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Article

AI-DRIVEN APPROACHES TO PREDICTING EMPLOYEES' JOB SATISFACTION FOR HR MANAGEMENT

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Abstract: Job satisfaction can be defined as employees having positive attitudes toward their present roles within an organization. Some of the factors that play a significant role include engagement, empowerment, commitment, and support. The purpose of this research is to analyze how AI impacts the assessment of job satisfaction using tools such as sentiment analysis, surveys, and machine learning algorithms, which include emotion detection. In this paper, we consider how AI is used for predicting job satisfaction among employees and stress the significance of developing AI-powered systems responsibly to ensure fairness and well-informed decision-making during human resource management. The different machine learning algorithms used in AI-based HR have been reviewed, which include logistic regression, random forest classifier, KNeighbors classifier, Support Vector Classifier (SVC), and XGBClassifier. Logistic Regression was the most accurate algorithm in terms of predicting employee job satisfaction. We discuss the basics of Logistic Regression in AI-based HR systems as well as difficulties that arise in the development of such systems.
Keywords: Artificial Intelligence (AI), Machine learning, Job satisfaction, HR Analytics.

1. Introduction

AI has come up with great improvements in many industries in recent times, and there is no doubt that it is playing a key role in solving business problems and improving organizational processes. The area where AI has huge potential for success is human resource management in predicting job satisfaction level of employees (Lodahl & Kejnar, 1965). Job satisfaction is crucial in determining attitude and performance of the employee. Satisfaction in work makes employees more motivated and committed towards their work, increasing their productivity. Satisfaction in work makes employees feel emotionally attached to the organization. In the end, satisfied employees tend to stay in the organization.

Organizations can come up with tailor-made strategies for improving the welfare of employees and achieving peak performance through prediction and analysis of the numerous variables that influence job satisfaction. Such AI-based solutions employ data analytics, machine learning, and other state-of-the-art technology to make sense of large datasets on employees (Shah et al. 2024). The predictions drawn from these findings can help HR units design policies and programs aimed at fostering an atmosphere conducive to positivity, boosting morale, and building employee loyalty. For example, AI can track patterns within employee feedback, performance evaluations, and workplace interactions to find out any red flags or opportunities for improving the performance of employees. The use of AI in human resources management enables businesses to proactively address any challenges that could affect the job satisfaction of their employees and take actions accordingly. The application of AI in human resource management offers several means of predicting and boosting job satisfaction for businesses (Priya et al. 2024).

The use of AI systems can help deal with the unconscious bias present within the recruiting and selection process as well as job satisfaction evaluation among employees. However, the human resource management team must ensure that any such AI-driven HR system is responsible, fair, and ethically usable by every user (Manoharan, 2024). The potential application of AI systems within the domain of human resource management exhibits considerable promise, contingent upon the absence of any inherent biases within the system and its utilization to enhance data-driven decision-making procedures (Ullah at al. 2024; Mandour, 2025).

Job satisfaction can be defined as the positive feelings experienced by a job after assessing its characteristics (Brown, 1996; Lodahl & Kejnar, 1965, Shan et al. 2014). If a person feels good about their job, they are deemed to have high job satisfaction. If a person has negative feelings about their job, they have low job satisfaction. This study discusses the potential of AI to measure employees' job satisfaction. Job engagement is related to job satisfaction and is the extent to which someone psychologically identifies with their occupation and values their perceived performance (Brown, 1996). According to previous research, psychological empowerment has a substantial effect on job attitudes and subsequent influence on performance behaviors (Zhang et al. 2022; Bugvi et al. 2024). Studies on organizational behavior have discovered that employees with a greater degree of psychological empowerment can better predict outcomes, including all four beliefs (impact, competence, meaningfulness, and self-determination). However, prior research indicates that meaningfulness empowerment beliefs exert strong effects on attitudes and strain, even when other factors are considered (Zhang et al. 2022; Thippo et al. 2022).

Employees who feel a sense of commitment to their organization often align with its goals and may be more inclined to stay. One effective way to assess this commitment is by exploring their emotional connection and the extent to which they resonate with the organization's values and principles (Mercurio, 2015; Zarwi et al. 2022; Hsiao et al. 2022; Manoharan, 2024). Workers who are committed are less likely to quit, even when unhappy, as they feel obligated to work hard (Shan, 2014). Employees' perception of organizational support is the degree to which an organization cares about it. People consider their organizations to be supportive when awards are fair, employees have a say, and supervisors are supportive (Aboramadan et al. 2022; Manoharan, 2024). This research centers on the application of AI in determining the level of job satisfaction through the use of approaches such as sentiment analysis, survey, machine learning model, and emotion detection techniques. The study examines the capacity of AI in predicting the level of satisfaction of employees and highlights the importance of having a fair AI-powered HR system that is data-driven. The study presents additional experiments conducted on different machine learning approaches in AI-powered HR management, which include Logistic Regression, Random Forest Classifier, KNeighbors Classifier, SVC (Support Vector Classifier), and XGBClassifier. The outcome of this study reveals that among these approaches, the one that is the most accurate is the approach of Logistic Regression. In addition, in this study, we also present the principles behind Logistic Regression in AI-powered HR systems. It further addresses the issues that one may face in developing AI-powered HR management systems, giving valuable information about possible obstacles.

