

Multi-layer Perceptron Model for Employees' Job Satisfaction Assessment

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ABSTRACT

Employees' job satisfaction plays a significant role in enhancing organizational productivity and promoting industrial harmony. In recent years, the assessment of job satisfaction has attracted considerable attention from researchers. Conventional evaluation methods, such as regression and other statistical models, often fail to adequately capture the complex and nonlinear interactions among the determinants of job satisfaction. Advances in machine learning have introduced intelligent techniques capable of modeling such complexities in human resource phenomena. However, existing studies are limited in the integration of machine learning outputs with practical human resource evaluation frameworks. This study proposes an intelligent framework based on a Multilayer Perceptron Artificial Neural Network (MLP-ANN) for the assessment of employees' job satisfaction. A total of twenty-two job-related attributes were obtained from structured questionnaires administered to employees of the Ministry of Science and Technology, Akwa Ibom State, Nigeria, yielding 450 data samples. The dataset was partitioned into training, testing, and validation sets using an 8:1:1 ratio. The MLP-ANN model, trained with a learning rate of 0.01, achieved an accuracy of 97.7% and a precision of 95.3% on the test dataset. The findings indicate that major factors influencing job satisfaction include satisfaction with salary, recognition by superiors, fairness in promotion policies, rewards for dedication, and opportunities for career advancement. The results demonstrate the suitability of neural network-based framework as a decision-support tool for enhancing industrial productivity and enabling proactive human resource management.

Keywords

Artificial neural network; Human resource analytics; Intelligent decision support; Employees satisfaction assessment.

1. INTRODUCTION

Employee satisfaction is a critical determinant of organizational productivity, stability, and industrial harmony [1]. It plays a vital role in shaping employee motivation, commitment, absenteeism, and turnover intentions, thereby directly influencing service quality and overall organizational performance. As a result, the need to understand and accurately assess job satisfaction has become increasingly important for

human resource managers, policymakers, and organizational researchers [2].

Traditionally, job satisfaction has been evaluated using statistical techniques such as descriptive analysis, correlation measures, and regression-based models applied to survey data. Although these approaches provide valuable insights, they are often limited by their underlying assumption of linear relationships between job satisfaction and its predictors. In reality, job satisfaction is a complex and multidimensional construct, influenced by the interaction of personal, organizational, and environmental factors. These interactions are frequently nonlinear, context-dependent, and difficult to model effectively using conventional parametric approaches [3].

In response to these limitations, recent advances in artificial intelligence and machine learning have created new opportunities for modeling complex human-centered phenomena. Artificial neural networks (ANNs), which are inspired by biological neural systems, have demonstrated significant capability in capturing nonlinear relationships, handling multicollinearity, and generalizing from large datasets [4][5]. Among ANN models, the multilayer perceptron (MLP) is particularly prominent due to its simplicity, flexibility, robustness, and strong approximation power in classification and prediction tasks. Despite the increasing adoption of machine learning techniques in human resource analytics, their application to job satisfaction assessment—particularly within public-sector institutions in developing economies—remains limited. Existing studies have predominantly concentrated on private-sector organizations and educational institutions, whereas empirical investigations within public-sector contexts and related institutions are relatively scarce. Furthermore, only a few studies have explicitly modeled job satisfaction as an ordinal outcome within an artificial neural network (ANN) framework, integrating survey-based human factors with computational intelligence to support practical decision-making processes. MLP models have been increasingly applied in organizational and industrial research for decision support, performance evaluation, and behavioral analysis [6][7]. Given these strengths, ANNs—especially MLP architectures—are well suited for modeling the inherent complexity of job satisfaction due to their superior learning and generalization capabilities [8][9].

This study proposes MLP-ANN framework for evaluating employees' job satisfaction using survey data, while simultaneously representing satisfaction levels as an ordinal

outcome. The overarching objective is to provide an intelligent decision support system for proactive organizational interventions. The remainder of this paper is structured as follows: Section 2 presents a review of related literature; Section 3 describes the materials and methods employed in the study; Section 4 discusses the results; and Section 5 concludes the study.

2. REVIEW OF RELATED WORKS

2.1 Job Satisfaction Determinants

Several studies have investigated employees' job satisfaction using conventional survey-based and statistical approaches. Evidence from both public and private educational institutions consistently identifies remuneration, fairness of promotion policies, leadership support, work environment, and employee recognition as key determinants of job satisfaction. For instance, León *et al.* [10] found that compensation, organizational support, and institutional type significantly influenced teachers' satisfaction levels in schools. In a similar vein, Özkan and Akgeç [11] demonstrated that teachers' job satisfaction is shaped by multilevel factors, including individual characteristics, school context, and leadership practices. Furthermore, systematic reviews have reinforced these findings, highlighting pay inequality, work–life balance, and organizational justice as critical determinants of employee motivation and job satisfaction across sectors [12].

Empirical evidence from developing country contexts reveals comparable patterns. Studies by Abiona *et al.* and Levi [13][14] showed that salary structure, job security, promotion opportunities, and managerial style are dominant factors influencing job satisfaction among employees in Nigerian organizations. Similarly, Tharu [15] investigated the determinants of job satisfaction among employees in saving and cooperative organizations using a multiple linear regression model based on cross-sectional survey data. The study employed a descriptive research design and collected primary data from a sample of 161 employees using structured questionnaires. While the regression results identified several significant predictors of job satisfaction, the model was limited in its ability to capture nonlinear interactions among certain variables, particularly relationships with co-workers and career development opportunities.

