International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(14s) 2026 pp. 782-791
https://doi.org/10.70917/ijcisim-2026-3678
Article

Building a Future-Ready India: The Role of Predictive HR Analytics in Employee Engagement and Job Satisfaction

Snigdha[1], Animesh Singh[2]

[1]School of Business, Manav Rachna University (MRU), Sector 43, Aravalli Hills, Delhi–Suraj Kund Road, Faridabad, Haryana – 121004, India.
Email: snigdha027@gmail.com
[2]School of Business (SOB), Manav Rachna University (MRU), Sector 43, Aravalli Hills, Delhi–Suraj Kund Road, Faridabad, Haryana – 121004, India.
Email: Animesh@mru.edu.in

Abstract: This paper delves into the transformative nature of HR in this field, particularly the potential impact of predictive analytics on better labour planning and customer experiences. Human resources analytics is gaining every more popularity, and will transform the HR in the future. These days, a number of organisations are exploiting Analytics. One way they meet this objective of increasing retention is by implementing HR Analytics to HR decision making. Another way is to get to know each and every one of their staff. Analytical tools are helping many organisations to build suitable strategies and knowledgeable decisions as a fact-based approach to labour management. The results of this research show that predictive HR analytics, when combined with data-driven initiatives, may significantly improve workplace motivation, satisfaction, and performance, which in turn helps achieve Viksit Bharat's objectives. The study also discusses the ethical concerns including privacy concerns, biases in prediction models, resistance to change and poor data quality which challenges in the HR field faced by predictive analytics when trying to integrate with HR.

Keywords: Predictive HR Analytics, Employee Engagement, Job Satisfaction, Machine Learning, Viksit Bharat, Workforce Optimization.

1. INTRODUCTION

Human resources (HR) analytics (HRA) is an area that is currently a hot topic of discussion among academics. The uses of data in HR can be referred to as ‘HR analytics', ‘human capital analytics' or workforce analytics. Human resource analytics is a relatively new discipline and has several different definitions. Payroll Analytics, according to Jabir et al. (2019), can be defined as: "processes to collect, transform and manage key HR related data and documents; analysis of data gathered using business analytics models; and dissemination of analyses to decision makers for making intelligent decisions.

“The greatest asset a company can rely on to outsmart other companies are their employees” (Falletta and Combs, 2021; Wirges and Neyer, 2023). HR professionals may say credibility is growing because it gives them statistically accurate information, and can be used for new policy as well as to implement current policy. Initially, HRM was a process that was related to payroll, leave management, compliance etc.

Human resources: All the labor for an organization. Today, human resources are a scarce resource due to their critical value, uniqueness, irreplaceability and consequently became strategic for the business organisations. This consequently puts employee retention in a strong position in terms of organisations' long-term retention capacity. In today's technologically fast-paced society, businesses have leveraged AI to aid in retention. As human resource management (HRM) becomes the most data-driven function in the organisations, the growing interest in the use of artificial intelligence (AI) by experts and academics (Vrontis et al., 2021) supports this. HR professionals are keenly interested in two aspects of Artificial Intelligence, AI's ability to analyze and process vast amounts of data (Vrontis et al., 2021) and AI's ability to use machine learning to make predictions based on historical data to forecast future results (Berhil et al., 2020). A company seeking the top talent would review the positions of its top talent and determine if it has any good people to fill the slots (after taking into account schoolwork, work experience and any other relevant factor). AI can analyze the data at significantly faster speeds than can a human. The AI can tell you which of these applicants really excelled in their onboarding process and at their best in performance reviews, and enhance its predictions for new hires. A renowned analytics specialist has indicated that analytics, the primary engine of business intelligence and a fundamental requirement for the continuous performance of an organisation, will transform HR practices (Fred and Kinange, 2015). Several fields have strong ties to analytics, including computer science, engineering, and science (Ghasemaghaei et al., 2018). All decisions are data- and fact-driven, which is even more critical in today’s complex corporate world (Andersen, 2017). Human resource management, which was once a theoretical discipline, has been revolutionized by data in several ways, including recruitment and staff management. “Human resource analytics are useful for data interpretation, which is of the highest significance”. According to Jugulum (2016), human resource analytics entails collecting and analysing data related to human resources in order to enhance organisational performance. This approach is known by many names according to Edwards et al. (2022): workforce analytics, talent analysis, and individual analysis. According to Chatterjee et al. (2022), HR analytics employs a range of data analysis techniques by leveraging information sourced from HR and organisational databases.

