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A Task Performance and Fitness Predictive Model Based on Neuro-Fuzzy Modeling

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Abstract: Recruiters' decisions in the selection of candidates for specific job roles are not only dependent on physical attributes and academic qualifications but also on the fitness of candidates for the specified tasks. In this paper, we propose and develop a simple neuro-fuzzy-based task performance and fitness model for the selection of candidates. This is accomplished by obtaining from Kaggle (an online database) samples of task performance-related data of employees in various firms. Data were preprocessed and divided into 60%, 20%, and 20% for training, validating, and testing the developed neuro-fuzzy-based task performance model, respectively. The most significant factors influencing the performance and fitness rating of workers were selected from the database using the principal component analysis (PCA) ranking technique. The effectiveness of the proposed model was assessed and discovered to generate an accuracy of 0.997%, 0.08% root mean square error, and 0.042% mean absolute error.

Keywords: neuro-fuzzy, modeling, task performance and fitness performance, prediction, artificial intelligence, practice

1. Introduction

Our world is transforming as a result of recent technological breakthroughs, particularly in the manners and ways that tasks are being carried out (Yu et al., 2019). This is also readily apparent in the vast majority of homes and businesses throughout the world where machines and intelligent robots are being used to assist in carrying out specific duties (Muro et al., 2019). In order to save time and produce better results, human energy is purposely directed toward controlling robots and machines, substantially reducing the amount of manual labor that could have been utilized. These have yielded positive outcomes (Tian et al., 2018), which do not only depend on one's physical attributes and academic standing but also on one's fitness for the task (Acemoglu & Restrepo, 2019). Recruiters frequently run background checks and take into account a variety of factors when choosing candidates for certain job opportunities (Manasa & Showry, 2018).

In most cases, the outcomes of these factors cause several obstacles and issues, including gender segregation among numerous recruiters and the prospective employment roles for the gender of employees (male and female). Late attempts to address the issues could have an impact on the entire organization (Mohr et al., 2017). The examination of pertinent aspects, such as movement restrictions, age differences between spouses, educational gaps, and power influencing task performance, is aided by the use of artificial intelligence (AI) enabled devices. By using AI models, uncertainties and ambiguities caused by incorrect forecasts (Alonso et al., 2018; Graham et al., 2019; Ribeiro et al., 2016) and erroneous ratings of each individual's task performance rate are removed (Ghafoor et al., 2015).

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2. Literature Review

Several studies (Kazmi et al., 2017; Sano et al., 2018; Zhao et al., 2019) have expressed differing views on the effectiveness of people's effort and performance in work environments. A study from the Institute for Women's Policy Research in 2019 revealed that empowerment measures (including psychological, social, and political freedom as well as autonomy in decision-making) help women perform better over time. The low occurrence or non-existence of the female gender's participation in decision-making processes in organizations and the society is sometimes referred to as the illegal denial of rights (Hegewisch et al., 2019). According to Obrenovic et al. (2020), the social well-being and safety of individuals affect both genders' performance. This was revealed in the findings from their developed empirical statistical job performance model with the integration of psychological elements as predictors of work performance. In addition, a five-point Likert scale questionnaire was used to record responses from about two hundred and eighty-seven (287) employees with different educational qualifications and who had spent at least three months in the organization's main department (accounting, manufacturing, marketing, and human resources management) in 2018. The purpose of choosing employees with educational backgrounds ranging from high school diplomas to master's degrees was to provide innovative solutions to managers at various levels to help them create a warm and welcoming workplace where employees can fully devote themselves to their careers and improve task performance.

A model created by Boudrias et al. (2011) was used to examine the quality of employees' psychological health in relation to work performance. Selected variables for the model included the supportive climate, staff optimism, well-being, distress, and procedural fairness. The model was also evaluated on a five-point Likert scale using cross-sectional interview data from about four hundred (400) teachers in the Nord-Pas de Calais region of France. Despite the geographical and time restrictions, the model demonstrated that the provision of educational tools for staff and other employees makes them benefit from the available relevant and engaging social circumstances. In a statistical analysis of the risk of automation conducted in Latin America, Egana-delSol et al. (2022) classified their research into three distinct stages based on the information acquired and used for the research. They explicitly identified the gender with the highest risk of losing their jobs (Egana-delSol et al., 2022) due to poor task performance rating. Kim et al. (2019) used qualitative elicited open-ended questions to conduct a thematic analysis for the risk identification, chances, and difficulties faced by women in the maritime industry, particularly with the operation of autonomous and remote-controlled vessels. Despite government and regulatory agencies' measures outlawing gender discrimination, they also took into account the idiosyncrasies of distinct jobs and role-based task (duties) activities connected with biases in businesses. Even though the proportion of women working in the maritime industry has steadily increased over time, there are still barriers like physical, social, and psychological issues (Chu et al., 2018; Frey & Osborne, 2017; Huo et al., 2018) affecting their performances.