In addition to the contribution to the development of AI-based Human Resource Management, this paper provides insight into the ways in which the employment of artificial intelligence technologies helps predict and estimate the level of employees' job satisfaction. Through the use of the mentioned approaches and such methods as sentiment analysis and emotion recognition, along with machine learning models, the paper provides an approach that can complement the existing conventional approaches to HRM. An important contribution provided by the research is associated with the use and comparison of several machine learning approaches, namely Logistic Regression, Random Forest, K-Nearest Neighbors, Support Vector Classifier (SVC), and XGBoost (XGBClassifier). Based on the results obtained from the experiments, it was possible to conclude that Logistic Regression was the most accurate model when predicting job satisfaction.

Moreover, the current research provides an in-depth look at the fundamentals of Logistic Regression and its implementation within the framework of AI-driven HR tools. The advantages of the use of the algorithm in terms of its simplicity, transparency, and performance are demonstrated, which makes the tool relevant to be applied in cases when explainability and accountability is of essence. Moreover, we stress out the significance of implementing AI in a responsible and ethically acceptable manner within the realm of HR practices. In our research, we draw attention to the need for fairness, transparency, and rational decision-making when designing AI systems, which affect the management of the workforce and employee satisfaction. Finally, the study puts forward a conceptual framework of the use of AI in HR analytics. The framework can be used for the monitoring of job satisfaction and HR decisions.

2. Review of Literature

It is very important to measure the degree of satisfaction among employees for a conducive working environment and increased productivity. Various studies have tried using AI-powered sentiment analysis and natural language processing (NLP) to measure the satisfaction level of employees through textual data obtained from various sources like employee surveys, feedback, and social media. Through AI, sentiments can be identified, important topics can be extracted, and analysis of the tone of the text can be performed to understand how employees feel about their jobs and organization (Garg et al. 2021; Putka et al. 2023; Sampath et al. 2024). Predictive analytics model has been built by utilizing AI to predict the job satisfaction level of employees on various parameters. The use of these models helps to analyze the patterns and correlations between various variables and predict the probability of an employee's job satisfaction or dissatisfaction (Wijngaards et al., 2020; Vashishth et al. 2025). AI tools can monitor digital footprints, including email correspondence, calendar appointments, and web activity to determine the level of engagement and job satisfaction among the workforce. Using patterns of the digital activities of the employees, AI algorithms can determine the signs of their dissatisfaction with the work, including less frequent interaction with colleagues, absence, and other changes in working habits. The use of virtual assistants and chatbots powered by AI technologies is becoming common in gathering employees' feedback and offering help (Garg et al. 2021; Zhang, 2024).

Recommendations provided by AI systems will help to improve employees' job satisfaction by suggesting interventions according to the specific needs and preferences of each worker. Analyzing past behaviors and collecting information, AI systems can give suggestions regarding how to train employees, develop a career path, or change working conditions to satisfy workers better (Jura et al. 2022; Shah et al. 2024; Priya et al. 2024). Given the increasing popularity of using AI systems to evaluate job satisfaction of employees, ethical concerns arise due to problems with privacy and data protection.

Experts have stressed the significance of developing and deploying responsible and transparent AI technologies that respect the privacy rights of workers and adhere to all necessary rules and regulations. In general, the literature points out that the use of AI technologies is beneficial in analyzing and improving employees' job satisfaction through the utilization of analytics, natural language processing, and personalization recommendations. Yet, it highlights the importance of ethical concerns in applying AI technology to ensure that it improves employee welfare and organizational performance (Jain et al. 2021; Manoharan, 2024; Sampath et al. 2024; Zhang, 2024; Vashishth et al. 2025). Measuring workers' level of contentment becomes highly significant for creating a positive organizational atmosphere and improving its productivity. In the domain of academic study and professional activity, there have been many studies on sentiment analysis using AI and NLP methods as a way to determine employees' satisfaction with their jobs (Mandour, 2025). It is related to the analysis of text-based data derived from different sources, including employee surveys, feedback, and social media (Ullah et al. 2024). AI technologies can recognize sentiments, identify important topics, and analyze the tone of the text to gain deep insights into the way employees view their jobs and organizational culture.

Furthermore, with the introduction of predictive models that use artificial intelligence technology, the whole process of measuring the level of job satisfaction among employees has become completely different. Such models employ machine learning algorithms and make predictions concerning the probability of employees feeling satisfied or dissatisfied at work taking into account various aspects such as workload, duties performed, relations within a team, and changes in an organization. The models identify connections between various aspects and thus reveal information about the key factors influencing the level of job satisfaction among employees. AI-based employee tracking tools have become vital means of measuring employee engagement and job satisfaction (Vashishth et al. 2025). These tools collect data on various digital footprints including emails, calendar appointments, and web browsing habits. Through analyzing this information, artificial intelligence algorithms can determine any signs of dissatisfaction among employees through their decreased activity and changes in their work routine.