Collectively, these findings underscore the inherently multidimensional nature of job satisfaction while highlighting the limitations of linear analytical techniques in adequately explaining the complex and interactive relationships among influencing variables.

2.2 Organizational Support and Work Environment

Beyond traditional economic determinants, recent studies increasingly highlight the influence of organizational knowledge systems, psychosocial work environments, and employee engagement in shaping job satisfaction. Phuong and Le Ha [4] demonstrated that effective knowledge management practices not only enhance employee satisfaction but also improve loyalty and job performance. Similarly, Obeng *et al.* [16] showed that the interaction among knowledge management cycles, organizational culture, and employee engagement exerts a significant impact on job satisfaction outcomes in contemporary organizations.

In addition, research focusing on workplace stress and quality of work life underscores their critical roles in employee satisfaction. Asoba and Mefi [17] identified ineffective stress management mechanisms as major contributors to reduced job satisfaction in higher education institutions. In a related study, Oleabhie [18] emphasized that the implementation of quality work-life programmes significantly improves employee morale

and productivity in Nigerian manufacturing firms. At a broader level, international assessments and systematic reviews reveal notable regional variations in job satisfaction while consistently reinforcing the importance of organizational support systems in enhancing employee well-being and performance [19][20].

2.3 Intelligent Models in Human Resource Analytics

Recent advances in machine learning and artificial intelligence have introduced robust techniques for modeling complex human resource phenomena. Among these, artificial neural networks (ANNs) have gained widespread application in prediction, classification, and decision-support systems due to their capacity to capture nonlinear relationships. Empirical evidence from diverse domains demonstrates that ANN-based models often achieve superior predictive performance compared to traditional statistical approaches [6][20][21].

In the domain of workforce and productivity modeling, advanced techniques such as deep learning and neuro-fuzzy systems have been successfully applied to forecasting, monitoring, and optimization tasks [3][7][22][23]. Chavez *et al.* [3] developed an ANN model using the Open University Learning Analytics dataset, leveraging behavioral indicators, such as student interaction patterns and assessment outcomes to predict academic performance, achieving an accuracy of 93.81%. Similarly, Arqawi *et al.* [23] reported an accuracy of 94.52% by incorporating data preprocessing techniques and Synthetic Minority Oversampling Technique (SMOTE) to address class imbalance prior to training deep learning models. In a related study, Raza *et al.* [24] integrated exploratory data analysis, feature engineering, and SMOTE-based balancing within an Extra Trees classifier framework, resulting in a prediction accuracy of 93%.

Furthermore, Al-Darraj *et al.* [25] proposed a deep neural network framework that systematically incorporated data preprocessing and class balancing techniques, achieving 91% accuracy on the original dataset and 94% after balancing. These findings collectively underscore the critical importance of rigorous data preprocessing and class imbalance mitigation in enhancing the performance of human resource analytics models. In addition, Bajhzer *et al.* [26] examined the effects of data preprocessing and model optimization on ANN-based employee performance prediction using multiple publicly available HR datasets. Their results indicate that appropriate feature selection and regularization consistently improve predictive performance, whereas principal component analysis (PCA)-based dimensionality reduction may reduce accuracy due to the loss of discriminative information. Notably, simplified ANN architectures demonstrated improved generalization capability, with top-performing configurations achieving an average accuracy of 90.08% across datasets.

Despite these advancements, a key limitation in existing studies is the lack of explicit integration between machine learning outputs and practical human resource evaluation frameworks. Many approaches either classify job satisfaction directly from Likert-scale responses or employ black-box machine learning models without translating continuous predictions into interpretable satisfaction levels that can guide managerial decision-making [8][15].

The present study proposes the application of a multilayer perceptron artificial neural network (MLP-ANN) to model employees' job satisfaction using empirical organizational data. In addition, the study introduces an ordinal representation of job satisfaction derived from continuous ANN predictions, thereby providing a structured and interpretable framework for integrating machine learning outputs into human resource decision-making processes.

3. MATERIALS AND METHODS

3.1 Research Design

This study adopted a quantitative, cross-sectional research design combined with an intelligent modelling approach. Primary data were collected through structured questionnaires, while a multilayer perceptron artificial neural network (MLP-ANN) is employed to model and assess employees' job satisfaction. The design is suitable for capturing complex, nonlinear relationships among multiple job satisfaction determinants within an organizational setting.

3.2 Population and Data Collection

The study population comprised employees of the Ministry of Science and Technology, Akwa Ibom State, Nigeria. A total of 510 questionnaires were administered using stratified random sampling to ensure adequate representation across departments and cadres. Participation was voluntary, and responses were anonymized to ensure confidentiality and reduce response bias. Sixty questionnaires returned with incomplete responses were excluded, resulting in 450 valid responses for the study. Responses were recorded on a five point Likert scale. A Cronbach's alpha value of 0.76 was obtained using SmartPLS software, indicating that the questionnaire items have acceptable internal consistency reliability.

The questionnaire included twenty-two job satisfaction related attributes presented in Table 1.