Significant resources and efforts are continually being used to address issues brought on by improper staff placement and subpar task performance ratings. Among these initiatives are the development of smart and AI-based devices to lessen stress (Jung & Yoon, 2017) in smart cities (Falco et al, 2018), AI practitioners' predictions of job displacement (Gruetzemacher et al., 2020) estimation of the rate of depression among workers using the Apriori algorithm, and forecasts of the susceptibility of occupations to computerization in the near future (Jena & Kamila, 2014). Mishra et al. (2022) revealed that the results generated from the Tauberian conditions by the convergence of a dual sequenced intuitionistic fuzzy normed spaces (IFNS) are significant for obtaining the weighted mean of computed nodes in some special cases. The development of a neuro-fuzzy-based model that can automatically predict task performance and fitness rate with accuracy comparison checks on three (3) machine learning models is our key addition to this body of knowledge. The remaining portions of this paper are organized as follows: In Section 3, the process for developing the Neuro-fuzzy task performance and fitness model is described including the implementation methods and outcomes are laid out in Section 4. Finally, the discussion and conclusion are presented in Section 4.

3. Research Methodology

The Takagi-Sugeno rule-based fuzzy inference engine containing a total of nine hundred and seventy-two (972) rules automatically generated from the trained datasets is used for the development of a neuro-fuzzy-based modeling technique for predicting task performance. The total procedure is broken down into four distinct phases, including:

3.1. Data collection

The main source of data was Kaggle. Kaggle is an online database repository with a wide variety of public datasets. The collected data were utilized to develop our task prediction model. The search terms "Health Status" and "Work Performance" were used to look up the database's most pertinent information. However, from the several lists of available datasets, the largest, most recent, and highly informative dataset containing relevant characteristics was chosen and downloaded for use.

3.2. Data pre-processing and modeling

The downloaded dataset comprised of fifteen different variables and about one thousand, two hundred and five (1205) severely skewed instances with one or more missing values. The variables were further reduced to seven (7) most important data attributes by the application of principal component analysis (PCA) technique which allowed one or more attributes to be varied as a way of determining their level of generalization on the entire dataset. The attributes represented by their featured components are analyzed by computing their corresponding Eigen values and vector representation. The most ranked attributes with the highest representation of the whole dataset are shown in Table 1. Instances having missing or null values greater than fifty percent (50%) of its constituents' data were dropped, thereby allowing appreciable instances with non-empty values available for the modeling. A mean normalization represented in Equation (1) was performed on the dataset to standardize the attributes value to a common range scale without loss of valuable information and distortion.

$$X(norm) = \frac{x - \mu}{X(\max) - X(\min)} \tag{1}$$

where X(norm) = Normalized value
$X(\max)$ = Maximum value of x
$\mu = sample\ mean$
$X(\min)$ = Minimum value of x
x = actual value

Furthermore, using Synthetic Minority Oversampling Technique (SMOTE), a randomly generated data samples were collected by selecting one or more k-nearest neighbors for the minority class attributes. This method helped to reduce overfitting by supplying equal samples of the minority class and also aided in the removal of associated data biases. The initial dataset was augmented with newly generated synthetic data that had identical features. These features make up about 50.2% of the new instance added to the dataset. The training, testing, and validation of the neuro-fuzzy-based task performance predicting model were implemented with the clean dataset partitioned in the 3:1:1 ratio, respectively.