The random forest model is a powerful machine learning technique. It has not only a good performance for a large variety of data types and complex situations but also a new perspective on proven approaches of data analysis. Traditional decision tree approach is unstable. Random Forest greatly increases the stability. This is based on an algorithm that follows the same principles as the traditional random forest model.

For HR departments, this can be used to find trends in employee management practices. The structure of the Random Forest algorithm is shown in Figure 1.

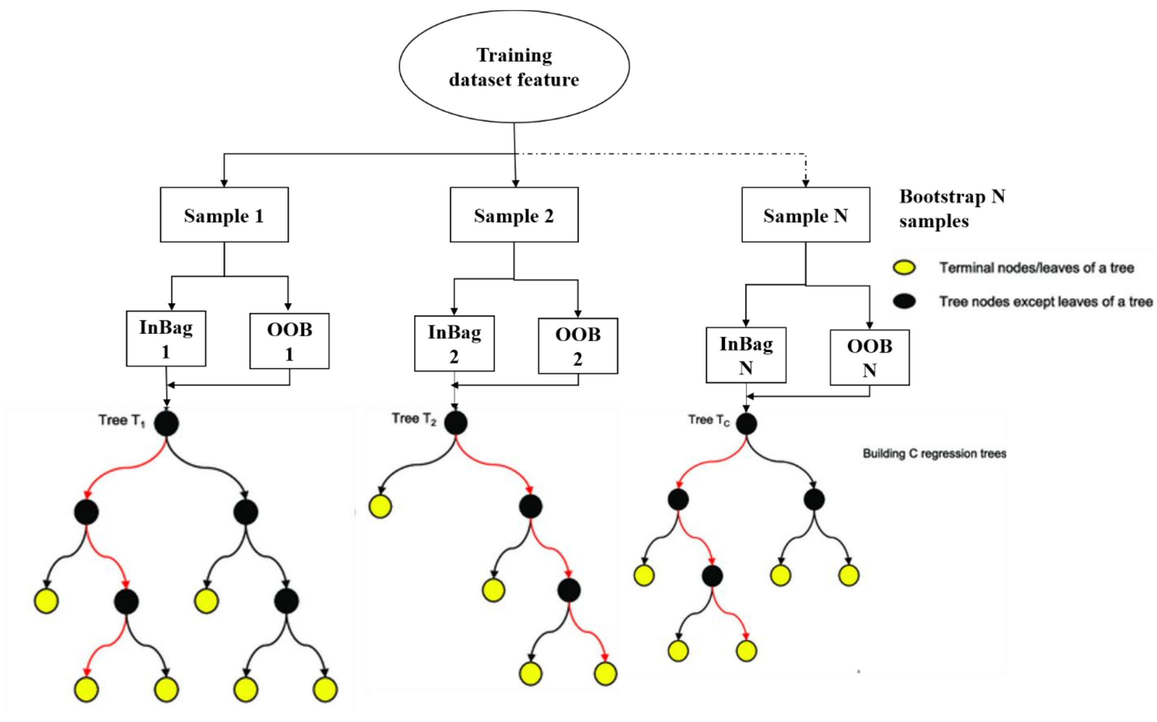

Figure 1: Represents the structure of the random forest algorithm.