Table 1. Job Satisfaction Attributes

SN	Attributes Description	Code
1	Satisfaction with salary	SWS
2	Opinion valued by superior	OVS
3	Fair policies for promotion	FPP
4	Reward for dedication and commitment	RDC
5	Opportunity for career growth	OCG
6	Who to meet for solution	WFS
7	Team provision of support	TPS
8	Adequate training to work	ATW
9	Team inspiration to do more	TIM
10	Manager treats workers equally	MTE
11	Resources and tools to work	RTW
12	Struggle to get information to do work	SID
13	Superior encouragement to give best	SEB
14	Manager praise for good job	MPJ
15	Job allows time for family after official hours	JAT
16	Job makes a positive difference in others life	JPD
17	Job causes unreasonable amount of stress	JUS
18	Willingness to work next three years	WNT
19	Understanding of role in organization	URO
20	Staying away from work based on feelings	SFW
21	Full understanding of organizational objectives	FUO
22	Enjoying being a member of Team	EMT

3.3 Data Pre-processing

Data preprocessing was conducted prior to model training to

improve learning efficiency and enhance generalization performance. Initial data screening involved the removal of incomplete and inconsistent responses to ensure data quality. Each respondent's overall job satisfaction score was computed by aggregating responses across all attributes, yielding scores ranging from 22 to 110. The dataset was subsequently partitioned into training, testing, and validation subsets using an 8:1:1 ratio.

3.4 Multilayer Perceptron Neural Network Design

The Multilayer Perceptron Artificial Neural Network (MLP-ANN) architecture illustrated in Figure 1 was developed for this study. The model adopted a three-layer feedforward structure comprising an input layer, a hidden layer, and an output layer. The input layer consisted of twenty-two nodes, each representing a job satisfaction attribute.

To enhance the network's ability to capture nonlinear relationships, the Rectified Linear Unit (ReLU) activation function was employed in the hidden layer, while a sigmoid activation function was applied in the output layer to constrain predictions within a bounded range. Model training was performed using the backpropagation algorithm, which iteratively minimizes classification error through gradient descent optimization.

error term. The mean squared error (MSE), as defined in

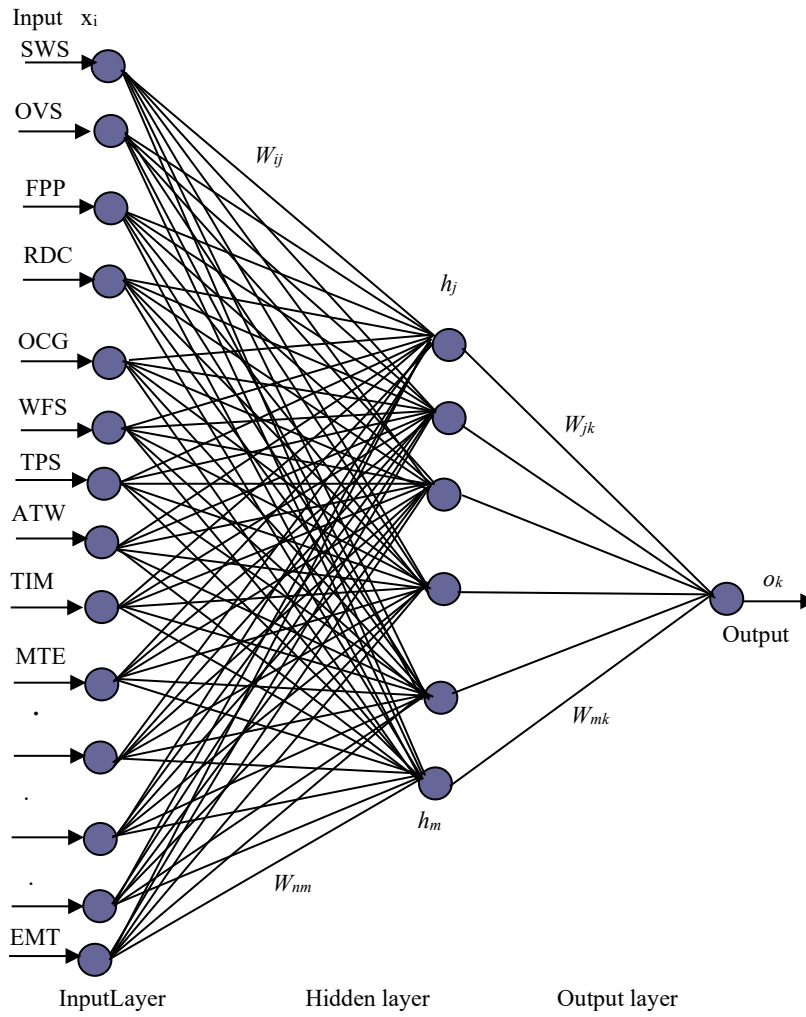


Figure 1. ANN-MLP Model for Job Satisfaction Assessment

From the artificial neural network model of Figure 1, a system of equations is formulated in (1) as follows:

$$\begin{aligned} w_{11}x_1 + w_{12}x_2 + \dots + w_{1n}x_n &= h_1^* \\ w_{21}x_1 + w_{22}x_2 + \dots + w_{2n}x_n &= h_2^* \\ &\vdots \\ w_{m1}x_1 + w_{m2}x_2 + \dots + w_{mn}x_n &= h_m^* \end{aligned} \quad (1)$$

where

$x_i: i=1,2,\dots,n$ is the job satisfaction input variables
 $h_j^*: j=1,2,\dots,m$ is the job satisfaction hidden layer pre-output
 W_{ij} is the weight on the connection from the i th node in the input layer to the j th node in the hidden layer.

The model defined in Equation (1) is expressed in matrix form in (2), subsequently compacted in (3), and then subjected to an activation function to obtain the hidden layer output, as shown in (4). Similarly, the computation at the output layer node is performed to produce the pre-output in (5). This expression is represented in vector form in (6), further simplified in (7), and then passed through an activation function to generate the final job satisfaction output in (8). The resulting output is subsequently classified as shown in (9) and formally instantiated in (10).