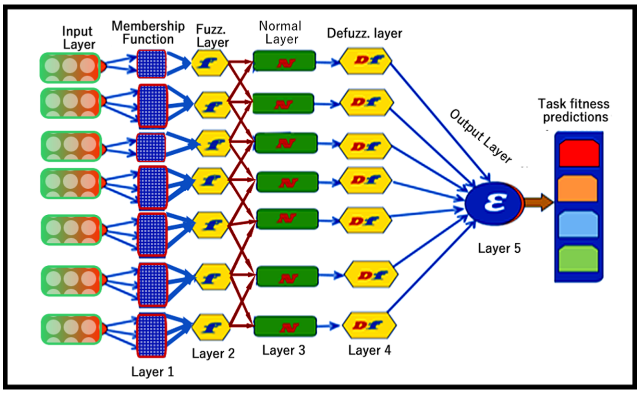
3.3. Model development

The prediction model was developed using a neuro-fuzzy system. The system uses neural networks for parameter (fuzzy rules and fuzzy sets) determinations from processed data samples. Our model consists of a feed-forward neural network with five layers and an input layer where the cleaned dataset is supplied for prediction. The following layer assigns a membership function to each crisp variable, and the third layer does fuzzification by generating fuzzy rules using the membership functions and data samples provided. By the application of the Gaussian membership function at the fuzzification phase in the hidden layer, the neuro-fuzzy-based model is constructed from seven input layers to generate a single value of output as shown in Figure 1.

Table 1
The neuro-fuzzy input/output variables

S/N	Attributes	Data type	Linguistic variables	Values
INPUT VARIABLES				
1.	Marital status	String	Single	1
			Married	2
2.	No of dependents	Numeric	Normal	0–3
			Average	4–6
			High	7+
3.	Sleep disorder	Numeric	Yes	1
			No	2
4.	Average work hours (week)	Numeric	Normal	0–20
			Medium	21–40
			High	41+
5.	Mentally drained	Numeric	Never/Occasionally	0–2
			Frequently	3–4
			Always	5+
6.	Job pressure	Numeric	Less stressful	1
			stressful	2
			very stressful	3
7.	Total life events (including personal illness, marital woes, the birth of a child, death of a spouse, change in sleep habits, trouble with the law, family or friend illness, financial woes, home change, social change, family death)	Numeric	Normal	0–3
			Challenging	4–6
			Difficult	7+
OUTPUT VARIABLES				
1.	Task performance and fitness rating	Numeric	Poor	1(0–25%)
			Fair	2(26–49%)
			Good	3(50–75%)
			Excellent	4(76–100%)

Figure 1
Schematic description of the neuro-fuzzy task fitness prediction model



The optimization is carried out at ten different epochs using a hybrid feed-forward method. It makes use of one thousand, nine hundred and ninety-two (1992) nodes, nine hundred and seventy-two (972) linear parameters, thirty-eight (38) non-linear parameters, and a set of rules that are recorded in its rule base. The Max-function combines the resulting rules and weights, and defuzzification is applied to the anticipated outcome using a weighted average function (wtaver) for further output classification into levels of task performance rating.