Virtual assistants and chatbots that leverage AI technologies have been found to play a critical part in gathering feedback from the employees and providing customized assistance (Dutta & Mishra, 2025). Such systems are efficient in conducting surveys, interviewing employees personally, and providing them with appropriate information in response to their feedback. Thus, they can significantly improve problems faced by the employees and improve their job satisfaction. Apart from that, AI recommendation systems have become efficient partners in boosting job satisfaction of the employees due to personal recommendations of action taken. Based on the analysis of historical data and behavioral patterns, these systems offer recommendations that include training programs, career growth paths, or changes to work schedule to meet employees' changing demands and needs. However, with the rise in the use of artificial intelligence for measuring employees' level of satisfaction, it is essential to find ways to deal with the ethical issues relating to privacy, consent, and data security. The researchers emphasize the significance of applying responsible AI solutions that prioritize the right to privacy of employees and strictly follow the appropriate guidelines (Taherdoost, 2025). In summary, it should be stated that the review of the literature suggests that there are numerous possibilities to apply AI for analyzing and increasing employees' job satisfaction, but in case the ethical questions are handled appropriately (Dutta & Mishra, 2025). AI is becoming a widely used tool in different areas of work including the assessment of employees' job satisfaction.

Quality of AI service refers to the extent to which the artificial intelligence performs its tasks effectively and efficiently. In the business environment, the quality of service that AI provides is pegged on the effectiveness, efficiency, and accuracy of the artificial intelligence in helping the employees in carrying out their activities. This will also be inclusive of the degree of transparency of the system. An effective AI service is one that enables the system to be able to assist in meeting the needs of the users and help in enhancing their work experience. This will have a positive impact on job satisfaction through AI satisfaction (Nguyen and Malik, 2022).

Although AI System Automation in operations management helps in increasing job satisfaction and engagement, it may have a negative effect on the positive effect of gigification (Braganza et al. 2021). AI-assisted satisfaction index models can effectively measure job satisfaction among college students, indicating AI's potential for evaluating job satisfaction in educational contexts (Jia, 2022). AI in recruitment can influence job seeker satisfaction, with self-efficacy playing a moderating and mediating role in this relationship (Jia, 2022). AI-based job recommendation systems can improve job search experiences and job satisfaction by providing personalized job recommendations (Duong & Thi, 2022; Patil et al. 2023).

AI service quality and preference have been shown to positively affect user satisfaction, which in turn, significantly affects the continuous usage intention of AI services on online job platforms (Lee, 2020). The integration of AI in job design, as suggested by the job characteristics model, can enhance employee engagement and job satisfaction (Kandpal et al. 2023). AI-enabled e-learning can enhance personal learning environments, which positively affects user satisfaction and attitudes towards the learning module (Kashive et al. 2020). AI has been increasingly utilized in various aspects of the workplace to enhance employee experiences and job satisfaction. Previous research has shown that AI technologies can significantly impact employees' job satisfaction by improving service quality and engagement. AI service quality positively influences employees' job satisfaction through AI satisfaction with service quality (Handra & Sundram, 2023). Dutta et al. (2023) conducted a field study in a multinational company and discovered that AI-enabled chatbots lead to augmented employee voice and engagement, ultimately contributing to increased job satisfaction. Moreover, the integration of AI in human-machine interaction technology has been shown to directly affect enterprise performance and employee satisfaction.

Lin et al. (2022) highlighted the impact of abusive management, self-efficacy, and AI-based human-machine interaction technology on corporate performance and employee satisfaction. Similarly, Li et al. (2022) explored the relationship between abusive management, self-efficacy, and corporate performance under AI, emphasizing the potential application of Human-Computer Interaction (HCI) technology in enterprise performance evaluation. Moreover, AI technologies have been utilized to forecast and examine employees' psychological states and work attitudes. Liu and Song (2022) employed AI affective computing to predict the psychological state of charismatic leaders and its impact on employees' work attitudes. This research has shown that AI technology can predict the psychological state of the employees and assist in their efficient management using predictive analysis. The literature review has revealed that AI is an important aspect when it comes to predicting and improving the job satisfaction of the employees due to better service quality and analysis of their psychological state. With the help of AI technology, it is possible to provide a more satisfying working environment for the employees.

It is from this literature review that it was noted that the technologies of artificial intelligence have a major effect on the job satisfaction of employees through the improvement in service quality, engagement, and psychological state analysis. The tools using AI technology determine the level of job satisfaction through analysis of textual information such as survey and social media, through which the algorithms of artificial intelligence can identify sentiments and issues. The AI-based monitoring software can be used to monitor the digital behavior in order to determine the levels of engagement and the indicators of dissatisfaction. The virtual assistants and chatbots can be used to provide feedback and personalized advice, while the AI recommendation software can be used to make interventions that would help to increase the level of job satisfaction. Nevertheless, the emergence of the AI technologies has been accompanied by a number of ethical issues related to privacy and security. Therefore, it appears that AI is quite a valuable tool for evaluating and improving job satisfaction.

