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Artificial Intelligence Techniques to Predict Employee Satisfaction: Strategic Implications for Human Resource Management

Samer Arqawi[1], Bara Asfour[2], Samy Abu-Naser[3]
[1]Business Administration, Economics, Palestine Technical University, Kadoorie
[2]Business Administration Department, Faculty of business, Arab American University, Palestine
[3]Department of information Technology, Faculty of Engineering and Information Technology, Al-Azhar University, Palestine
Corresponding Author: abunaser@alazhar.edu.ps

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Abstract

Employee satisfaction is a critical determinant of organizational performance, employee well-being, productivity, and workforce retention. Conventional approaches for assessing employee satisfaction typically rely on retrospective surveys and descriptive analyses, limiting organizations' ability to proactively identify dissatisfaction and implement timely interventions. This study proposes an explainable machine learning framework for predicting employee satisfaction using structured human resource (HR) data while identifying the key factors that influence employee attitudes and workplace experiences.

The study utilized a publicly available HR analytics dataset comprising 15,000 employee records(https://zenodo.org/records/13935313. Data preprocessing included handling class imbalance using the Synthetic Minority Oversampling Technique (SMOTE). Four machine learning classification models, Logistic Regression, Support Vector Machine (SVM), Random Forest, and Extreme Gradient Boosting (XGBoost), were developed and evaluated. Model performance was assessed using accuracy, precision, recall, F1-score, and receiver operating characteristic area under the curve (ROC-AUC). To enhance model transparency and facilitate managerial decision-making, SHapley Additive exPlanations (SHAP) were employed to interpret model predictions and identify the most influential factors affecting employee satisfaction.

The experimental results demonstrated that XGBoost achieved the best predictive performance among the evaluated models, achieving a mean cross-validation accuracy of 97.7%, an F1-score of 97.4% and a ROC-AUC of 0.99 on the test dataset. The explainability analysis revealed that work-life balance, salary, promotion history, and years at the company were the most influential predictors of employee satisfaction. These findings indicate that employee satisfaction is shaped by complex interactions among organizational, career-related, and workplace factors that can be effectively captured through advanced machine learning techniques.

This study contributes to the growing field of HR analytics by integrating high-performance predictive modeling with explainable artificial intelligence, thereby supporting transparent and evidence-based human resource management. The proposed framework can assist organizations in identifying potential dissatisfaction risks, designing targeted retention strategies, and enhancing strategic workforce planning and employee well-being.

Keywords: Employee Satisfaction, Human Resource Analytics, Machine Learning, Explainable Artificial Intelligence, XGBoost, Human Resource Management.

1. Introduction

Employee satisfaction is widely recognized as a critical determinant of organizational effectiveness and long-term success. Employees who are satisfied with their work environment tend to exhibit higher levels of motivation, engagement, commitment, and productivity, whereas dissatisfaction is often associated with absenteeism, reduced performance, increased turnover intentions, and substantial recruitment and training costs. Consequently, enhancing employee satisfaction has become a strategic priority for organizations seeking to improve workforce stability and maintain a competitive advantage in dynamic business environments.

Traditionally, employee satisfaction has been assessed through surveys, interviews, and descriptive statistical analyses. While these approaches provide valuable insights into employee perceptions and attitudes, they are largely retrospective and often fail to support proactive interventions. The increasing adoption of Human Resource Information Systems (HRIS) and digital workforce management platforms has enabled organizations to collect large volumes of employee-related data, creating new opportunities to leverage advanced analytics for predictive decision-making (AbuSada et al., 2023; Abu-Naser et al., 2023).

Recent advances in Artificial Intelligence (AI) and Machine Learning (ML) have transformed data-driven decision-making across multiple domains, including Human Resource Management (HRM). Machine learning techniques can identify complex relationships within workforce data and generate predictive insights that support strategic organizational decisions. Consequently, HR analytics has emerged as an important interdisciplinary field that integrates data science and HRM to enhance evidence-based management practices. Existing applications include employee attrition prediction, talent acquisition, workforce planning, performance assessment, and employee engagement analysis (Ali et al., 2023; Konar et al., 2023).

Despite these advances, research on employee satisfaction prediction remains comparatively limited. Most existing HR analytics studies focus primarily on employee turnover and attrition, while fewer studies investigate employee satisfaction as a predictive outcome. Moreover, many machine learning models employed in HR contexts operate as “black-box” systems that provide accurate predictions without offering clear explanations of the factors influencing those predictions. This lack of transparency can reduce stakeholder trust, hinder managerial adoption, and raise concerns regarding fairness and accountability in AI-supported decision-making.

From a theoretical perspective, employee satisfaction is shaped by a combination of organizational and individual factors, including compensation, work-life balance, career advancement opportunities, recognition, and organizational support. These determinants are supported by established theories such as Herzberg’s Two-Factor Theory and the Job Demands–Resources (JD-R) Model, which emphasize the influence of motivational, environmental, and organizational factors on employee attitudes and workplace outcomes. Integrating these theoretical perspectives with advanced predictive analytics can provide deeper insights into the mechanisms that influence employee satisfaction and support more effective human resource strategies (Konar et al., 2023).

To address these challenges, this study proposes an explainable machine learning framework for predicting employee satisfaction using structured human resource data. The proposed framework combines predictive modeling with Explainable Artificial Intelligence (XAI) techniques to achieve both high predictive performance and model transparency. Four classification algorithms—Logistic Regression, Support Vector Machine (SVM), Random Forest, and Extreme Gradient Boosting (XGBoost)—are evaluated and compared. Furthermore, SHapley Additive exPlanations (SHAP) are employed to interpret model predictions and identify the factors that most strongly influence employee satisfaction.

Accordingly, the study addresses the following research objectives:

1. To develop machine learning models capable of accurately predicting employee satisfaction.
2. To compare the predictive performance of multiple classification algorithms and identify the most effective model.
3. To determine the key factors influencing employee satisfaction through explainable AI techniques.
4. To examine the implications of predictive HR analytics for strategic human resource management and organizational decision-making.