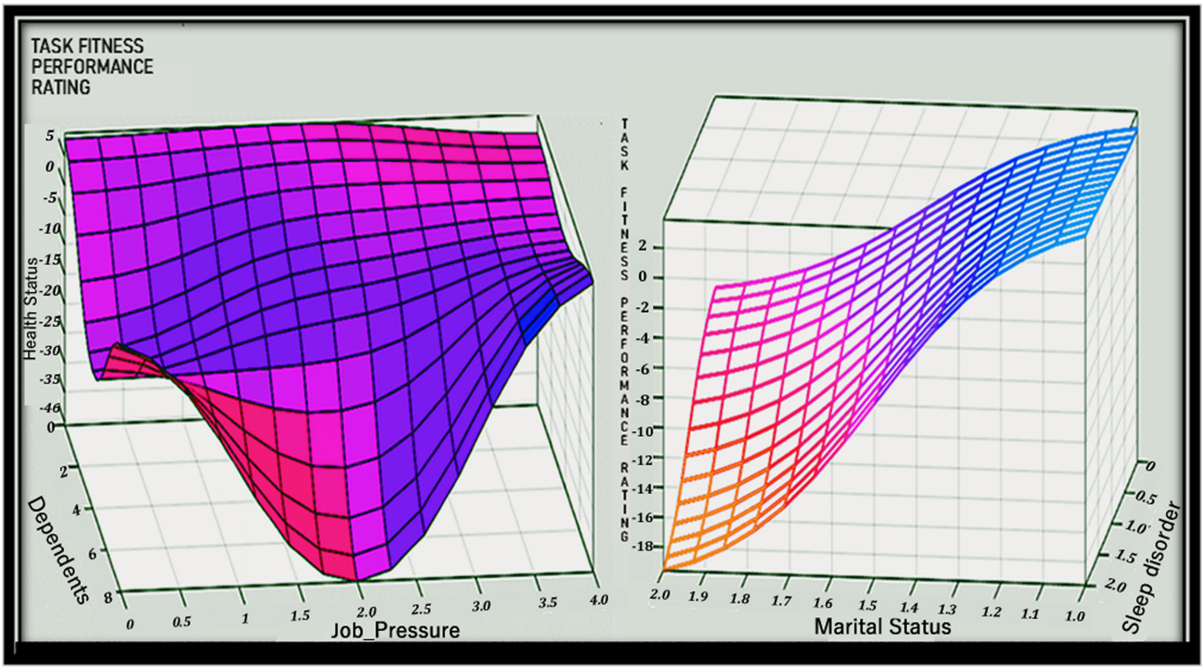
3.4. Training, testing, and evaluation

The model acquired its knowledge from the training performed using the cleaned dataset. Two distinct datasets (testing and validation sets) containing one thousand, four hundred and forty (1440) instances are presented for both testing and validation. Alignment and correlation measures are taken based on the learned features and inference system rules stored in the rule base using the Euclidean distance function. The created model's accuracy is determined by putting it to the test on new samples of instances drawn from various datasets at various epoch levels. Evaluation criteria including accuracy rate, precision rate, recall rate, and confusion matrix are utilized for the assessment of the Neuro-fuzzy task performance prediction model. The generated results and accuracy comparison score of the three (3) selected machine learning models are documented in Table 2 and Figure 2. The prediction algorithm and evaluation comparison formula are also given as shown in Algorithm 1 and Equations (2), respectively.

Table 2
The result from selected learners' evaluation metrics

S/n	Model	Accuracy	F-measure	Area under curve (AuC)	Root mean square error (RMSE)	Root-square error (RSE)	Mean square error (MSE)	Mean average error (MAE)
1.	Decision tree	82.7	0.819	0.96	1.21	−0.91	1.48	0.99
2.	Naïve Bayes	64.3	0.638	0.71	1.07	−0.48	1.14	0.86
3.	Support Vector Mechanism	66	0.652	0.78	1.06	−0.45	1.12	0.84

Figure 2
Machine learners' accuracy comparison score



Algorithm 1: The task performance training Neuro-fuzzy Algorithm

INPUT: $r_{1,\cdot,}$ r_k, k-dimension vector, (well-collated dataset)
OUTPUT: Y, Prediction Value (Task Performance ratings)
1 BEGIN
2 { ɘ
*3 **R** ← $r_{1,\cdot,}$ r_k // load reduced data set*
*4 **Generate FIS***
5 For each parameter q ϵ α do
6 Weight = $\frac{w_1 z_1 + w_n z_n}{w_1 z_1}$ // hybrid Train network
7 RMSE = MSE //test the FIS model
8 MSE = $\frac{1}{n}\sum_{t=1}^{n}(F_t - y_t)^2$
9 Return Y (Task performance Prediction)
10 }
11 END

The relative average error (RAE) observed in this research is 7.09%. It is depicted mathematically as shown in Equation (1) below.

$$\delta = \sum_{i=1}^{n} / \frac{Va - Ve}{Ve} / \; x\ 100\ \% \tag{2}$$

where Va = Predicted Approximated Value and Ve = True /Exact Value

$$\text{Root Mean Square Error (RMSE)} = \left(\sum_{i=1}^{n}(y_i - y_i)^2/n\right)^{1/2} \tag{3}$$

where n = total number of instances, Σ = summation and $(y_i - y_i)^2$ = differences squared.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)/n \tag{4}$$

where $\hat{y}_i$ = prediction, yi = true value, n = total number of instances

$$RRSE = \sqrt{\left(\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(Z_i - z_i)^2}\right)} \tag{5}$$

where y_i= the value predicted for sample case i (out of n sample cases); Z_i= the actual target value for sample case i.