The predicted output is then compared with the corresponding actual output, and the difference between them constitutes the

Equation (11), is employed as the loss function to iteratively update the connection weights during each training epoch. This process continues until the error converges to an acceptable threshold.

$$\begin{bmatrix} w_{11} & w_{12} & \dots & w_{1n} \\ w_{21} & w_{22} & \dots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{m1} & w_{m2} & \dots & w_{mn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} h_1^* \\ h_2^* \\ \vdots \\ h_m^* \end{bmatrix} \quad (2)$$

$$\sum_{j=1}^m \sum_{i=1}^n w_{ij} x_i = h_j^* \quad (3)$$

$$h_j = \max(0, h_j^*) \quad (4)$$

$$w_{11}h_1 + w_{12}h_2 + \dots + w_{1m}h_m = o_k^* \quad (5)$$

$$\begin{bmatrix} w_{11} & w_{12} & \dots & w_{1m} \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \\ \vdots \\ h_m \end{bmatrix} = o_k^* \quad (6)$$

$$\sum_{k=1}^p \sum_{j=1}^m w_{jk} h_j = o_k^* \quad (7)$$

$$\hat{O}_k = f(O_k^*) = \frac{1}{1 + e^{-O_k^*}} \quad (8)$$

$$\hat{O}_k = \begin{cases} \text{low} & \text{if } a \leq \hat{O}_k < b \\ \text{Moderate} & \text{if } b \leq \hat{O}_k < c \\ \text{High} & \text{if } c \leq \hat{O}_k \leq d \end{cases} \quad (9)$$

$$O_k = \begin{cases} \text{low} & \text{if } 22 \leq O_k < 51 \\ \text{Moderate} & \text{if } 51 \leq O_k < 80 \\ \text{High} & \text{if } 80 \leq O_k \leq 110 \end{cases} \quad (10)$$

$$MSE = \frac{1}{n} \sum_{k=1}^n (O_k - \hat{O}_k)^2 \quad (11)$$

where

- w_{jk} is a matrix of weights that connects the k th-output layer node to the j th node in the
- O_k^* is the pre-output at k -th data point
- e is standard exponential function
- O_k is the actual output at k -th data point
- \hat{O}_k is the computed output at k -th data point
- a is the minimum value of the output variable
- b lower class limit of the middle class
- c is the upper class limit of the middle class
- d is the maximum value of the output variable
- MSE is the mean squared error
- n is the total number of data points

The mean squared error (MSE), as defined in Equation (11), was employed as the loss function during model training. Similarly, the validation loss was computed using the validation dataset to assess generalization performance. Both training and validation losses were continuously monitored to mitigate the risk of model overfitting.

A trained MLP-ANN provides valuable insight into the contribution of input variables to the output, making it a robust tool for addressing prediction and classification problems [21][27]. In this study, the MLP-ANN was configured with a single output neuron to estimate a continuous job satisfaction score. This design aligns with the inherently ordinal nature of employee satisfaction, as opposed to treating it as a purely nominal classification problem.

Rather than employing a multi-output softmax configuration, the continuous output was subsequently mapped into three ordered satisfaction categories—low, moderate, and high—using empirically defined threshold values derived from the job satisfaction scale. This threshold-based classification approach preserves the ordinal relationships among satisfaction levels while avoiding the additional model complexity associated with enforcing discrete class boundaries during training.

Such an approach is particularly appropriate when job satisfaction is conceptualized as a graded construct, as it enables the neural network to learn underlying nonlinear patterns prior to discretization for interpretability and managerial decision support. Consequently, the proposed method achieves a balance between predictive accuracy, conceptual consistency, and practical applicability within the domain of human resource analytics.

4. RESULTS AND DISCUSSION

4.1 Model Implementation

The multilayer perceptron artificial neural network (MLP-ANN) was implemented using the TensorFlow-Keras framework within the Python programming environment. Job attribute importance evaluation, as well as model training and

performance assessment, were conducted using the Scikit-learn, NumPy, and Pandas libraries.

The model was developed using a dataset comprising 450 samples, which were partitioned into training, validation, and testing subsets in the ratio of 8:1:1, respectively. Specifically, 360 data samples were used for training the MLP-ANN to learn patterns associated with employees' job satisfaction, while 45 samples were utilized for validation to optimize hyperparameters and mitigate overfitting. The remaining 45 samples were reserved for testing to evaluate the generalization performance of the model on previously unseen data. Model training was performed over 100 epochs, using varying learning rates and hidden neuron configurations, as summarized in Table 3.

The correlations of job satisfaction variables with employee's job satisfaction output were obtained using pandas library in Python environment. Figure 2 illustrates the variables importance and contributions to output. Figure 3 presents the job satisfaction variables in descending order of importance. The results reveal that SWS, OVS, FPP, RDC, OCG, WFS, and TPS are the most significant determinants of job satisfaction. These factors should therefore be prioritized and sustained by employers to enhance employees' satisfaction, thereby contributing to improved organizational productivity and overall performance.