With the advancement of technology, predictive analytics has had a profound impact on HR and is already making a strong impact in many areas of many organizations (Huda & Ardi, 2021). Predictive Analytics: using Statistical Models, Data mining, Machine learning and AI to predict future events from past data. These forecasts can apply to operational issues like positions, attrition rates or strategic issues like talent acquisition/ workforce planning. Increased use of predictive analytics is being employed by many companies in order to enhance their performance, lower costs, and streamline operations (Parmar, 2020; Tuboalabo, Buinwi, Okatta & Johnson, 2024). This is especially the case in the HR sector. As mentioned by Gupta and Sharma (2022) if a business lacks the relevant staff members' skill sets and time, it will fail to meet the needs of the business. This requires efficient planning of the work force and this is where predictive analytics may come in handy. "The human resources department can use patterns in the data to help forecast future staffing needs based on recruitment, employee turnover, productivity and other metrics." Understanding the needs and wants of the client (Fallucchi, Coladangelo, Giuliano, & William De Luca, 2020) enables businesses to foresee issues and take measures to prevent unnecessary job positions and their associated costs and aggravation. Besides, Data Driven Decision Making is not just significant to HR Planning. Predictive analytics can be applied to other HR areas like talent acquisition, performance management and employee engagement. In HR, for instance, predictive models can be employed for many reasons including predicting turnover, high-performing candidates in hiring, employee happiness and productivity, you name it. Organisations are now aware of the value of Human Capital and the capacity to use data to inform HR decision-making is turning out to be a competitive advantage (Dahlbom, et al., 2020; Ucha, Ajayi, & Olawale, 2024).

IBM makes it easier for employees to align their personal career goals to the goals of the organisation; this leads to higher levels of engagement and happiness, resulting in higher retention and productivity.

2. LITERATURE REVIEW

A cross-sectional research was conducted by *Henry et al. (Orusa-Ejo & Joy Amina, 2018)* to examine the impact of Predictive Analytics (PHRA) on HRM practices in Port Harcourt. The study used a questionnaire survey to gather data. There was a self-administered approach for the distribution of the questionnaires, and 159 respondents from various levels of the HR practitioner community in Port Harcourt contributed data for analysis using the SPSS statistical program. We computed standard deviations and mean scores to find out how well the PHRA worked for the HR professionals who were part of the study. To know the kind of relationship between PHRA and HRM practice we conducted a correlation analysis. The results of the correlation study revealed that the HRM techniques in the study were highly correlated with PHRA. The results showed that PHRA plays an important role in improving HRM practice outcomes. "Thus, the research suggested that human resource management professionals incorporate PHRA into their procedures." The study further revealed that descriptive analytics is the level most of the practitioners at Port Harcourt are at. Another restriction was the respondents' lack of identification and application of proper procedures.

Dimpy et al. (Handa & Garima, 2014) discussed that the HR department is acknowledged by big businesses as a strategic partner. HR analysis can give HR actions direction so that HR may be a reliable strategic partner. However, it is frequently observed that HR lacks the analytical and data-driven decision-making skills necessary to impact strategy. The idea of creating measurements that can gauge how HR operations affect an organization's bottom line was first put forth by Dr. Jac Fitz-enz in 1978.

Predictive analytics' greatest contribution to workforce planning is the ability to understand optimal placement. Workforce allocation is the allocation of workers to the specific tasks and locations for the business to ensure that a workforce is appropriately strategized for a business workload. Manpower allocation has been dealt with by earlier methods which are either based on stateless models or simple heuristics and cannot describe the complexity and dynamism of today's business operations. HR experts can leverage predictive analytics to better tackle these challenges and more efficiently allocate staff *(Aggrawal & Pandey, 2024).* By integrating various data sources, including historical workforce data, performance metrics and external factors such as market dynamics and customer trends, predictive models can help businesses determine optimal staffing allocations. By analyzing data on past traffic and events in the area and the weather, predictive analytics can help retailers forecast foot traffic. This data can help HR to make sure that they are distributing staff equitably to meet the demand during peak periods, but not spreading themselves thin during slower periods, according to *Tuboalabo, Buinwi, Buinwi, et al. (2024).* Predictive analytics can be applied to the day-to-day and long-term decision-making process on where to allocate workers. Businesses can use prediction models to evaluate whether they should make a move for instance into a new market, a new store or release a new product. HR professionals can configure several situations to see how best to allocate the labour between everyone seeking ways to be flexible and improve production, and those looking to reduce costs and work in an efficient manner *(Barreiro & Treglown, 2020).*