The graphical representation of the effects of the variables (factors) and the results produced by this model offers detailed information on enhancing individual's task fitness for job roles. For example, in Figure 3, the effect of sleep problems is shown to have a negative impact on work performance. Any form of diagnosed sleep disorder will affect the fitness and ability of individuals to function successfully at work, particularly when they are given responsibilities or tasks that necessitate long hours and extra time to complete. According to the analysis in Figure 4, married people are less productive than the singles at equal time interval. This fact is dependent on some variables, including the fact that married women may have more tasks and obligations in the home in addition to their official responsibilities. Some jobs and tasks may be delegated to others when necessary to achieve a balance for the best work performance. This result may also reflect the impact of being engaged or in a committed relationship. The higher the work hours (commitment to official work) of an engaged person, the higher the level of productivity. However, both individuals can schedule time together to take care of their relationship requirements, possibly during weekends or holidays, and ensure that work hours do not negatively impact the relationship.

Furthermore, the combination of job stress with the regular occurrence of any unpleasant life event as shown in Figure 5 has

Figure 3
Effects of work hours and sleep disorder on task performance

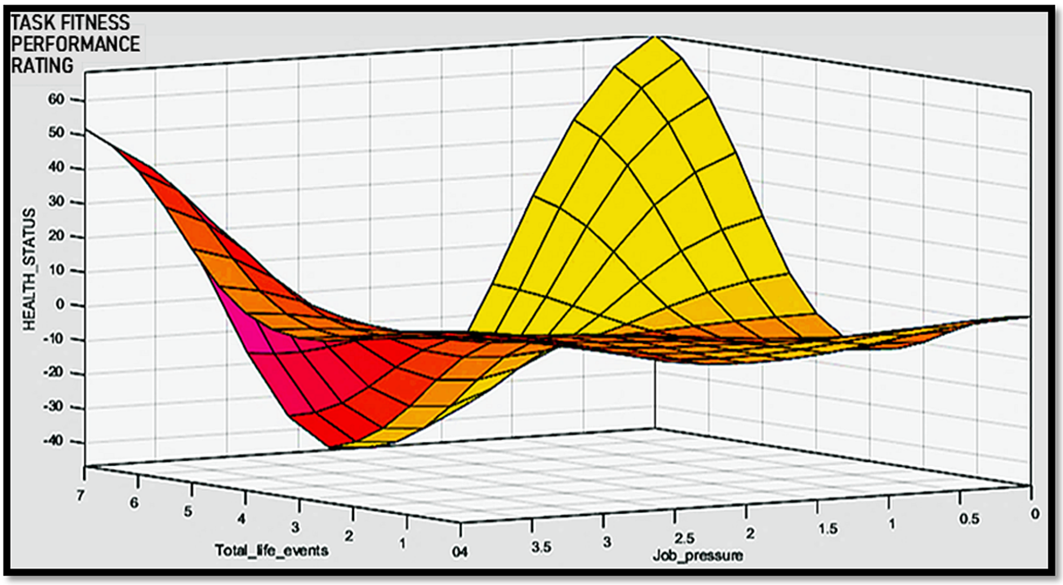


Figure 4
Job pressure vs dependent and marital status vs sleep disorder effect

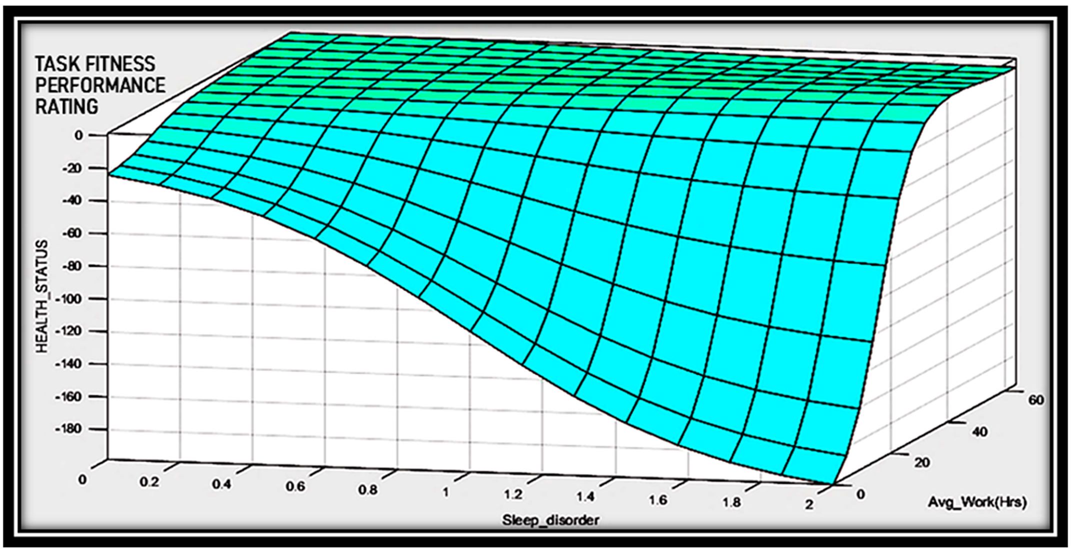
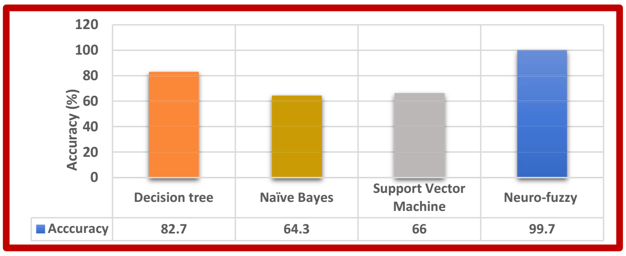


Figure 5
Combine chart of inevitable life events and job pressure on task performance



a negative impact on people's fitness for certain tasks and ability to perform at work. The organization's employees and workforce are negatively impacted by job pressure. If not managed effectively, it has subtle ways of making workers feel unimportant, lose confidence, and be unproductive. Occasionally, increased work demands may prevent employees from completing their tasks and responsibilities. This provides insight into developing a good work relationship between employers and employees in an organization including allowing enough time for jobs that could be performed manually or through technology.

4. Conclusion