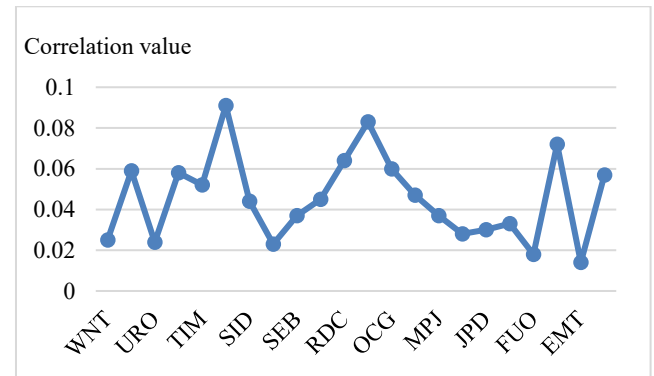


Figure 2. Graph of Job Satisfaction Attribute Importance

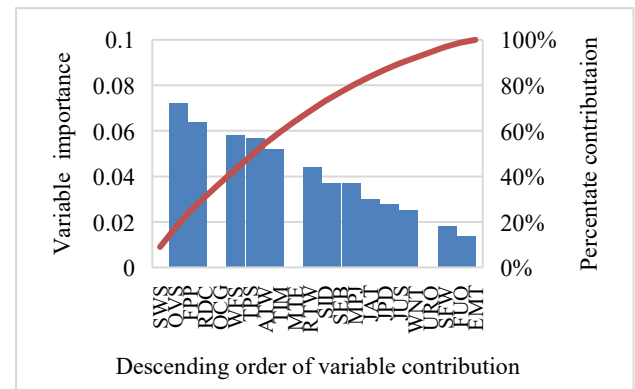


Figure 3. A graph of Ordered Variable Contribution

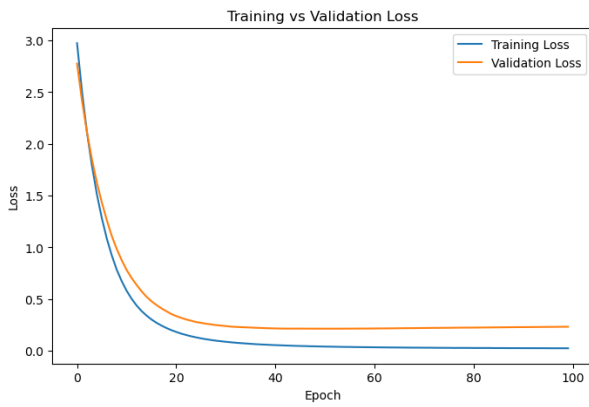


Figure 4. A Graph of Training versus Validation Loss

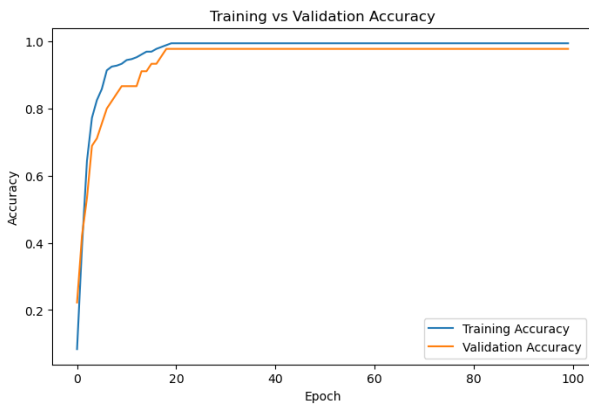


Figure 5. A Graph of Training versus Validation Accuracy

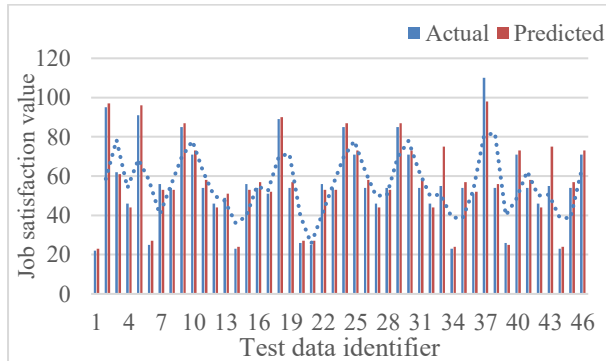


Figure 6. A Chart of Actual and Predicted Output

Table 2 Actual and Predicted Output

Test ID	Actual Output		Predicted Output	
	Value	Class	Value	Class
1	22	Low	23	Low
2	95	High	97	High
3	62	Moderate	61	Moderate
4	46	Low	44	Low
5	91	High	96	High
6	25	Low	27	Low
7	56	Moderate	53	Moderate
8	54	Moderate	53	Moderate
9	85	High	87	High
10	71	Moderate	73	Moderate
11	54	Moderate	58	Moderate
12	46	Low	44	Low
13	49	Low	51	Moderate
14	23	Low	24	Low

15	56	Moderate	53	Moderate
16	54	Moderate	57	Moderate
17	51	Low	52	Low
18	89	High	90	High
19	54	Moderate	57	Moderate
20	26	Low	27	Low

4.2 Model Performance Analysis

The training and validation loss curves over 100 epochs are presented in Figure 4. The training loss initially starts at approximately 3.0 at epoch 0 and exhibits a sharp decline between epochs 10 and 20. Beyond this point, the rate of decrease becomes more gradual, with the loss approaching 0.02 between epochs 40 and 100. This pattern indicates that the model effectively learns the underlying structure of the training data.

Similarly, the validation loss begins at approximately 2.8 and decreases rapidly within the first 20 epochs. It reaches a minimum value of 0.22 and stabilizes between epochs 30 and 40, after which a slight upward trend is observed. This behavior suggests that the model initially generalizes well to unseen data but experiences diminishing improvement beyond epoch 40. The subsequent rise in validation loss indicates the onset of overfitting, where the model begins to over-specialize on the training data at the expense of generalization. To address this, an early stopping mechanism was implemented in Python, with the optimal model weights obtained at epoch 35, thereby preserving generalization performance.

Figure 5 illustrates the training and validation accuracy curves. The training accuracy begins at approximately 0.08, while the validation accuracy starts at a relatively higher value of 0.23 within the first five epochs. The training accuracy increases rapidly, reaching values between 0.94 and 0.97 within epochs 5 to 15. During the same interval, validation accuracy ranges between 0.85 and 0.92, reflecting the model's strong ability to capture salient patterns in the data. At epoch 20, both curves stabilize with only a minimal gap between them, indicating convergence and a well-generalized model.