The objective of this research is to examine the use of AI technology to measure and predict the level of job satisfaction of employees in organizations. This study is aimed at finding out factors like engagement, empowerment, commitment, and support, which affect the job satisfaction of an individual. This research will discuss the use of AI technologies like sentiment analysis, surveys, and emotion recognition to gauge the feelings of employees. Machine learning algorithms like Logistic Regression, Random Forest, K-Nearest Neighbor, Support Vector Classifier, and XGBoost will be used and compared for their effectiveness in predicting job satisfaction. Of those, Logistic Regression was found to be the most accurate, which made it necessary to dig into more details about it and its suitability for HR analytics. The general aim of this research is to provide support for HR management through the introduction of predictive AI systems, which would make it possible to better monitor the well-being and involvement of employees. This research highlights the importance of using responsible AI techniques that will allow one to be more fair and transparent while making decisions in the sphere of HR processes. Through encouraging people to use more interpretable AI models, the research helps create more trustworthy workforce analysis tools.

3. AI for Employee Job Satisfaction Prediction

Employee engagement includes an individual's interest, contentment, and enthusiasm towards work responsibilities. Assessing the attributes of a role directly contributes to the level of job satisfaction. A job is more than a task such as paperwork, coding, customer service, or driving, which involves interacting with colleagues and supervisors, adhering to organizational protocols, establishing power dynamics, achieving performance benchmarks, being resilient in adverse working conditions, and adapting to new technologies. Determining an employee's job satisfaction involves several calculations that consider various components. Top management should place importance on the satisfaction that employees derive from their roles, as this significantly shapes their overall productivity. While a contented workforce does not guarantee organizational success, empirical evidence indicates that managerial efforts aimed at improving employee job satisfaction are likely to yield greater organizational efficiency, increased customer contentment, and improved profits.

Exploration of AI's potential as a tool to assess and quantify employee job satisfaction has been a topic of interest. AI-based approaches and techniques have proved very useful for understanding the sentiment and engagement of employees, thus helping organizations get insight into their work environment and improve on that basis. Leveraging the knowledge gained through our study about the application of AI in organizational behavior in measuring and improving employee job satisfaction, along with existing literature (Yu et al. 2023; Ramachandran et al. 2022; Garg et al. 2022; Chowdhury et al. 2023) in this field, we present different ways (Table 1) to apply AI to predict job satisfaction.

Table 1 AI Methods and its features

AI Methods	Features	References
Sentiment Analysis	Sentiment analysis is the method by which natural language processing is used for detecting emotionality in the text, enabling organizations to measure reviews and employee feedbacks. The AI will analyze emails, surveys, chats on social media platforms and other forms of written communications to gauge employees' job satisfaction and workplace environment.	Lucci et al. 2022
Pulse Surveys	The pulse survey is a short and periodic survey conducted among the employees to get an understanding of their job roles, communications, relations, and workplace environment. The process of conducting such surveys can be automated using artificial intelligence, and it provides quick feedback on various work-related issues.	Lucci et al. 2022
Texts Analytics	The capacity of AI to analyze verbal and written communication and to be able to interpret emotional signals and linguistic patterns that can indicate levels of job satisfaction. The application of this technique is possible for both recorded communications and written ones.	Lucci et al. 2022
Employee Engagement	The engagement of an employee in their work is their enthusiasm and love for their work. Recommendations can be personalized using technology based on AI to tailor them according to the preferences, skills, and goals of the employees.	Vallabhaneni et al. 2024
Behavioural Analytics	The Behavioral analysis is one of the critical concepts of business analytics whereby organizations can get insights about the behavior of their customers using digital platforms such as e-commerce sites, mobile applications, chat	Theodorakopoulos et al. 2024

	platforms, email, Internet of things, and connected devices. The concept also entails analyzing employees' behavior in digital settings.	
Predictive Analytics	AI can make use of historical information of employees who held the same position or role to predict trends of employee satisfaction and foresee any problems that may arise. This helps organizations address them before they become big problems.	Ravichandran et al. 2023
Audio and Video Analytics	AI can analyze photographs and videos of the activities of the employees within the organization. This is done in order to measure the emotions that the employees have as well as their level of engagement.	Neuhofer et al. 2021
Machine Learning Models	Through the use of past employees' data, the machine learning models will be able to learn about patterns and relationships that may affect employee satisfaction. The models help make predictions and recommendations concerning job satisfaction.	Lucci et al. 2022
Emotion Recognition	AI can recognize facial expressions and speech tones, which can help it recognize and understand emotions. The technology can uncover the disposition and attitudes of employees in workplace environments.	Kapoor and Verma, 2024

4. Machine Learning Algorithm for Employee Job Satisfaction Prediction

There are several machine learning techniques such as Logistic regression, Random forest classifier, KNeighbors classifier, and Support vector classifier (SVC).Logistic regression is a popular machine-learning technique and a user-friendly statistical method used to predict binary outcomes, meaning an outcome with only two possible values, typically denoted as 0 and 1. The Random Forest classifier is an ensemble learning approach that constructs multiple decision trees to enhance classification accuracy and robustness. This classifier builds multiple decision trees using subsets of training data and features, allowing it to handle high-dimensional data and multicollinearity without overfitting, although it can be sensitive to sampling design. The model converges to a stable generalization error as the number of trees increases, with the performance relying on the strength and correlation of individual trees.