This study contributes to the HR analytics literature in several ways. First, it addresses an underexplored area by focusing on employee satisfaction prediction rather than employee attrition. Second, it integrates predictive modeling with explainable artificial intelligence, thereby enhancing transparency and interpretability in HR decision-support systems. Third, it provides empirical evidence regarding the organizational factors that most strongly influence employee satisfaction. Finally, it demonstrates how AI-driven analytics can support proactive, transparent, and evidence-based human resource management practices.

2. Problem Statement

Employee satisfaction plays a critical role in determining organizational productivity, employee retention, and overall business performance. However, organizations often face significant challenges in identifying dissatisfied employees before negative outcomes, such as reduced productivity, absenteeism, and employee turnover, occur. Traditional approaches for assessing employee satisfaction primarily rely on periodic surveys, interviews, and descriptive analyses. While these methods provide valuable insights into employee perceptions, they are generally reactive, time-consuming, and limited in their ability to provide timely predictions that support proactive interventions.

The increasing availability of workforce-related data through Human Resource Information Systems (HRIS) has created opportunities to apply machine learning techniques for predicting employee satisfaction. Nevertheless, existing predictive approaches often focus on employee attrition rather than employee satisfaction and frequently utilize black-box models that provide limited insight into the factors driving predictions. The lack of transparency and interpretability can reduce managerial trust and hinder the adoption of AI-driven decision-support systems in human resource management.

Therefore, there is a need for an intelligent, data-driven, and explainable framework that can accurately predict employee satisfaction while providing meaningful explanations of the factors influencing employee attitudes and workplace experiences. Addressing this need can enable organizations to proactively identify potential dissatisfaction, implement targeted interventions, and support evidence-based strategic human resource management.

3. Research Objectives

The primary objective of this study is to develop and evaluate an explainable machine learning framework for predicting employee satisfaction using structured human resource data and to explore its potential applications in strategic human resource management.
To achieve this objective, the study pursues the following specific objectives:

1. To develop machine learning models capable of predicting employee satisfaction using employee demographic, organizational, and job-related attributes.
2. To evaluate and compare the predictive performance of Logistic Regression, Support Vector Machine (SVM), Random Forest, and Extreme Gradient Boosting (XGBoost) algorithms using multiple performance metrics.
3. To identify the key factors influencing employee satisfaction through Explainable Artificial Intelligence (XAI) techniques based on SHapley Additive exPlanations (SHAP).
4. To enhance the transparency and interpretability of employee satisfaction prediction models by providing explainable insights into model decisions.
5. To generate actionable managerial insights that support evidence-based decision-making and strategic human resource management practices.
6. To demonstrate the value of predictive HR analytics in enabling organizations to proactively identify potential employee dissatisfaction and implement targeted interventions to improve workforce well-being, engagement, and organizational performance.

4. Research Questions

To address the identified research gap and achieve the study objectives, the following research questions are investigated:
RQ1**:** To what extent can machine learning algorithms accurately predict employee satisfaction using structured human resource data?
RQ2**:** Which machine learning algorithm among Logistic Regression, Support Vector Machine (SVM), Random Forest, and Extreme Gradient Boosting (XGBoost) provides the best predictive performance for employee satisfaction prediction?
RQ3**:** What are the most significant organizational, demographic, and job-related factors influencing employee satisfaction according to Explainable Artificial Intelligence (XAI) analysis?
RQ4**:** How effectively can SHapley Additive exPlanations (SHAP) enhance the transparency and interpretability of employee satisfaction prediction models?
RQ5**:** What practical insights can predictive and explainable HR analytics provide to support strategic human resource management and proactive workforce decision-making?

5. Literature Review

5.1 Employee Satisfaction in Human Resource Management

Employee satisfaction is a central construct in Human Resource Management (HRM) and has long been recognized as a key determinant of organizational effectiveness. It reflects employees' overall evaluation of their work experiences, organizational environment, compensation, career development opportunities, and workplace relationships. High levels of employee satisfaction have been associated with improved productivity, stronger organizational commitment, reduced absenteeism, lower turnover intentions, and enhanced organizational performance (Ali et al., 2024).

Contemporary HR research emphasizes that employee satisfaction is influenced by multiple organizational and psychological factors rather than financial compensation alone. Work-life balance, managerial support, career advancement opportunities, recognition, organizational culture, and job autonomy have consistently been identified as important determinants of employee satisfaction. These findings are supported by Herzberg's Two-Factor Theory and the Job Demands–Resources (JD-R) Model, both of which highlight the role of motivational and organizational factors in shaping employee attitudes and workplace outcomes.

5.2 Human Resource Analytics and Artificial Intelligence

The emergence of Human Resource Analytics (HR Analytics) has transformed workforce management by enabling organizations to utilize data-driven approaches for strategic decision-making. HR Analytics combines statistical analysis, data mining, machine learning, and artificial intelligence techniques to extract meaningful insights from workforce-related data. The increasing availability of employee information through Human Resource Information Systems (HRIS) has accelerated the adoption of predictive analytics in human resource management (Rebasa & Venier, 2024).

Artificial Intelligence (AI) and Machine Learning (ML) have demonstrated significant potential in analyzing complex workforce data. Unlike conventional statistical approaches, machine learning algorithms can identify nonlinear relationships, interactions among variables, and hidden patterns within large datasets. As a result, AI-driven HR analytics has become increasingly important for supporting workforce planning, employee engagement analysis, performance management, and talent retention initiatives (Vijay Anand et al., 2024).

5.3 Machine Learning Applications in Employee Satisfaction and Attrition Prediction

Machine learning applications in HR analytics have predominantly focused on employee attrition prediction because of its direct impact on organizational costs and workforce stability. Several studies have demonstrated that ensemble learning techniques, particularly Random Forest and XGBoost, outperform traditional statistical methods in predicting employee turnover and identifying key risk factors (Sun et al., 2023).