The comparison between actual and predicted job satisfaction values is shown in Figure 6. Table 2 presents a comparative evaluation of the model's performance across the first 20 test observations. Each observation consists of actual output, a numerical predictor (value), alongside the corresponding class label. The classification framework employed is ordinal in nature, comprising three ordered categories—Low, Moderate, and High—as defined in Equation (10).

Out of the 20 observations, the model correctly classified 19 instances, with only one instance misclassified. The high level of accuracy in classification demonstrates strong predictive capability and indicates that the model effectively captures the underlying structure of the classification problem.

The single misclassification occurs at Test ID 13, where the actual class is Low, but the model predicts Moderate. It is obvious that the corresponding actual value (49) lies close to the decision boundary separating the Low and Moderate classes. This suggests that the error arose from boundary ambiguity rather than a fundamental flaw in the model's logic. Importantly, no severe misclassifications were observed (there was no instance where High is predicted as Low or vice versa), which further underscores the model's stability and consistency. The model exhibits near-perfect classification performance, making it highly suitable for decision-support applications.

Evaluation on all 45 test data samples using the trained MLP-ANN model still resulted in only one misclassification. This

corresponds to a classification error rate of 2.3% and an overall classification accuracy of 97.7%, demonstrating the robustness and predictive effectiveness of the model.

Other performance metrics such as accuracy, precision, recall, and F1-score were computed for models with one, two, and three hidden layers, as summarized in Table 3. Accuracy represents the overall proportion of correctly classified instances, while precision measures the proportion of true positive predictions among all predicted positive instances. Recall (sensitivity) indicates the proportion of actual positives correctly identified by the model. The F1-score, defined as the harmonic mean of precision and recall, provides a balanced evaluation of model performance, particularly in the presence of class imbalance.

Table 3. MLP-ANN Performance Metrics

No. of Hidden layers	Hidden layer neuron	Learning rate	Accuracy %	Precision %	Recall%	F1 Score %	
1	10	0.01	95.2	93.4	92.6	91.3	
	11	0.01	96.4	95.2	93.5	92.2	
	12	0.01	97.7	95.3	94.6	93.2	
	13	0.01	96.8	94.2	93.3	92.1	
	14	0.01	95.3	94.7	92.9	91.4	
	15	0.01	95.6	95.2	92.1	91.9	
	10	0.02	93.1	91.3	91.5	90.2	
	11	0.02	94.7	94.1	92.6	91.3	
	12	0.02	96.8	95.0	93.9	92.6	
	13	0.02	95.7	93.8	92.4	91.3	
	14	0.02	94.2	92.9	91.1	90.1	
	15	0.02	93.3	93.2	90.2	89.4	
	2	10	0.01	93.1	92.6	90.3	89.3
		11	0.01	95.7	94.2	92.5	91.1
		12	0.01	94.4	94.2	93.4	91.9
13		0.01	92.2	91.1	90.4	87.1	
14		0.01	91.1	90.2	87.9	85.4	
15		0.01	89.6	88.2	87.1	84.3	
10		0.02	83.1	81.3	80.5	80.2	
11		0.02	82.5	83.1	82.4	82.3	
12		0.02	85.8	85.0	83.6	82.4	
13		0.02	85.7	83.9	82.3	81.7	
14		0.02	84.2	80.6	81.3	80.1	
15		0.02	83.3	83.1	80.2	82.4	
3		10	0.01	83.1	82.3	80.3	81.2
		11	0.01	85.1	84.2	82.5	81.1
		12	0.01	84.2	84.0	83.4	81.4
	13	0.01	82.8	81.9	80.2	81.3	
	14	0.01	81.3	80.5	80.0	79.4	
	15	0.01	79.6	78.9	77.4	74.3	
	10	0.03	73.2	71.3	70.5	70.2	
	11	0.03	72.3	73.2	72.1	72.1	
	12	0.03	75.4	75.0	73.3	72.4	
	13	0.03	75.3	73.4	72.8	71.5	
	14	0.03	74.2	70.6	71.8	70.1	
	15	0.03	73.3	73.1	70.8	69.4	

Table 3 summarizes the performance of the MLP-ANN under different model configurations, considering variations in the number of hidden layers (one to three), the number of neurons per hidden layer (ten to fifteen), as well as variation in learning rates between 0.01 and 0.03. Model performance was assessed using accuracy, precision, recall, and F1-score.

The MLP-ANN model with a single hidden layer and a learning rate of 0.01 consistently outperformed deeper architectures. Increasing the number of neurons beyond this point led to declining performance, hence, suggesting diminishing returns with higher model complexity. When the learning rate was increased to 0.02 and 0.03 performance declined across all neuron settings. Introducing a second hidden layer resulted in further performance degradation. The lowest performance was observed for MLP-ANN models with three hidden layers, thereby indicating reduced generalization capability and increased training instability for deeper architectures.

The results indicate that model performance is strongly influenced by network depth and learning rate. Increasing network depth beyond one hidden layer does not improve classification performance for the present task. Experimental evaluation across multiple architectures revealed that a single hidden layer with 12 neurons and a learning rate of 0.01 produced optimal performance, achieving 97.7% accuracy, 95.3% precision, 94.6% recall, and 93.2% F1-score.