The pace of technological change and evolution of various sectors has made the need of continual skill development more important in the workforce planning. Being able to spot potential skill voids through predictive analytics and channel development efforts and training to fill these before affecting performance within the organisation is vital. Through analysis of current workforces and considering the projected future demands of the organization, HR can use predictive models to identify potential labor gaps early on, allowing them to plan for future needs and recruit accordingly *(Esan, Ajayi, & Olawale, 2024).* A business that is planning to release a new product or plainly to enter into a brand new field, for instance, may call for personnel that have either particular know-how or technical competencies. We can use predictive analytics to analyse the current skills of the workforce and see whether more training or recruitment is required. Organisations may develop tailored training programs in advance to prepare their staff for the shift, thereby reducing disturbance and ensuring a seamless transition *(Ucha et al., 2024).*

C. Swarnalatha et al. (Swarnalatha & Sureshkrishna, 2013) note that employee engagement and happiness at work are important for boosting morale at workplace. It is important for managers to do their best to increase the morale and productivity in workplace. "The Indian automotive sector was taken into consideration for this study, in terms of employee engagement and job satisfaction." The automobile industry is a well-established and fast growing industry of the global economy. Automotive products and accessories are attractive to the consumer and have growth earnings in the industry. The present study explained how employee involvement can help to increase the morale of the employees on the job and their commitment towards the success of their company. 315 samples were collected. The results of the literature analysis were used by the researchers in designing a questionnaire.

G. Delina et al (Delina & Samuel, 2020) has explained that the term "employee engagement" is now nearer to the management theory because it has a positive effect on the performance of an organisation and commercial excellence. This study aimed to analyze the employee engagement of the IT professionals in South India based on the variable vigour, dedication, and absorption using the UWES scale. There is a clear relationship between demographic variables and levels of engagement. This study also examined the impact of satisfaction derived from employee engagement programs on overall employee satisfaction and engagement.

3. METHODOLOGY

3.1 Design:

The research approach adopted in this study was that of a mixed methods design, which comprised quantitative and qualitative methods to research, implement and evaluate predictive HR analytics. Data related to HR is collected from various sources of organisations in India such as IoT (Internet of things) of technologies and systems used for HR Practices. These include employee engagement surveys, performance reviews, recruitment practices, real-time employee interaction and health indicators. The data is used to build a predictive machine learning model in Python using real-time data fetched from IoT-enabled systems and HR datasets. The block design shown in Figure 2 was used in this research to explore the predictive analytics tools.