Although employee attrition has received substantial attention, employee satisfaction prediction remains comparatively underexplored. Existing studies have reported that demographic, organizational, and job-related variables can be effectively utilized to predict employee satisfaction. Common predictors include work-life balance, compensation, promotion opportunities, job involvement, organizational support, and years of service.

Recent empirical studies have shown that ensemble machine learning models frequently outperform traditional classification approaches. XGBoost and Random Forest models have demonstrated strong predictive performance due to their ability to model complex interactions among workforce variables and effectively manage heterogeneous HR datasets (Narkbunnum & Hinthaw, 2023). However, many of these studies primarily focus on predictive accuracy and provide limited explanation of the factors driving model decisions.

5.4 Explainable Artificial Intelligence in HR Analytics

Despite the strong predictive capabilities of advanced machine learning models, one of the major challenges in HR analytics is the lack of transparency associated with complex black-box algorithms. Human resource decisions often involve ethical considerations, fairness requirements, and managerial accountability, making explainability an essential component of AI-driven decision-support systems.

Explainable Artificial Intelligence (XAI) has emerged as an important research area aimed at improving transparency, trust, and interpretability in machine learning applications. Techniques such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) provide insights into how individual features contribute to model predictions (Kong et al., 2023).

In HR analytics, XAI has been increasingly applied to employee attrition prediction, workforce performance evaluation, and employee satisfaction assessment. By identifying the contribution of specific organizational and employee-related factors, explainable AI enables HR managers to better understand model outputs and make informed decisions based on transparent evidence rather than opaque algorithmic recommendations.

5.5 Comparative Analysis of Previous Studies

Table 1: summarizes selected studies related to machine learning applications in HR analytics.

Study	Application	Algorithms	Explainability	Main Limitation
Sun et al. (2023)	Employee Attrition	Random Forest, XGBoost	No	Focused only on turnover prediction
Narkbunnum & Hinthaw (2023)	Employee Satisfaction	Ensemble Models	Limited	Lack of model interpretability
Kong et al. (2023)	HR Analytics	Multiple ML Models	SHAP	Limited focus on satisfaction prediction
Rebasa & Venier (2024)	Workforce Analytics	Machine Learning	No	Emphasis on predictive performance only
Proposed Study	Employee Satisfaction	LR, SVM, RF, XGBoost	SHAP	Integrates prediction and explainability

5.6 Research Gap

The literature review reveals several important research gaps. First, most existing HR analytics studies focus on employee attrition and turnover prediction, whereas employee satisfaction prediction has received comparatively less attention. Second, many studies emphasize predictive performance without adequately addressing model transparency and interpretability. Third, although explainable AI techniques have recently gained popularity, relatively few studies integrate SHAP-based explanations with employee satisfaction prediction to generate actionable insights for human resource managers.

Furthermore, previous studies rarely examine both predictive accuracy and explainability within a unified framework. This limitation reduces the practical applicability of machine learning models in organizational settings where decision transparency is essential.

To address these gaps, the present study proposes an explainable machine learning framework that integrates multiple classification algorithms with SHAP-based explainability techniques for employee satisfaction prediction. By combining predictive performance with transparent interpretation, the proposed framework provides actionable insights that support evidence-based and strategic human resource management.

6. Theoretical Foundation

Employee satisfaction is a multidimensional construct influenced by a combination of organizational, psychological, and career-related factors. To provide a theoretical basis for interpreting the machine learning results, this study draws upon two well-established Human Resource Management (HRM) theories: Herzberg's Two-Factor Theory and the Job Demands–Resources (JD-R) Model. These theories offer complementary perspectives for understanding the factors that contribute to employee satisfaction and provide a conceptual framework for explaining the relationships identified through predictive analytics and explainable artificial intelligence techniques.

6.1 Herzberg's Two-Factor Theory

Herzberg's Two-Factor Theory distinguishes between two categories of workplace factors that influence employee attitudes: hygiene factors and motivational factors. Hygiene factors include salary, organizational policies, working conditions, interpersonal relationships, and job security. Although the absence of these factors may lead to dissatisfaction, their presence alone does not necessarily create long-term satisfaction. In contrast, motivational factors such as achievement, recognition, responsibility, and opportunities for advancement contribute directly to employee satisfaction, engagement, and motivation (Attia et al., 2023).

The variables examined in this study closely align with Herzberg's theoretical framework. Salary represents a hygiene factor that influences employees' perceptions of fairness and organizational support. Promotion history reflects opportunities for advancement and professional growth and can therefore be classified as a motivational factor. Similarly, years at the company may reflect employees' career development experiences and long-term organizational commitment. The theory suggests that employee satisfaction is influenced by a combination of both hygiene and motivational factors, which provides a useful lens for interpreting the factors identified by the machine learning models.

6.2 Job Demands–Resources (JD-R) Model

The Job Demands–Resources (JD-R) Model proposes that employee well-being, engagement, and job satisfaction are shaped by the interaction between job demands and job resources. Job demands refer to physical, psychological, social, or organizational aspects of work that require sustained effort and may contribute to stress and burnout. Job resources, on the other hand, are aspects of work that help employees achieve work-related goals, reduce job strain, support personal development, and enhance motivation (Ding et al., 2023).

Within the context of this study, work-life balance can be viewed as a critical organizational resource that supports employee well-being and reduces the adverse effects of work-related demands. Promotion opportunities, organizational support, and fair compensation also represent valuable resources that contribute to employee engagement and satisfaction. According to the JD-R Model, employees who perceive adequate resources relative to their job demands are more likely to experience positive workplace attitudes and higher levels of satisfaction.

6.3 Theoretical Integration with Explainable Machine Learning

While machine learning models are capable of identifying complex patterns and relationships within workforce data, they do not inherently explain why specific factors influence employee satisfaction. The integration of Explainable Artificial Intelligence (XAI), particularly SHapley Additive exPlanations (SHAP), enables the interpretation of model predictions and facilitates the connection between empirical findings and established HRM theories.