The high level of accuracy achieved in this work could be attributed to the relative homogeneity of the study population, as well as the adoption of a continuous output learning approach prior to mapping predictions into ordinal classes. This modelling strategy enhanced class separability and significantly improved predictive performance. These results emphasize the importance of careful selection of network architecture and hyperparameters in achieving optimal artificial neural network (ANN) performance, while avoiding unnecessary model complexity.

4.3. Related Work Comparison

The summary of methods used and results obtained by the proposed study compared with that of other researchers in the domain of employees' job satisfaction are presented in Table 4.

Table 4. Comparison of Related Works.

Related Work	Method	Results
Our proposed study Employees' job satisfaction assessment	Employed Multilayer perceptron artificial neural network to assess employees' job satisfaction using empirical organizational data. Designed job satisfaction as an ordinal outcome derived from continuous ANN predictions.	Achieved accuracy of 97.7% and precision of 95.3% on the test data.
Chavez <i>et al.</i> [25] Student's performance prediction	Used Artificial neural network model with open University Learning dataset	Achieved accuracy of 93.81%.
Arqawi <i>et al.</i> [23] Prediction of employee attrition and performance	Applied data preprocessing and SMOTE for class imbalance handling before training deep learning models	Obtained 94.52% in accuracy metrics

Raza <i>et al.</i> [24] Prediction of employee attrition	Integrated exploratory data analysis, feature engineering, and SMOTE-based balancing to optimize an Extra Trees classifier	Obtained prediction accuracy of 93%.
Al-Darraj <i>et al.</i> [25] Prediction of employee attrition	Employed Deep neural network framework that systematically integrated data preprocessing and class balancing techniques.	Achieved 91% accuracy on the original dataset and 94% accuracy after balancing of dataset.
Bajhzer <i>et al.</i> [26] Prediction of employee performance	Optimization techniques on artificial neural network (ANN)-based prediction of employee performance in HR. Used feature selection, feature extraction, principal component analysis (PCA) to reduce model complexity	Achieved average accuracy of 90.08%.

Table 4 compares the proposed study with selected recent machine-learning applications in human resource analytics. While several related works focus on employee attrition or performance prediction and employ deep learning models with extensive preprocessing and class-balancing techniques, the present study specifically addresses employee job satisfaction, a multidimensional and subjective construct. The proposed multilayer perceptron model demonstrates that a carefully tuned simple ANN architecture, combined with continuous output learning and subsequent ordinal classification, can achieve superior predictive performance without unnecessary model complexity. Although different datasets were used in the studies presented in Table 3—making direct methodological comparison difficult—the proposed approach achieved an accuracy of 97.7% and a precision of 95.3%, outperforming the compared studies, whose reported accuracies range from 90.08% to 94.52%. In addition, the proposed approach offers improved interpretability and practical relevance for organizational decision support.

5. CONCLUSION

This study developed and evaluated a multilayer perceptron artificial neural network (MLP-ANN) model for assessing employee job satisfaction using survey-based data. The empirical findings demonstrate that key factors—namely satisfaction with salary, quality of supervisory relationships, fairness of promotion policies, recognition, and opportunities for career development—play a significant role in shaping overall job satisfaction. The high classification accuracy achieved by the model further confirms the effectiveness of neural network approaches in capturing the complex, nonlinear relationships inherent in employee satisfaction dynamics.

By modeling job satisfaction as a continuous variable and subsequently mapping it into ordered categories, this study provides a novel and structured framework that bridges the gap between machine learning outputs and practical human resource decision-making. This approach not only preserves the ordinal nature of job satisfaction but also enhances interpretability for managerial applications. Consequently, the proposed framework offers a robust decision-support tool capable of informing proactive human resource strategies aimed at improving employee well-being and organizational performance.

The contributions of this study are both methodological and practical. Methodologically, it demonstrates the applicability of a relatively simple MLP architecture in modeling complex human-centered phenomena, while also highlighting the importance of data preprocessing, model optimization, and performance evaluation in achieving reliable predictive outcomes. Practically, it provides actionable insights for policymakers and organizational leaders, particularly within public-sector institutions in developing economies, where empirical evidence on job satisfaction remains limited.

In light of these findings, organizations are encouraged to adopt data-driven approaches for monitoring and enhancing employee satisfaction, with particular emphasis on the identified key determinants. Future research may extend this work by incorporating temporal modeling techniques, such as recurrent neural networks (RNNs), to track changes in job satisfaction over time. Additionally, reinforcement learning approaches could be explored to develop adaptive systems for optimizing employee engagement and organizational interventions.

6. CONFLICT OF INTEREST

The authors declare no conflict of interest.

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8. REFERENCES

- [1] Tria, J. Z. (2023). Job satisfaction among educators: A systematic review. *European Journal of Educational Research*, 12(2), e2310
- [2] Abuhashesh, M., Al Dmour, R., and Masa'deh, R. (2019). Factors affecting employees' job satisfaction. *Journal of Social Sciences*, 8(2): 1–14.
- [3] Chavez, H., Chavez-Arias, B., Contreras-Rosas, S., Alvarez Rodriguez, J. M., and Raymundo, C. (2023). Artificial neural network model to predict student performance using nonpersonal information. *Frontiers in Education*, 8, 1106679.
- [4] Phuong, T. T., and Le Ha, N. T. (2022). Knowledge management, employee satisfaction, employee loyalty and job performance: A proposed study. *International Journal of Information, Business and Management*, 14(1):1–16.
- [5] Udoh, S. S., Asuquo, D. E., & Inyang, U. G. (2018). Adaptive neuro fuzzy model for oil pipeline monitoring in a cluster based sensor network. *World Journal of*