Moreover, it provides internal estimates to track error rates and assesses variable importance. The KNeighbors Classifier is a versatile machine learning algorithm used for various classification tasks, such as thalassemia screening, handwritten character recognition, text classification, intrusion detection, epilepsy diagnosis, vehicle-type recognition, face recognition, credit scoring, and environmental monitoring. The Support Vector Classifier (SVC) is a type of Support Vector Machine (SVM) used for classification tasks in various fields, such as chemistry, remote sensing, text classification, electrical fault diagnostics, and cancer genomics, known for its high accuracy, privacy-preserving capabilities, and effectiveness with high-dimensional data. The XGBClassifier is a machine-learning algorithm that utilizes an advanced implementation of a gradient boosting framework. This classifier is part of the XGBoost library, which stands for eXtreme Gradient Boosting and is known for its performance and speed in classification tasks.

4.1 Dataset

For assessing the employees' satisfaction using machine learning algorithm, dataset (Employee Name, Age, Monthly Salary, Workload (in hours per day)), Feedback score on employer provided by employee, Job Satisfaction as either 0 or 1) of 1098 employees were collected from a medium-sized IT company (pseudonym "Mavel") in India which typically exhibits the following profile. The dataset was collected during 2023-2024. The dataset was collected from 1,098 employees of Mavel, a medium-sized IT company, during the 2023–2024 through a combination of HR records and employee surveys. Employee Name, Age, Monthly Salary, and Workload (in hours per day) were obtained from the company's internal HR management system, ensuring accurate and up-to-date records. Meanwhile, Feedback Score on the employer and Job Satisfaction (categorized as 0 for dissatisfied and 1 for satisfied) were gathered through an anonymous employee survey conducted quarterly. The survey was constructed in a way that respondents would feel comfortable and provide true information while keeping everything confidential and unbiased. Our data collection was being overseen by their HR department. Usually, the number of employees at Mavel Company varies from five to six thousand people. Their staff consists of a variety of workers, including experienced specialists and fresh graduates. Unlike many other corporations, this organization has a flatter organizational hierarchy. It is very likely that there are various departments, including software development, IT services, human resources, finance, marketing, and sales. This company provides all kinds of IT services, which include software development, IT consultation, applications, maintenance, infrastructure, cloud, and digital transformations.

Clients can be both from home as well as abroad and can belong to various fields like financial sector, healthcare, educational institutions, e-commerce firms, logistics firms, and more. Firms may even collaborate with governmental bodies. The headquarters and important business centers are always situated in important cities where there is a strong presence of IT sector, like Bangalore, Hyderabad, Pune, Mumbai, etc. There is an innovative working culture in Mavel. Employee development plays an important role in the firm and there is scope for training and promotion. The company has a technology stack that includes programming languages such as Java, Python, C#, and JavaScript. In addition, it may use frameworks and tools such as Angular, React, and Node.js, and databases such as MySQL, PostgreSQL, and MongoDB. The company complies with the best practices in terms of software testing and quality assurance as well as security measures. The firm concentrates on growing its revenues through diversification of its services, entering new markets, and building partnerships with other companies. The company meets all the standards and legal requirements concerning data protection, labor regulations, and intellectual property. The firm is dedicated to providing high-quality IT services as well as bearing responsibility for its staff and community.

4.2 Results

We supplied the dataset (Employee Name, Age, Monthly Salary, Workload (in hours per day), Feedback score on employer provided by employees, Job Satisfaction (as either 0 or 1) of 1098 employees from the Company Mavel during 2023-2024 as input to five machine learning models, namely Logistic Regression, Random Forest Classifier, KNeighbors Classifier, Support Vector Classifier (SVC), and XGB Classifier. We executed the model with the input variables Employee Name, Age, Monthly Salary, Workload, Feedback score on employer provided by employee, and the target variable as Job Satisfaction. During execution, the training and testing ratios were 80:20. We obtained the following results:

Table 2. Accuracy of ML Models – Prediction of Job Satisfaction

Machine Learning (ML) Model	**Accuracy (in %)**
Logistic Regression()	74.43
Random Forest Classifier()	72.27
KNeighbors Classifier()	71.31
Support Vector Classifier (SVC)	54.50
XGBClassifier()	67.44

A line graph illustrated in Figure 1 is intended to show the percentages of accuracies that have been achieved by various classifiers. The classifiers mentioned above include various machine learning models such as logistic regression, random forest, k-nearest neighbors (KNeighbors), Support Vector Classifier (SVC), and eXtreme Gradient Boosting Classifier (XGB). All those classifiers were evaluated based on their ability to classify objects from the dataset and the accuracy of the classification, which is then reflected in percentages of accuracies in the graph. The percentages of accuracy that are shown in the figure vary greatly from 54.50% to 74.43%. Very low accuracy (54.50%) is not a common phenomenon, which implies that the reliability of the classification made by the classifier is significantly lower than random guesses and may indicate serious problems like data mislabeling or overfitting. On the other hand, positive accuracy numbers imply that the performance of classifiers is good at different levels, which means that the higher the number, the better the classifier performs. The line graph presented in Figure 1 represents a very helpful instrument for comparative analysis because it allows contrasting the effectiveness of various classifiers. Analyzing the trends and patterns represented on the graph, one can understand the advantages and disadvantages of each particular classifier. This information can be useful for making decisions about choosing an appropriate classifier for some dataset.