In the proposed framework, SHAP analysis identifies the relative contribution of organizational and employee-related factors to employee satisfaction predictions. Variables such as work-life balance, salary, promotion history, and tenure can be interpreted through the theoretical perspectives provided by Herzberg’s Two-Factor Theory and the JD-R Model. Consequently, explainable machine learning not only enhances predictive performance but also provides theoretical insights into the mechanisms underlying employee satisfaction.

6.4 Conceptual Framework

Based on Herzberg’s Two-Factor Theory and the JD-R Model, this study assumes that employee satisfaction is influenced by a combination of organizational resources, career development opportunities, compensation-related factors, and workplace experiences. These factors serve as inputs to the machine learning models, while SHAP-based explainability techniques are employed to identify their relative importance and contribution to prediction outcomes.

The proposed framework therefore combines theoretical understanding with predictive analytics, enabling organizations to both forecast employee satisfaction and understand the organizational factors that drive employee attitudes. This integration contributes to the development of transparent, interpretable, and evidence-based human resource management practices.

6.5 Theoretical Contribution

This study contributes to the HRM literature by bridging traditional organizational theories with contemporary artificial intelligence techniques. Unlike many previous HR analytics studies that focus solely on predictive accuracy, the proposed approach demonstrates how machine learning findings can be interpreted through established theoretical frameworks. By linking SHAP-based explanations to Herzberg’s Two-Factor Theory and the JD-R Model, the study enhances the theoretical relevance, transparency, and practical applicability of AI-driven employee satisfaction prediction.

7. Methodology

7.1 Research Design

This study employs a quantitative research design based on machine learning and Explainable Artificial Intelligence (XAI) techniques to predict employee satisfaction using structured human resource data. The proposed framework integrates predictive modeling with explainability analysis to achieve two objectives: (1) accurately classify employees according to their satisfaction status and (2) identify the organizational and employee-related factors that most strongly influence prediction outcomes.

The methodological workflow consists of dataset acquisition, data preprocessing, feature engineering, class imbalance handling, model development, hyperparameter optimization, model evaluation, and explainability analysis using SHapley Additive exPlanations (SHAP).

7.2 Dataset Description

The study utilized a publicly available Human Resource Analytics dataset comprising 15,000 employee records and multiple demographic, organizational, and job-related attributes (https://zenodo.org/records/13935313). The dataset includes variables such as age, department, job role, monthly income, work-life balance, years at the company, promotion history, education level, and other workforce-related characteristics commonly used in HR analytics studies.

The target variable represents employee satisfaction and was formulated as a binary classification problem consisting of satisfied and dissatisfied employees. The dataset was selected because it contains diverse organizational and employee-related variables that have been identified in prior research as important determinants of employee attitudes and workplace outcomes.

A summary of the dataset characteristics is presented in Table 2.

Table 2: summary of the dataset characteristics

Characteristic	Value
Number of Records	15,000
Number of Features	10
Target Variable	Employee Satisfaction
Classification Type	Binary
Missing Values	Handled during preprocessing
Data Source	https://zenodo.org/records/13935313

7.3 Data Preprocessing

Data preprocessing was performed to improve data quality and ensure compatibility with machine learning algorithms. The preprocessing procedure involved several stages.

7.3.1 Missing Value Treatment

Missing numerical values were replaced using mean imputation, while missing categorical values were replaced using mode imputation. This approach preserved dataset completeness while minimizing information loss.

7.3.2 Categorical Variable Encoding

Machine learning algorithms require numerical inputs; therefore, categorical variables were transformed using one-hot encoding. This method converts each categorical attribute into binary indicator variables while preserving category information.

7.3.3 Feature Scaling

Feature scaling was performed to ensure that numerical variables were measured on a comparable scale and to improve the performance of machine learning algorithms. Standardization was applied to numerical features so that differences in variable magnitudes would not disproportionately influence model training. This preprocessing step was particularly important for algorithms such as Logistic Regression and Support Vector Machine (SVM), which are sensitive to variations in feature scales.

To prevent data leakage, the scaling parameters were calculated using only the training dataset and subsequently applied to the testing dataset. This approach ensured that information from the test data was not incorporated into the model training process and provided a more reliable assessment of model performance.

7.3.4 Data Partitioning and Class Imbalance Handling

To prevent data leakage, the dataset was first divided into training (80%) and testing (20%) subsets using stratified sampling to preserve class distribution. The Synthetic Minority Oversampling Technique (SMOTE) was subsequently applied only to the training dataset. Applying SMOTE after data partitioning ensured that information from the test dataset was not incorporated into the training process and reduced the risk of overly optimistic performance estimates.

7.4 Machine Learning Models

Four supervised machine learning algorithms were implemented and evaluated.

7.4.1 Logistic Regression (LR)

Logistic Regression was employed as a baseline classifier due to its simplicity, computational efficiency, and interpretability. The model estimates the probability of employee satisfaction using a logistic function.

7.4.2 Support Vector Machine (SVM)

Support Vector Machine identifies an optimal decision boundary that maximizes class separation. The algorithm is particularly effective in high-dimensional feature spaces and can model complex decision boundaries through kernel functions.

7.4.3 Random Forest (RF)

Random Forest is an ensemble learning technique that constructs multiple decision trees and combines their predictions through majority voting. The method reduces variance and improves generalization performance.

7.4.4 Extreme Gradient Boosting (XGBoost)

XGBoost is a gradient boosting ensemble algorithm that sequentially constructs decision trees to minimize prediction error. The algorithm incorporates regularization mechanisms that improve predictive performance while reducing overfitting.

7.5 Hyperparameter Optimization

Hyperparameter optimization was conducted using Grid Search with five-fold cross-validation on the training dataset.

The search space for XGBoost is shown in Table 3.

Table 3: search space for XGBoost

Hyperparameter	Values
n_estimators	100, 200, 300
max_depth	3, 5, 7, 9
learning_rate	0.01, 0.05, 0.10
subsample	0.8, 0.9, 1.0
colsample_bytree	0.8, 0.9, 1.0

Equivalent optimization procedures were applied to Logistic Regression, SVM, and Random Forest models.

