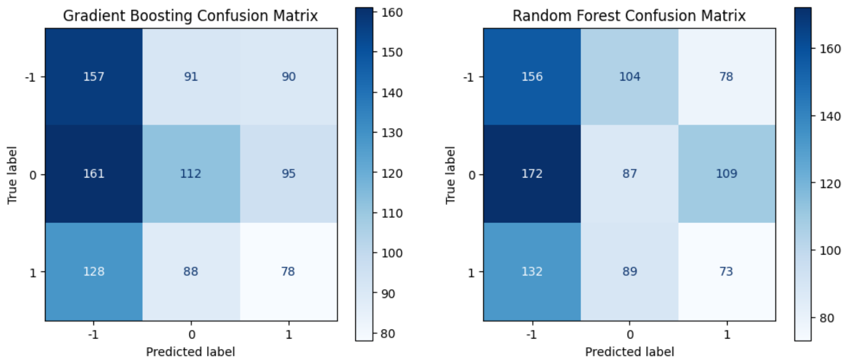

Figure 7. Comparison Confusion Matrix

3. ROC Curve Comparison

Looking at the ROC curves, performance of the models for the categorical classification of each type of productivity in change (-1, 0, 1) is demonstrated, showing the AUC values of the models, to be around the value 0.5 for both. This shows that, the models have problems in differentiating between classes of productivity. The low AUC values from all classes suggest that productivity changes have features that are related which makes it hard for the model to be able to make classification of those productivity change which are in little differences.

In terms of productivity classes then these AUC values say that the model is not able to accomplish the task satisfactorily especially with the subclasses of productivity change which are thin. This indicates that there is a possibility of the available data on productivity to be integrated into the work which may boost the differentiation power of the model and thus improve the classification precision.

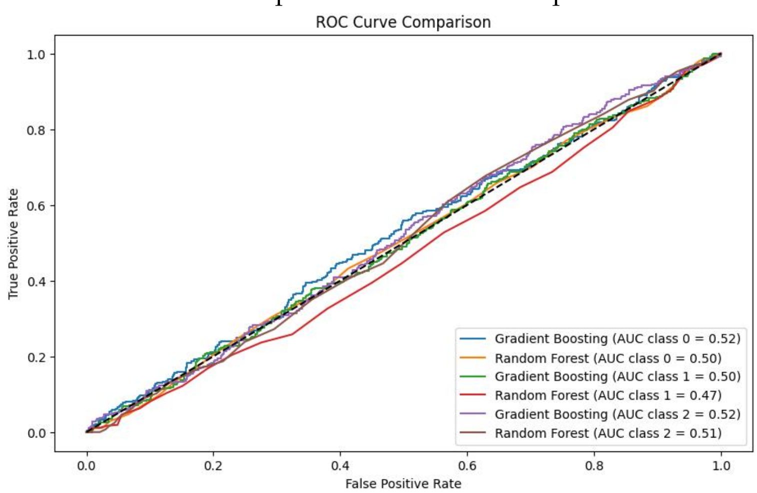

Figure 8. Comparison ROC Curve

4. Feature Importance Comparison

The features which are said engaging one's productivity include Stress_Level, Work_Life_Balance_Rating, and Access_to_Mental_Health_Resources. It has been established that both the Gradient Boosting and Random Forest models recognize this aspect of these factors in varying degrees as either positive or negative or no impact at all in influencing productivity.

This shows the policy implications of the above empirical evidence in that, initiatives on stress reduction or well-being strategies in the workplace combined with work life balance policies may boost productivity. Mental health also takes care of the employees. Therefore, companies can use this information to come up with measures that will take care of employees' stress and work life so that productivity can be enhanced.