- Applied Science and Technology, 10(1B): 184–190.
- [6] Udoh, S. S., Umoh, U. A., Umoh, M. E., and Udo, M. E. (2019). Diagnosis of prostate cancer using soft computing paradigms. *Global Journal of Computer Science and Technology: Neural and Artificial Intelligence*, 19(2): 19–26.
- [7] Udoh, S. S., Inyang, U. G., Umoh, U. A., George, U. D., Etuk, U. R., Akpan, T. B., and Basse, E. M. (2023). Deep learning based neural network modelling for cassava yield prediction. *International Journal of Scientific and Engineering Research*, 14(8): 1–18.
- [8] Udoh, S. S., Ekong, K. C., Usip, P. U., Asuquo, D. E., Moffat, I. U., George, U. D., and Umoh, U. A. (2024). Intelligent discrete event system specification for monitoring cyber-attacks in airports. *International Journal of Scientific Research and Development*, 3(8): 63–72.
- [9] Udoh, S. S., George, U. D., & Etuk, U. R. (2023). Cassava yield forecasting using artificial neural network. In *Contemporary Discourse on Nigeria's Economic Profile: A Festschrift in Honour of Prof. Nyaudoh U. Ndaeyo* (pp. 667–679). Uyo: University of Uyo Press.
- [10] León, H. C. R., Navarro, E. R., Meléndez, L. V., Salazar, T. D. R. M., Yuncor, N. R. C., and María, E. M. (2021). Job satisfaction factors in secondary school teachers: Public and private institutions in a Peruvian region. *Cypriot Journal of Educational Sciences*, 16(6):3317–3328.
- [11] Özkan, U. B., and Akgenç (2022). Teachers' job satisfaction: Multilevel analyses of teacher, school and principal effects. *Forum for International Research in Education*, 7(3):1–23.
- [12] Hasyim, H., and Bakri, M. (2024). Pay and incentive inequality: A systematic review of their effects on work motivation. *Paradoks: Jurnal Ilmu Ekonomi*, 7(1): 69–84.
- [13] Abiona, B. G., Adenuga, O. O., Adeosun, K. G., Fapojuwo, O. E., and Roseje, T. O. (2023). Assessment of job satisfaction among employees of Animal Care Services Konsult Limited, Ogun State, Nigeria. *FUDMA Journal of Sciences*, 7(3): 257–265.
- [14] Levi, N. N. (2023). Evaluation of employees' job satisfaction in three private organizations in Edo State, Nigeria. *International Journal of Management and Entrepreneurship Research*, 5(11):814–830.
- [15] Tharu, R. P. (2019). Multiple regression model for job satisfaction of employees in saving and cooperative organizations. *International Journal of Statistics and Applied Mathematics*, 4(4): 43–49.
- [16] Obeng, H. A., Arhinful, R., Mensah, L., and Owusu Sarfo, J. S. (2024). Influence of knowledge management cycle on job satisfaction and organizational culture considering employee engagement. *Sustainability*, 16(20): 8728.
- [17] Asoba, S. N., and Mefi, N. P. (2021). Monitoring and management mechanisms on stress in higher education institutions in Eastern Cape Province, South Africa: A critical review. *Academy of Entrepreneurship Journal*, 27(2): 1–11.
- [18] Oleabhiye, E. J. (2025). Impacts and benefits of quality work life programmes in Nigerian manufacturing companies. *International Journal of Research and Innovation in Social Science*, 9(16): 1–15.
- [19] Sunn, C. Y., Peng, C. N., Qing, S. Z., Norhayati, W., Othman, B. W., Yusop, Y. M., and Anuar, M. (2024). Factors affecting job dissatisfaction in Asia: A systematic review. *International Journal of Academic Research in Business and Social Sciences*, 14(11): 1112–1127.
- [20] Statista Research Department (2024). APAC: Employee job satisfaction by country 2024. Statista Report, Statista Inc., Germany.
- [21] Udoh, S. S., Akinyokun, O. C., Inyang, U. G., Olabode, O., and Iwasokun, G. B. (2017). Discrete event based hybrid framework for petroleum pipeline activity classification. *Journal of Artificial Intelligence Research*, 6(2):39–50.
- [22] Udoh, S. S., Obot, O. U., George, U. D., and Isong, E. B. (2012). Modified (s, S) inventory model using artificial neural network. *International Journal of Scientific and Engineering Research*, 3(5): 992–995.
- [23] Arqawi, S., Rumman, M., Zitawi, E., Abunasser, B., and Abu-Naser, S. A. (2022). Predicting employee attrition and performance using deep learning. *Journal of Theoretical and Applied Information Technology*, 100(21): 6526–6536.
- [24] Raza, A., Munir, K., Almutairi, M. I., Younas, F., and Fareed, M. S. (2022). Predicting employee attrition using machine learning approaches. *Applied Sciences*, 12(13), 6424.
- [25] Al-Darraj, S., Honi, D. G., Fallucchi, F., Abdulsada, A. I., Guliano, R., and Abdulmalik, H. A. (2021). Employee attrition prediction using deep neural networks. *Computers*, 10(11): 141.
- [26] Bajhzer, R. M., Alsenani, Y., Jambi, S., and Hasanin, T. (2026). ANN based employee performance prediction: A comparative analysis of optimization techniques. *International Journal of Advanced Computer Science and Applications*, 17(3): 1098–1105.
- [27] Udoh, S. S., Usip, P. U., George, U. D., & Akpan, I. E. (2024). Adaptive neuro fuzzy based depression detection model for students in tertiary education. In *Applied Machine Learning and Data Analytics* (pp. 156–167). Cham: Springer.