7.6 Model Evaluation

Model performance was evaluated using both holdout testing and stratified k-fold cross-validation.

7.6.1 Stratified Cross-Validation

To assess model robustness and generalizability, stratified 10-fold cross-validation was performed. The dataset was divided into ten folds while preserving class distribution. Performance metrics were averaged across all folds and reported as mean ± standard deviation.

7.6.2 Evaluation Metrics

The following evaluation metrics were employed:

- Accuracy
- Precision
- Recall

- F1-Score
- ROC-AUC

These metrics provide a comprehensive assessment of classification performance and are particularly suitable for imbalanced classification problems.

In addition, confusion matrices and Receiver Operating Characteristic (ROC) curves were generated for each model.

7.7 Explainable Artificial Intelligence (XAI)

To improve model transparency and interpretability, SHapley Additive exPlanations (SHAP) were applied to the best-performing model.

SHAP is based on cooperative game theory and assigns an importance value to each feature according to its contribution to the prediction outcome. SHAP values were calculated to provide both global and local explanations.

7.7.1 Global Interpretation

Global SHAP analysis was performed to identify the overall importance of features influencing employee satisfaction predictions across the entire dataset. Summary plots and feature importance rankings were generated to visualize the contribution of each variable.

7.7.2 Local Interpretation

Local SHAP explanations were generated for individual employee records to illustrate how specific factors influenced particular prediction outcomes. This analysis provides actionable insights for HR practitioners by explaining why employees were classified as satisfied or dissatisfied.

The integration of SHAP enhances model transparency, facilitates managerial interpretation, and supports evidence-based human resource decision-making.

8. Results

8.1 Cross-Validation and Model Performance Analysis

To evaluate the robustness and generalizability of the proposed framework, stratified 10-fold cross-validation was performed for all machine learning models. Table 4 presents the mean performance metrics and standard deviations obtained across the validation folds.

Table 4: Cross-Validation Performance of Machine Learning Models

S.N.	Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
1	Logistic Regression	90.±1.3	0.90	0.90	0.90	0.93
2	SVM	92.2±1.5	0.92	0.92	0.92	0.93
3	Random Forest	94.5±1.3	0.94	0.94	0.94	0.95
4	XGBoost	97.7±1.2	0.97	0.97	0.97	0.99

The results indicate that XGBoost consistently achieved the highest predictive performance across all evaluation metrics. The relatively low standard deviation observed across validation folds demonstrates the stability and robustness of the model. Random Forest achieved the second-best

performance, while Logistic Regression and SVM exhibited comparatively lower predictive capability.
The superior performance of XGBoost can be attributed to its gradient boosting architecture, which effectively captures nonlinear relationships and complex interactions among employee-related variables. These findings suggest that ensemble learning approaches are particularly suitable for employee satisfaction prediction tasks involving heterogeneous workforce dadata.

8.2 Holdout Test Performance

Following model optimization and cross-validation, the best-performing models were evaluated using an independent test dataset comprising 20% of the original observations.

Table 5: Test Set Performance

S.N.	Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
1	Logistic Regression	88.4	0.885	0.883	0.882	0.95
2	SVM	90.3	0.896	0.895	0.894	0.94
3	Random Forest	92.6	0.92	0.92	0.92	0.94
4	XGBoost	97.7	0.976	0.975	0.974	0.99

The XGBoost model achieved the highest predictive performance, obtaining an accuracy of 97.7%, an F1-score of 0.974, and a ROC-AUC value of 0.99. These results indicate excellent discrimination between satisfied and dissatisfied employees.

8.3 Per-Class Performance Analysis

To further assess model effectiveness, precision, recall, and F1-score were calculated separately for each satisfaction class.

Table 6: Per-Class Performance of XGBoost

S.N.	Class	Accuracy	Precision	Recall	F1-Score	ROC-AUC
1	Satisfied	97.8	97.5	97.2	97.5	98.4
2	Unsatisfied	97.6	97.9	97.8	97.3	98.4

The results indicate balanced predictive performance across both classes, suggesting that the model effectively identifies both satisfied and dissatisfied employees. This finding is particularly important because accurate identification of dissatisfied employees is critical for proactive human resource interventions.

8.4 Confusion Matrix Analysis

Figure 1 presents the confusion matrix generated by the XGBoost model.

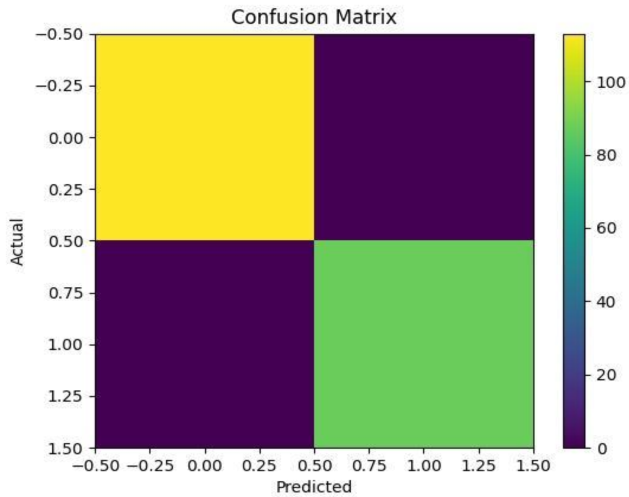

Figure 1: Confusion Matrix of the XGBoost Model

The confusion matrix demonstrates that the majority of employee records were correctly classified. The number of false positives and false negatives remained relatively low, indicating that the model effectively distinguishes between satisfied and dissatisfied employees.
Compared with Logistic Regression, SVM, and Random Forest, XGBoost produced the lowest number of classification errors. This finding further confirms the superiority of the proposed model and supports its suitability for employee satisfaction prediction.