The introduction of the developed neuro-fuzzy-based model employed in the automatic prediction of task fitness performance rating has accomplished the goal of this paper. The number of dependents, typical work hours, job demands, the prevalence of sleep disorders, and life events have been identified as factors impeding employees' fitness for task and their ability to function optimally. Employees' spirits are dampened, and their task fitness performance rating is negatively impacted by the frequent occurrence of unpleasant incidents (sickness, loss of property or the life of close relatives, accidents, natural disasters). In addition, our findings revealed that positive work performance is inversely correlated to both the frequency of unpleasant life events and a high level of job pressure. The task fitness performance rating will improve and have a favorable effect, especially on how well humans carry out their assigned task when job pressure is kept at a manageable level and life events are avoided or well-managed. It was also observed that when there was a shift of sleep disorder from 0.2 to 1.6 on the rating scale, the task fitness rating also moved from 30 to 180, respectively. This implies that frequent experiences of sleep disorder decrease fitness for task accomplishment.

Furthermore, compared to workers who are mentally fit, individuals who frequently experience memory loss or had been diagnosed with dementia make relatively little contribution. Before assigning responsibilities and during job placements, special concern and attention (physical, medical, and psychological) should be given. Another technique to guarantee improved productivity and work performance is to successfully manage and control the number of dependents over time. Tasks and activities that have a significant negative impact on a person's psychological health should be avoided, and working hours should be regulated.

In conclusion, the Naive Bayes learner generated the lowest accuracy rate of 64.3%. The decision tree and support vector machine learners also produced accuracy rates of 82.7% and 66%, respectively. The proposed neuro-fuzzy-based model has the best accuracy of 99.7%. The accuracy of these models in predicting how well humans would execute tasks may be leveraged to create autonomous task performance prediction systems. It will also assist in resolving issues related to the selection and placement of workers for specific task. This article will also contribute to the body of knowledge in this area of research.

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Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in Kaggle dataset, Employee Attrition and Factors at https://www.kaggle.com/datasets/thedevastator/employee-attrition-and-factors

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