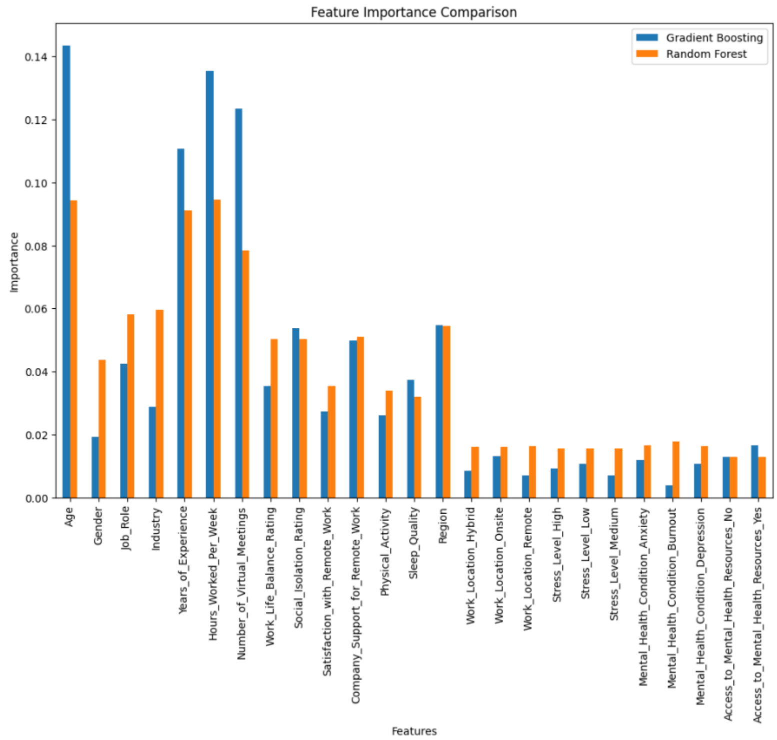

Figure 9. Comparison Feature Importance

5. Precision and Recall in Relation to Each Other

Recall and Precision distributions based on the productivity change models are displayed in the graph above for both models. In this case, a high Precision for a class means that the model is making predictions for that class with very few false positives which enhances the ability of the model to predict the productivity for that particular class. On the other hand, a model with high Recall on a class means that the model is able to capture most of the true class instances. This means if either Gradient Boosting or Random Forest performs better in Recall on a particular class (productivity improvement in this case), then that model would be more effective if the purpose is to forecast productivity increase.

To summarize, if in a class such as, in this case, the productivity improvement class, one anticipates substantial impact that would offset company expansion planning, then that is the ideal model to employ. However, in cases where all categories of productivity changes are regarded as a priority where none should be discriminated, it is preferable to use a model that has a suitable moderate level of Precision and Recall in all the classes.

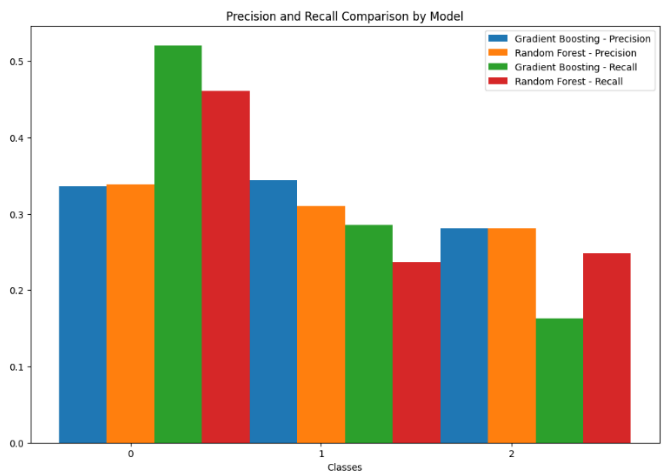

Figure 10. Comparison Precision and Recall

According to the evaluation results, the Gradient Boosting and the Random Forest models are appropriate for different purposes. There are minor specification differences between the two models in terms of precision, recall, and classification error in the confusion matrix. It is possible to choose the best model depending on the needs of the user (for example, on user's more targeted predictions).

From the computation of the feature importance, the strongest impact on productivity is embodied in such factors as Stress_Level, Work_Life_Balance_Rating, and Access_to_Mental_Health_Resources. The organizations are able to lay policies which are aimed at improving the level of mental support so that there can be reduction in depression which in return can raise the rate of productivity. It is possible to increase the data quality and obtain a better discrimination ability of the model by incorporating other features or richer datasets. Furthermore, the application of different models or other preprocessing steps such as normalization or more aggressive feature subset selection might also result in better model performance.