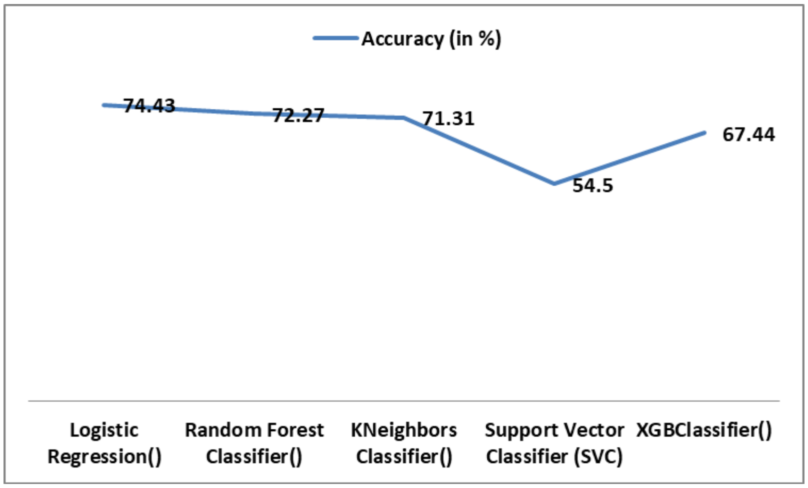

Figure 1. Accuracy of ML Models for Predicting Job Satisfaction of Employees

The table below illustrates the accuracy levels of the five different machine learning models employed to predict job satisfaction of employees. Below is a brief description of how each of these models performed. From Table 1 above, the Logistic Regression model scored the highest accuracy at 74.43%. This model uses a linear method and is used widely for binary classification to predict the likelihood of the occurrence of an event in a given class. The Random Forest Classifier model had an accuracy level of 72.27%. This model uses the method of ensemble learning to classify data by combining several decision trees together to minimize overfitting and maximize prediction accuracy. The KNeighbors Classifier model had an accuracy of 71.31%.

On the other hand, Support Vector Classifier (SVC) model has the least accuracy at 54.50%. The Support Vector Classifier model, which relies on support vector machine, seeks to create a hyperplane that maximizes the distance between the classes. Lastly, the XGBClassifier model has an accuracy of 67.44% with the help of Extreme Gradient Boosting algorithm (XGBoost). Table 2 shows the comparison of the performance of the models in predicting job satisfaction. The Logistic Regression model is the most efficient model, followed by the SVC model. The accuracies of the other models fall within these two extremes. The information about the performance of the machine-learning models can be deduced from Table 2, which shows their accuracy rates. The mean accuracy rate for the five models is 67.99%, while the standard deviation is 7.95%. The minimum accuracy rate was 54.50%, recorded for the Support Vector Classifier, while the maximum accuracy rate was 74.43%, observed in the Logistic Regression model. The median accuracy was 71.31%, while the interquartile range was from 67.44% to 72.27%. Performance-wise, the Logistic Regression model provided an accuracy of 74.43%, closely followed by the Random Forest and KNeighbors Classifiers.

In this case, the Support Vector Classifier had the lowest accuracy of 54.50%, while the accuracy of XGBClassifier is 67.44%. Confidence intervals at 95% for the accuracies of different models are shown below: Logistic Regression (58.84%, 90.02%), Random Forest Classifier (56.68%, 87.86%), KNeighbors Classifier (55.72%, 86.90%), Support Vector Classifier (38.91%, 70.09%), and XGB Classifier (51.85%, 83.03%). These confidence intervals reflect the variation between the models' performances, especially for the Support Vector Classifier with its wide interval. According to statistical analyses, the Logistic Regression model has the best performance among other models. At the same time, the Support Vector Classifier has the worst performance.

4.3 Logistic Regression Method

From Table 2 and Figure 1, it can be seen that amongst all the ML models under consideration, Logistic Regression comes out to be the best model owing to its accuracy in predicting employees' job satisfaction. In the ensuing sections, the proposed machine learning algorithm for the ML technique is presented. This ML algorithm is known as Logistic Regression and is labeled as Algorithm 1.0. It also describes how this algorithm works. We think that this machine learning algorithm can be employed for predicting job satisfaction of employees and taking corrective action for human resource management. Logistic regression is a common practice in a lot of different disciplines, thanks to its versatility and efficiency in managing binary outcomes using one or more independent variables. The major application of logistic regression lies within the logistics industry, as it is commonly used to manage many problems. The use of logistic regression can range from predicting the number of people affected by a disease, measuring consumer satisfaction, and analyzing the punctuality of logistics. In regard to logistics, logistic regression can be applied for managing binary outcomes, which include determining whether a delivery is delivered early or late.