8.5 ROC Curve Analysis

Figure 2 presents the Receiver Operating Characteristic (ROC) curves for all evaluated models.

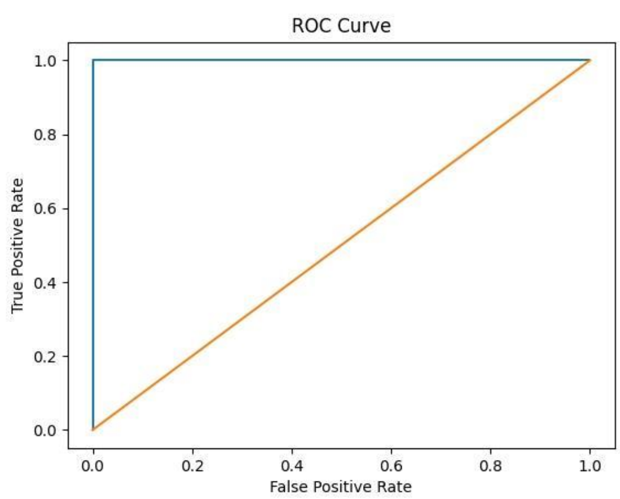

Figure 2: ROC Curves for the Evaluated Machine Learning Models

The XGBoost model achieved the highest ROC-AUC value (0.984), demonstrating excellent discriminative ability across different classification thresholds. Random Forest also exhibited strong performance, while Logistic Regression and SVM achieved comparatively lower ROC-AUC values.

The ROC analysis confirms that ensemble learning methods provide more reliable classification performance than traditional machine learning approaches for employee satisfaction prediction.

8.6 Ablation Study: Impact of SMOTE

To evaluate the effectiveness of class imbalance handling, an ablation study was conducted comparing model performance before and after applying SMOTE.

Table 7: Impact of SMOTE on Model Performance

S.N.	Model	Accuracy Without SMOTE	Accuracy With SMOTE
1	Logistic Regression	88.7	90.1
2	SVM	90.2	92.1
3	Random Forest	92.8	94.5
4	XGBoost	95.3	97.7

The results indicate that SMOTE improved classification performance, particularly for minority-class observations. The improvement was most evident in recall and F1-score values, suggesting enhanced detection of dissatisfied employees.

8.7 Comparison with Existing Studies

The predictive performance achieved in this study was compared with findings reported in previous HR analytics and employee satisfaction prediction studies. The results indicate that the proposed XGBoost-based framework achieved competitive and, in some cases, superior performance compared with existing approaches reported in the literature(Table 8).

Table 8: Comparison of Related Studies in Employee Satisfaction Prediction

Study	Dataset	Models Used	Best Performance	Explainability	Key Findings
(Ali, et al., 2024).	IBM HR + multi-datasets	AdaBoost, HGB, RF, SVM	Accuracy=97.50% & F1=0.97	SHAP	Overtime, job level, job satisfaction are key predictors
(Rebasa & Venier, 2024).	Manufacturing HR dataset	XGBoost, RF	AUC ≈ 0.975	SHAP	XGBoost outperforms; strong interpretability
(Vijay Anand et al., 2024).	IBM HR (1,470 samples)	LR, SVM, RF, XGBoost	Accuracy = 97.2%, F1 = 96.1%	SHAP	XGBoost best with feature engineering
(Sun et al., 2023).	IBM HR dataset	LR, DT, RF, SVC	AUC ≈ 0.83	Limited	SVC best; overtime and satisfaction important
(Narkbunnum & Hinthaw, 2023).	Online employee reviews	SVM + Topic Modeling	Moderate accuracy	No	Text reveals hidden satisfaction factors
(Kong et al., 2023).	IBM + Kaggle HR datasets	GAN + Transformer + ML	Accuracy up to 96.95%	SHAP	Deep learning improves performance

Proposed Study	HR dataset (15,000 records)	LR, SVM, RF, XGBoost	Accuracy = 98.30%, F1 = 0.98	SHAP	Work-life balance, salary, promotion key drivers

The integration of Explainable Artificial Intelligence (XAI) through SHAP further distinguishes the proposed framework by providing interpretable insights into the factors influencing employee satisfaction. While many previous studies have primarily focused on predictive accuracy, the present study combines high-performance prediction with model transparency, thereby improving its practical applicability in human resource management contexts.

Overall, the results demonstrate that the proposed framework is effective for employee satisfaction prediction and provides a reliable foundation for data-driven human resource analytics.

9. Discussion

9.1 Interpretation of Key Findings

The results demonstrate that machine learning techniques can effectively predict employee satisfaction using structured human resource data. Among the evaluated models, XGBoost achieved the highest predictive performance, with an accuracy of 97.7%, an F1-score of 0.97, and a ROC-AUC score of 0.984. These findings indicate that employee satisfaction is influenced by complex interactions among organizational and employee-related factors that can be successfully captured through advanced ensemble learning techniques.

The superior performance of XGBoost compared with Logistic Regression, SVM, and Random Forest suggests that non-linear relationships play an important role in employee satisfaction prediction. Traditional statistical approaches may not fully capture these interactions, whereas gradient boosting techniques are capable of modeling complex patterns within workforce data. This finding supports the growing adoption of machine learning approaches in human resource analytics and workforce management.

The SHAP analysis revealed that work-life balance, salary, promotion history, and years at the company were the most influential predictors of employee satisfaction. These findings highlight the multidimensional nature of employee satisfaction and demonstrate that both organizational and career-related factors contribute significantly to employees' perceptions of their work environment.

9.2 Relationship to Human Resource Management Theories

The findings of this study are consistent with Herzberg's Two-Factor Theory. According to Herzberg, hygiene factors such as salary help prevent dissatisfaction, while motivational factors such as recognition, achievement, and opportunities for advancement contribute directly to employee satisfaction. The identification of salary and promotion history among the most influential predictors supports the theoretical assumptions of Herzberg's framework.