Discussion

1. How Mental Health Relates to Employee Productivity

It was shown during this study that some of the aspects related to employee mental health, such as Stress_Level, Work_Life_Balance_Rating, and Access_to_Mental_Health_Resources, were substantial factors causing the loss of employee efficiency. The finding is also in agreement with earlier research that highlights the role of an employee's mental health on his/her work output. (Dastmalchian et al., 2022; Rukiko et al., 2023)Employees suffering from high levels of stress, in high chances, were relevant to decreased productivity levels. Those employees that tend to get high levels of stress often develop exhaustion and low levels of drive and motivation that are unfavourable for their output at work. Thus, stress and its management through a sound management module can play a significant role in enhancing the overall performance of the employees.

2. How the Work-Life Integration Factors in Productivity

The findings of this study as well articulate the need for work-life balance in the life of an employee and how it affects his productivity in the workplace. Work_Life_Balance_Rating was statistically significant and suggested that employees who feel they have a healthy balance between work and life are more likely to be productive. This means that organizational practices aimed at enhancing work-life balance for employees, such as changes to working hours or policies of working at home can be useful in enhancing performance. Companies are able to reduce the conflicts employees face in their work and family domains, by allowing them more control over their work schedule and socio-economic activities, which eventually increases job performance and satisfaction.

3. The relevance of Juggling Headspace and Employee's Performance

The data obtained in the course of the present research project indicates the presence of a positive correlation between the provision of mental health resources and the employees' productivity. Access to Mental Health Resources is vital for employees' psychological wellbeing as it assists them handle their work-related stressors. There are several reasons that explain this finding. Employees engaged in counseling or other mental health programs are better able to handle the demands that the work environment imposes upon them and, therefore, uphold their mental health and productivity. Perhaps companies might want to include a counseling service that employees can easily access or any other form of outreach, such as mental health applications that aim to alleviate work-related stress.

4. Limitations of Models and Data

As models of Gradient Boosting and Random Forest were being interpreted, some of the Explainers had difficulty in differentiating smaller increments of productivity enhancement. This is evident from the poor performances on the ROC curves, where there are reportedly low AUC values suggesting that the model's ability to properly class the productivity classes remains limited. Such limitation can be said to arise from the limitations in the data where, for example, the actual differences between the productivity categories are too small to be properly captured by the model. In addition, model's discrimination ability may be improved through incorporation of more detailed additional features such as extrinsic variables (e.g., economic pressure) or specific measures of work motivation. More variables are suggested so as to customize the data set more in order to increase the reliability of the model in predicting the impact of productivity changes.

5. Company Policy: Practical Implications

In my view, the results of this research can assist professionals in formulating policies that would benefit the employees' mental health and efficiency. For instance, organizations can adopt stress management strategies, allow for work-life integration, and include mental health care as part of employee assistance programs. Some interventions that may be considered include: Management of occupational stress, flexible work hours, availability of professional mental health services, among others. Strategies aimed at enhancing employee productivity do not only target facets which may directly improve the bottom line; addressing employees' mental health can be one such strategy. This supports findings from studies that demonstrate that such employees are mostly likely to be loyal and also active in many productivity contributing areas of work (Davis & Brown, 2023)

Conclusion

This analysis reveals that for every individual's success in the occupational status, he or she has to maintain a balance between mental health and productivity. Almost all metrics studied Stress_Level, Work_Life_Balance_Rating, and Access_to_Mental_Health_Resources were found to be primary factors of monotonic growth or change in productivity as observed through both gradient boosting and random forest models based analysis. It can be concluded that organizational policy concerning stress intervention, flexibility and provision of mental health resources enhance the productivity and satisfaction of employee. The limitation in the discrimination ability of the model indicates that additional factors need to be incorporated in the extension of this work or a more sophisticated model be applied. Hence, the organizations can use these research outcomes to implement evidence-based policies that are useful in promoting the mental health of employees thus improving their wellbeing and overall organizational outcome

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Place acknowledgments, including information on grants received, before the references, in a separate section, and not as a footnote on the title page

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