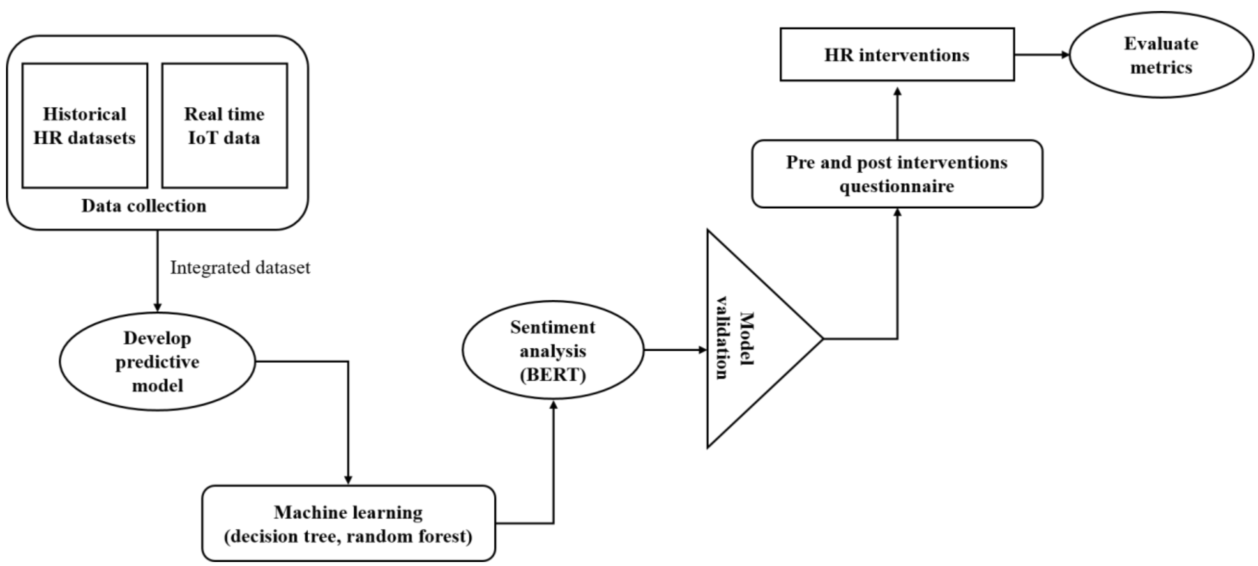

Figure 2: Represents the block design used to explore the predictive analytics tools in this investigation.

Decision tree and random forest algorithms are employed in attrition risk forecasting, manpower need, and employee motivation. Through the aid of AI and natural language processing methods like BERT, sentiment analysis is integrated for estimating employee morale and level of satisfaction. To validate whether the model accurately predicts HR outcomes, it is validated in the chosen enterprise. Realistic HR interventions are thereby recommended based on prediction. Pre-intervention and post-intervention questionnaires are sent to determine the effect of intervention and intervention on employee satisfaction and involvement. Workers' level of satisfaction, productivity indexes, and turnaround rates are metrics used in determining model effectiveness.

3.2 Sample:

A dataset of the HR management of an organization is taken as a sample for this research. Higher scores on the table signify higher engagement. Positive and negative rates of feedback spur employee communication and attitude. Higher positive feedback can be related to higher morale. Individual performance is highlighted by the table's monthly productivity and achievement levels for gauging effectiveness. Parameter such as time to hire and cost per hire offers insight into hiring effectiveness. Hours per week reflect the degree of teamwork required, necessary for innovation and productivity. Table 1 displays the HR dataset that has been utilized for training and testing the predictive model.

Table 1: Represents the HR related-datasets used for the model training and testing.

Engagement score	**Positive Feedback Rate (%)**	**Negative Feedback Rate (%)**	**Monthly Productivity (Units/Employee)**	**Goal Achievement Rate (%)**	**Time to Hire (Days)**	**Cost per Hire (₹)**	**Collaboration Hours (Hours/Week)**
78	85	15	120	92	30	50,000	8
85	88	12	130	95	28	48,000	9
92	90	10	140	98	25	52,000	7.5
88	87	13	125	93	32	51,000	8.5
76	80	20	110	85	35	47,000	7

3.3 Instruments:

This research uses various sources to gather data and insights related to employee engagement and HR practices. Various surveys, feedback mechanisms, and pulse checks are conducted to collect employee engagement metrics. Several industry reports and Organizational HR systems are used to evaluate the parameters such as cost per hire and time to hire to recognize this as an important aspect of workforce efficiency. This study employs a random forest regression model in predicting the scores of engagement using this study. The data is found using software such as the staff management system, and predictions are made using software like Python. Academics and researchers rely on publications such as papers and studies that build on the earlier work to have a better understanding of the predictive HR analytics tools.

3.4 Data collection:

Cost per hire is the most important factor influencing employee engagement, according to the results of running this data through the prediction model. Emotion and communication among employees are crucial, as shown by the outcomes of both positive and negative effective feedback. Concerning participation, productivity—an indication of impact—ranks second. Coordination is crucial since other factors, such the rate of goal accomplishment and the quantity of hours worked per week, also have a significant role. Results showing the effect of HR indicators on engagement ratings are shown in Table 2 by means of feature significance scores derived from the constructed prediction model.