Algorithm 1.0: Employee Job Satisfaction Prediction Using Logistic Regression

Input:

- Dataset $D = \{(X_1, y_1), (X_2, y_2), \dots, (X_n, y_n)\}$ where X_i represents the feature vector for the i^{th} employee and y_i represents their corresponding job satisfaction level.
- Features: $X_i = (x_{i1}, x_{i2}, \dots, x_{id})$ where d is the number of features.
- Target variable: y_i indicating job satisfaction level.

Output: Trained logistic regression model.

Different Steps in Algorithm 1.0:

Step 1: Data Pre-processing

- Handle missing values.
- Encode categorical variables if any.
- Split the dataset into training and testing sets.

Step 2: Feature Scaling

- Standardize the feature values to have a mean of 0 and a standard deviation of 1.

Step 3: Model Training

- Initialize logistic regression model parameters θ to zeros or small random values.
- Define the logistic function: $h_\theta(X) = \frac{1}{1+e^{-\theta^T X}}$.
- Define the cost function: $J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}[y_i \log(h_\theta(X_i)) + (1 - y_i)\log(1 - h_\theta(X_i))] + \lambda\sum_{j=1}^{d}\theta_j^2$ (regularized logistic regression).
- Minimize the cost function using optimization techniques like gradient descent or other optimization algorithms.

Step 4: Model Evaluation

- Make predictions on the test set using the trained model.
- Calculate evaluation metrics such as accuracy, precision, recall, and F1-score.
- Analyze the classification report and confusion matrix to understand the model's performance.

Step 5: Deployment

- Deploy the trained model into the production environment.
- Integrate it with the company's systems for real-time or batch prediction of employee job satisfaction.

Note: Ensure to tune hyperparameters like regularization parameter λ, learning rate, and others to optimize model performance. Additionally, consider incorporating cross-validation for hyperparameter tuning and model selection.

Through the use of logistic regression, logistic firms will be able to determine factors that influence the punctual delivery of goods and possible ways of improving their business processes. In the following, the algorithm proposed in this paper to predict job satisfaction of employees by the use of the machine learning technique known as logistics regression is presented. Logistic regression is capable of handling multinomial responses that have more than two classes allowing multi-classification problems within logistics such as classification of credit scores of firms depending on predictor variables. This technique is straightforward and easy to understand and implement even by people of different levels of knowledge about statistics. It is versatile and can be applied in different fields including logistics due to its applicability in different types of data and research questions.

Description of Algorithm 1.0 to evaluate the employee's job satisfaction through the logistic regression method starts with the data pre-processing step where missing data in the data set is managed, and the categorical variables are encoded in numbers (for example, the name of the department). Data were split into training and testing datasets. The variables were standardized, i.e., brought to a mean equal to 0 and standard deviation equal to 1, providing the consistency of input data and possibly improving the model performance. In the model training step, the logistic regression parameters are initialized to 0 or very small random numbers and tuned during the training process. Logistic function gives the probability of the job satisfaction, while the cost function evaluates its compliance with the actual label. Regularization is added to the cost function in order to prevent overfitting. The parameters of the model are optimized through optimization techniques like gradient descent to reduce the cost function. After the process of training, the performance of the model is evaluated based on certain performance indicators such as accuracy, precision, recall, and F1-score to determine how efficient the model is and what improvements are necessary. From the classification report and confusion matrix, one can determine the problems like false positives and false negatives. Lastly, the trained model is deployed to predict employee job satisfaction.

5. Designing Effective AI-Powered HR Systems: Insights and Best Practices

The emergence of AI-powered HR management systems has the capacity to greatly improve the performance of HR managers in assessing the degree of satisfaction in a large number of workers (Cathey et al. 2021). With the help of such systems, HR managers will be able to identify those individuals who show a high degree of dissatisfaction with their current jobs. This will enable organizations to easily recognize employees who have the potential of leaving the organization. There are various implications that may come up because of inclusiveness when AI-powered HR management systems are biased. It is important to adopt an AI-driven HR system considering ethics for various reasons. Explainable AI systems, as opposed to other types of AI systems, are designed to enhance our understanding of the underlying mechanisms that have contributed to a particular outcome. The emergence of explainable AI can be attributed to the recognition of certain limitations encountered during the early phases of AI development. During this temporal epoch, both users and algorithm designers were confronted with an abrupt and formidable revelation that the apprehension or articulation of the rationale behind the outcomes generated by an AI system was often elusive.

The search for an AI-driven HR system that ethically evaluates employee job satisfaction is complex (Cathey et al. 2021). Armed with our understanding of the applications of AI to organizational behavior, the following is a checklist drawn from related prior research (Yu et al. 2023; Ramachandran et al. 2022; Garg et al. 2022; Chowdhury et al. 2023) on the suitability of AI in assessing the job satisfaction of employees. This outlines a set of key questions in which customers should ask an IT vendor to deliver AI-driven HR products to ensure that the product is fair, unbiased, and effective. These questions were designed to probe different aspects of the AI-driven HR product, as discussed below.