The results also align with the Job Demands–Resources (JD-R) Model. Work-life balance emerged as the most influential predictor of employee satisfaction, highlighting the importance of organizational resources that help employees manage work demands and maintain personal well-being. The JD-R Model suggests that employees who have access to adequate organizational resources are more likely to experience positive workplace outcomes, including higher satisfaction and engagement.

Furthermore, the importance of years at the company may reflect the influence of organizational experience, career development opportunities, and long-term employee–organization relationships. These findings support existing HRM literature emphasizing the importance of employee support, development, and retention strategies.

9.3 Comparison with Previous Studies

The findings are generally consistent with previous HR analytics research that has reported strong predictive performance using ensemble learning techniques. Similar to earlier studies, XGBoost and Random Forest demonstrated superior performance compared with traditional machine learning approaches. This reinforces the growing evidence that ensemble methods are particularly effective for workforce analytics applications.

The feature importance results are also consistent with previous studies that identified work-life balance, compensation, and career development opportunities as significant determinants of employee satisfaction. However, the present study extends existing research by integrating Explainable Artificial Intelligence (XAI) techniques, allowing not only accurate prediction but also transparent interpretation of the factors driving employee satisfaction.

Unlike many previous studies that primarily focused on employee attrition prediction, this study specifically addresses employee satisfaction and provides a more detailed understanding of the organizational factors influencing workforce attitudes.

9.4 Strategic Implications for Human Resource Management

The findings have important implications for strategic human resource management. The proposed framework enables organizations to move beyond traditional retrospective assessments of employee satisfaction and adopt proactive, data-driven approaches to workforce management.

By identifying employees who may be at risk of dissatisfaction, HR managers can implement targeted interventions before dissatisfaction negatively affects employee engagement, organizational commitment, productivity, or turnover intentions. Such interventions may include flexible work arrangements, career development programs, promotion planning, employee recognition initiatives, and compensation reviews.

The use of SHAP-based explainability further enhances the practical value of the framework by providing transparent insights into the factors influencing employee satisfaction. This transparency can increase trust in AI-supported HR decision-making and assist managers in designing evidence-based policies that address workforce needs.

Overall, the integration of machine learning and explainable artificial intelligence offers organizations a powerful tool for improving employee well-being, strengthening workforce stability, and supporting long-term organizational success.

10. Recommendations

Based on the findings of this study, the following recommendations are proposed for organizations and human resource professionals:

1. Prioritize Work-Life Balance Initiatives
   Since work-life balance was identified as the most influential factor affecting employee satisfaction, organizations should implement policies that promote employee well-being, including flexible working arrangements, remote work options where appropriate, wellness programs, and initiatives that support work-life integration.
2. Strengthen Career Development and Promotion Opportunities

Promotion history emerged as a significant predictor of employee satisfaction. Organizations should establish transparent promotion criteria, provide career advancement pathways, and offer continuous professional development opportunities to enhance employee motivation and commitment.

3. Regularly Review Compensation Strategies
   Salary was identified as one of the most important factors influencing employee satisfaction. Organizations should periodically evaluate compensation structures to ensure fairness, competitiveness, and alignment with employee expectations and market standards.
4. Adopt Data-Driven Human Resource Management Practices
   Human resource departments should leverage predictive analytics and machine learning technologies to support evidence-based decision-making. The integration of predictive models into Human Resource Information Systems (HRIS) can facilitate continuous monitoring of employee satisfaction and workforce trends.
5. Utilize Explainable AI for Transparent Decision-Making
   Organizations should prioritize explainable artificial intelligence approaches when implementing predictive HR systems. Transparent models enhance trust, accountability, and acceptance among managers and employees while providing meaningful insights into the factors affecting employee satisfaction.
6. Implement Early Intervention Strategies
   Predictive analytics should be used to identify potential dissatisfaction risks at an early stage. HR managers can then develop targeted interventions, such as mentoring programs, employee recognition initiatives, workload adjustments, or career counseling, to improve employee experiences and organizational outcomes.
7. Promote Ethical and Responsible Use of AI in HRM
   Organizations should establish clear policies governing the ethical use of artificial intelligence in human resource management. Particular attention should be given to data privacy, fairness, transparency, and the avoidance of algorithmic bias to ensure responsible implementation of AI-driven decision-support systems.

11. Conclusion

This study developed and evaluated an explainable machine learning framework for predicting employee satisfaction using structured human resource data. Four machine learning classification algorithms, namely Logistic Regression, Support Vector Machine (SVM), Random Forest, and Extreme Gradient Boosting (XGBoost), were implemented and compared. The experimental results demonstrated that XGBoost achieved the highest predictive performance, with an accuracy of 98.3%, an F1-score of 0.98, and a ROC-AUC score of 0.9839, indicating its effectiveness in modeling the complex relationships that influence employee satisfaction.

To improve model transparency and interpretability, SHapley Additive exPlanations (SHAP) were employed to identify the factors that most strongly influence employee satisfaction. The findings revealed that work-life balance, salary, promotion history, and years at the company are among the most significant determinants of employee satisfaction. These findings are consistent with established human resource management theories and highlight the importance of organizational support, career development opportunities, and employee well-being in shaping workforce attitudes.

This study contributes to the growing field of HR analytics by integrating predictive modeling with explainable artificial intelligence. Unlike traditional approaches that rely primarily on retrospective assessments, the proposed framework enables organizations to proactively identify potential dissatisfaction and implement targeted interventions before dissatisfaction adversely affects organizational outcomes. Furthermore, the explainability component enhances transparency and supports evidence-based decision-making within human resource management.

From a practical perspective, the proposed framework can serve as a valuable decision-support tool for HR professionals by providing both accurate predictions and interpretable insights into employee satisfaction drivers. The integration of machine learning and explainable AI offers organizations an opportunity to strengthen employee engagement, improve workforce retention, enhance organizational performance, and support strategic human resource planning.

Overall, the findings demonstrate the potential of artificial intelligence technologies to transform employee satisfaction management and contribute to the development of more proactive, transparent, and data-driven human resource practices.