Table 2: Shows the outcomes when HR related datasets in processed through a predictive model based on a random forest model.

Feature	**Importance**
Cost per Hire (₹)	0.209489
Negative Feedback Rate (%)	0.182586
Positive Feedback Rate (%)	0.181773

Monthly Productivity (Units/Employee)	0.163439
Collaboration Hours (Hours/Week)	0.104905
Goal Achievement Rate (%)	0.103621
Time to Hire (Days)	0.054187

3.5 Data analysis:

The random forest regression model is employed to predict the engagement scores based on several HR metrics. Model performance analysis is given below:

a)*Mean Squared Error (MSE):*

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

The calculated MSE is found to be 0.1764, which is quite low, showing a low error in prediction on tests with a small dataset. R2 cannot be calculated since the sample taken was too small. The used model breaks down feature importance by examining the degree to which each measure helped reduce the impurity in the decision tree. Cost per hire is the most important predictor of engagement values, a key factor in satisfaction and efficiency. Feedback is about the importance of employee sentiment. There are other factors as well that are less influential than the others.

b) *Equations Used in Predictive Modeling*

Random Forest Regression model is an ensemble of decision trees:

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} f_t\,(X)$$

Here, $f_t(X)$ signifies the prediction from tree t, and T is the total number of trees.

4. RESULT AND DISCUSSION

To forecast scores using a variety of HR metrics, the offered code makes use of a random forest regression model. The model is initially presented with a small data set which includes lots of characteristics. The "pandas" package is then used to arrange the data into a dataframe. The autonomous feature “engagement score” is the same for all of the dependent variables. There is a function called "Train_test_split" which splits the data into two sets, training set and test set. Random Forest regressions with one hundred decision trees can be built, and the accuracy can be improved by creating and merging numerous decision trees using a training set. Mean squared error can be used to estimate the model's performance regarding checking prediction error and R2, which is a measure that explains data variation. The model training and testing code of the study is displayed in Figure 3.

```python
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score
data = {
    "Engagement Score": [78, 85, 92, 88, 76],
    "Positive Feedback Rate (%)": [85, 88, 90, 87, 80],
    "Negative Feedback Rate (%)": [15, 12, 10, 13, 20],
    "Monthly Productivity (Units/Employee)": [120, 130, 140, 125, 110],
    "Goal Achievement Rate (%)": [92, 95, 98, 93, 85],
    "Time to Hire (Days)": [30, 28, 25, 32, 35],
    "Cost per Hire (₹)": [50000, 48000, 52000, 51000, 47000],
    "Collaboration Hours (Hours/Week)": [8, 9, 7.5, 8.5, 7]
}
df = pd.DataFrame(data)
X = df.drop("Engagement Score", axis=1)
y = df["Engagement Score"]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
y_pred = rf_model.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print("Mean Squared Error:", mse)
print("R-squared Score:", r2)
feature_importances = pd.DataFrame({
    'Feature': X.columns,
    'Importance': rf_model.feature_importances_
}).sort_values(by='Importance', ascending=False)
print("\nFeature Importances:")
print(feature_importances)
```

Figure 3: Pictured below is the code that went into making the prediction model.

Research Algorithms such as Decision tree and Random forest, function very well. Artificial intelligence systems, such as BERT, make it easy to assess worker happiness and morale (Bello et al., 2023). From these findings, it is clear that predictive analytics can enhance HR decision-making, and consequently can help organisations overcome obstacles. “Another major benefit to this study is the ability to address staff concerns through data”. The HR personnel can use these predictive tools when the model pinpoints the reasons for dissatisfaction to take the proper action. Organisations can fill in the skill gaps with specialised training programmes which can enhance communication among employees and also build up a positive work culture. Evaluation of the random forest regression model behaviour in predictive HR analytics is done by feature significance curves as illustrated in Figure 4.