Although this research identifies some key factors in considering AI-based HR solutions, it is highly situational and cannot be used as an universal guideline for all vendors and consumers. Nonetheless, it is suggested that each consumer should pay special attention to how a certain vendor addresses the issue of biases in their AI-powered solution. In other words, the consumers can try to learn more about the techniques used by the vendor to identify, measure, and address various kinds of biases that may occur during the life cycle of the product. Yet, it is possible that these techniques will be quite different in scope and efficiency depending on the vendor and the product they offer. It may be beneficial for the consumers to get acquainted with the techniques applied by the vendor for detecting biases in their product. Consumers may wish to ask about the frequency of applying those techniques – whether it is done weekly, monthly, quarterly, etc.

Moreover, whereas certain vendors may assert conformity with accepted industry standards for bias assessment and reduction, others do not necessarily conform consistently to such standards. The customer should, therefore, establish what standards, if any, the vendor adheres to, and evaluate how relevant those standards might be for the intended use case scenario. Also, the customer should find out if the AI technology is compliant with relevant laws and regulations, e.g., EU's AI Act or similar regional regulation, appreciating the fact that compliance may vary from one jurisdiction to another depending on the maturity level of the product. The last context-dependent criterion pertains to the nature of training data. It is imperative for customers to ask how the vendors make sure that the data sets used are diverse enough. Nevertheless, the ability of the vendors to provide guarantees regarding data representativeness, as well as the way this issue affects fairness, varies depending on the system in use. Customers using such systems may notice differences in outcomes or recommendations made for various employee categories. Such differences should raise questions with regard to how the system makes the inferences and what kind of data contributes to these inferences, as well as whether the matter has been addressed by the vendors before.

The composition of the development team is yet another factor that can affect product performance. It would be helpful for clients to learn more about the diversity of this team and its experience, including domain-specific expertise, for instance, familiarity with human resources and algorithmic fairness. But organizational priorities can be quite diverse, and not all vendors attach much importance to team diversity or multidisciplinary expertise. Additionally, clients may want to get certain proof of performance of the product, for example, in terms of evaluating job satisfaction among various employee categories (new hires versus long-term employees). However, such data on the performance of the product in action may be lacking or insufficient in terms of generality and applicability. Finally, customers may need to find out whether the AI system has passed robustness testing. But there is no standard approach to robustness testing, and it does not necessarily mean that it will work properly everywhere.

Machine Learning (ML) is an essential part of artificial intelligence (AI), where learning through data analysis, pattern recognition, and making decisions without much human input is possible. In regards to AI-enabled HR systems, machine learning algorithms analyze enormous amounts of data about employees, such as metrics, feedback, surveys, and behaviors, to produce insights and predictions related to their performance and future actions, for instance, job satisfaction or risks of leaving the company. This way, AI systems get the ability to grow smarter and to make better decisions regarding HR management. Hence, machine learning contributes to AI as the main power source that drives it.

6. Conclusions

The current research is part of an increasing trend of studying the uses of artificial intelligence in human resource management in the form of analyzing the accuracy of different machine learning algorithms to predict the level of job satisfaction among employees. By using sentiment analysis and emotion recognition, along with the survey results, the study provides a perspective of how AI technology can provide a deeper understanding of the emotional and psychological state of employees. Logistic Regression was the most accurate out of the analyzed machine learning algorithms.

Besides being technical in nature, the study puts emphasis on the ethics and the responsible application of AI in assessing job satisfaction. In ensuring that the assessment process is ethical, the study underscores the need for using AI tools that respect the autonomy of employees and minimize bias in workforce evaluation. Through the analysis of some of the difficulties that may arise when applying AI in HR operations, such as poor data quality and algorithmic fairness, the study provides insight into what the future research should focus on.

Our research highlights the ability of AI-based HR solutions to assess and forecast employee job satisfaction. Using a combination of different techniques, like sentiment analysis, surveys, and machine learning algorithms, companies can obtain valuable knowledge about their employees' well-being and motivation. Logistic Regression is the most suitable algorithm for job satisfaction prediction and forecasting that provides valid and accurate results. However, despite all its benefits, the use of AI in HR management faces certain difficulties, which include questions concerning the fairness, ethics, and confidentiality of using data.

The main focus of this research paper is to highlight the immense capacity of AI-enabled HR systems to effectively analyze and predict job satisfaction among employees. With advanced tools of analysis, such as sentiment analysis, survey analysis, and machine learning models, it is possible to acquire a full knowledge of the wellbeing and job satisfaction of employees. Logistic Regression is, specifically, the best model for predicting job satisfaction because it gives highly accurate results. But using AI in HR is not an easy task; there are several issues that arise from its use. Organizations have to be mindful about employing responsible practices in the development and deployment of such systems, focusing on the importance of being transparent in the process of AI decision making, accountability, and diversity in perspectives. In the future, research is supposed to be geared towards optimizing the AI algorithms with an improvement of their efficiency and flexibility as well as dealing with ethical and privacy issues. Continual evaluation and updates of AI-based HR systems are essential to maintain their efficiency and relevancy.

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