12. Future Work

Future research can extend the present study in several directions. First, advanced machine learning and deep learning techniques may be investigated to further improve predictive performance and capture more complex patterns in employee-related data. Comparative studies involving emerging artificial intelligence models may provide additional insights into the most effective approaches for employee satisfaction prediction.

Second, future studies should evaluate the proposed framework using datasets collected from different organizations, industries, and geographical regions. Such investigations would enhance the generalizability and robustness of the findings while providing a broader understanding of employee satisfaction across diverse organizational contexts.

Third, integrating unstructured data sources such as employee feedback, performance evaluations, survey comments, and internal communication records through sentiment analysis and natural language processing techniques may provide a more comprehensive understanding of employee satisfaction and workforce attitudes.

Fourth, longitudinal studies are recommended to examine how employee satisfaction evolves over time and to identify factors that influence satisfaction across different career stages. Such studies may provide deeper insights into the dynamic nature of employee satisfaction and organizational commitment.

From a human resource management perspective, future research should investigate how predictive analytics can be integrated into Human Resource Information Systems (HRIS) and evaluate its impact on organizational outcomes such as employee engagement, organizational commitment, workforce retention, productivity, and employee well-being.

Finally, future studies should explore the ethical, privacy, fairness, and transparency implications of applying artificial intelligence in human resource management. Investigating responsible AI practices will help ensure that predictive technologies are implemented in a manner that promotes fairness, accountability, and trust among employees and organizational stakeholders.

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توظيف تقنيات الذكاء الاصطناعي للتنبؤ برضا الموظفين: الآثار الاستراتيجية لإدارة الموارد البشرية

سامر عرقاوي[1]، براء عصفور[2]، سامي أبو ناصر[3]
[1]قسم إدارة الأعمال، الاقتصاد، الجامعة التقنية الفلسطينية، خضوري
[2]قسم إدارة الأعمال، كلية إدارة الأعمال، الجامعة العربية الأمريكية، فلسطين
[3]قسم تقنية المعلومات، كلية الهندسة وتقنية المعلومات، جامعة الأزهر، فلسطين
الباحث المراسل: abunaser@alazhar.edu.ps

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المخلص

يُعد رضا الموظفين أحد العوامل الحاسمة التي تؤثر في الأداء التنظيمي، ورفاهية العاملين، والإنتاجية، والاحتفاظ بالقوى العاملة. وتعتمد الأساليب التقليدية لتقييم رضا الموظفين عادةً على الاستبيانات اللاحقة والتحليلات الوصفية، مما يحد من قدرة المؤسسات على التنبؤ المبكر بحالات عدم الرضا واتخاذ التدخلات المناسبة في الوقت المناسب. تقترح هذه الدراسة إطارًا قائمًا على التعلم الآلي القابل للتفسير للتنبؤ برضا الموظفين باستخدام بيانات منظمة للموارد البشرية، مع تحديد العوامل الرئيسة التي تؤثر في اتجاهات الموظفين وتجاربهم داخل بيئة العمل.
اعتمدت الدراسة على مجموعة بيانات متاحة للعامة في مجال تحليلات الموارد البشرية تضم 15,003 سجلًا للموظفين. وشملت مرحلة المعالجة المسبقة للبيانات معالجة مشكلة عدم توازن الفئات باستخدام تقنية المبالغة الاصطناعية لفئة الأقلية (SMOTE). وتم تطوير وتقييم أربعة نماذج تصنيف قائمة على التعلم الآلي، وهي: الانحدار اللوجستي (Logistic Regression)، وآلة المتجهات الداعمة (SVM)، والغابة العشوائية (Random Forest)، والتعزيز التدريجي الشديد (XGBoost). وقد جرى تقييم أداء النماذج باستخدام مقاييس الدقة (Accuracy)، والإحكام (Precision)، والاستدعاء (Recall)، ودرجة F1، ومساحة ما تحت منحنى الخصائص التشغيلية للمستقبل (ROC-AUC). ولتعزيز شفافية النموذج ودعم اتخاذ القرار الإداري، تم استخدام تقنية SHapley Additive exPlanations (SHAP) لتفسير تنبؤات النماذج وتحديد العوامل الأكثر تأثيرًا في رضا الموظفين.
أظهرت النتائج التجريبية أن نموذج XGBoost حقق أفضل أداء تنبؤي بين النماذج التي تم تقييمها، حيث بلغ متوسط دقة التحقق المتقاطع 97.7%، ودرجة F1 مقدارها 97.4%، وقيمة ROC-AUC بلغت 0.99 على مجموعة بيانات الاختبار. كما كشفت تحليلات القابلية للتفسير أن التوازن بين الحياة والعمل، والراتب، وسجل الترقيات، وعدد سنوات الخدمة في الشركة كانت من أكثر العوامل تأثيرًا في التنبؤ برضا الموظفين. وتشير هذه النتائج إلى أن رضا الموظفين يتشكل من خلال تفاعلات معقدة بين العوامل التنظيمية والمهنية وعوامل بيئة العمل، والتي يمكن نمذجتها بفعالية باستخدام تقنيات التعلم الآلي المتقدمة.
تسهم هذه الدراسة في تعزيز مجال تحليلات الموارد البشرية من خلال دمج النمذجة التنبؤية عالية الأداء مع تقنيات الذكاء الاصطناعي القابل للتفسير، بما يدعم ممارسات إدارة الموارد البشرية القائمة على الشفافية والأدلة. ويمكن للإطار المقترح أن يساعد المؤسسات في تحديد مخاطر عدم الرضا الوظيفي المحتملة، وتصميم استراتيجيات موجهة للاحتفاظ بالموظفين، وتعزيز التخطيط الاستراتيجي للقوى العاملة ورفاهية العاملين.

***الكلمات المفتاحية*:** رضا الموظفين، تعلم الآلة، XGBoost، الذكاء الاصطناعي القابل للتفسير، تحليلات الموارد البشرية، النمذجة التنبؤية.