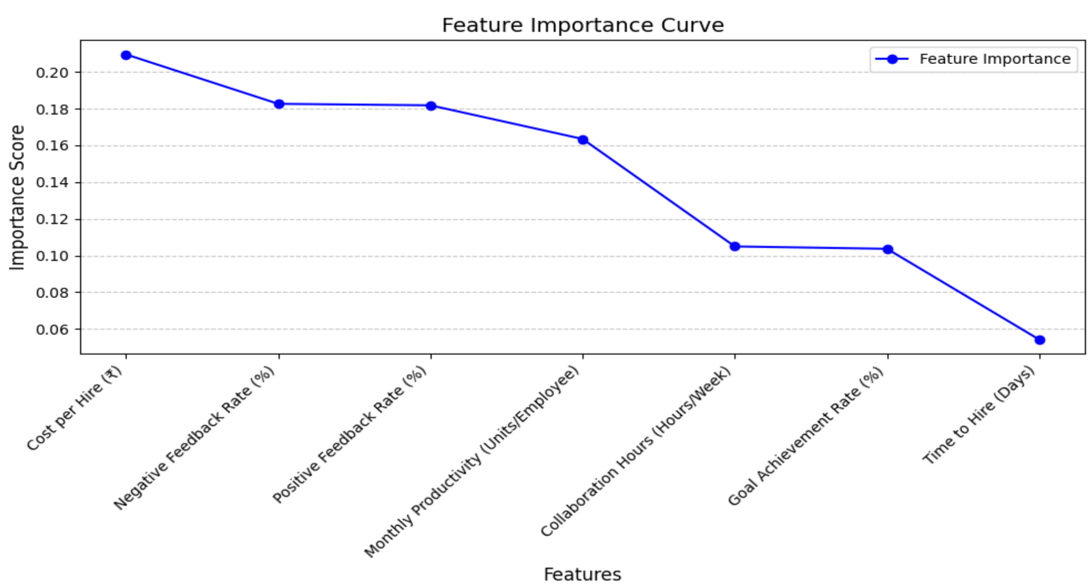

Figure 4: Shows the feature importance curve obtained from the developed model.

Pre and post-intervention surveys are necessary to measure the change in the employee satisfaction and engagement level. “This investigation also mentions the importance of predictive analytics in optimizing HR plans and strategies for various purposes, such as talent acquisition, retention, and management of individual performance in the organization". By using such predictive tools, HR can refine their hiring and recruitment process once they analyze the historical hiring data. This also assists in forecasting leadership issues of the future and assists in succession planning actions (Adiazmil. S. et al., 2024; Brownell, 2005).

This study also clarifies some of the implementation issues. If the data is massive and from various sources, much work is needed to preprocess and standardize the data. Data privacy with sensitive employee data is another key concern mentioned. Predictions of accuracy may be affected by biases in the data sets. Based on the results of this study, future research on the subject of 'predictive HR analytics' can be developed. Moving forward, there is potential to use more sophisticated tools, such as 'Generative AI' for more complex forecasting or to further expand the use to the 'gig economy' and incorporate 'gig workers'. 'Blockchain technology' could be used to allow secure data sharing between organisations, while maintaining transparency and improving data privacy. Further, 'deep natural language processing models' may offer real-time 'sentiment analysis' data which can be used to enhance predictions on employee morale and satisfaction.

5. CONCLUSION

This study has brought forth a series of important findings and results by classifying and assessing the effectiveness of corporate human resource data according to the random forest method. "With the growing capabilities of IT, the importance of the efficient management of human resources in today's businesses has also grown". The method suggested in this research can be used in the processes of data processing and analysis to provide more insight and better HRM decisions. The predictive tools that leverage Generative AI and blockchain technologies have the potential to further accelerate innovation in labour management in the future.

Author Declaration Form

1.Manuscript Details

Title of the Manuscript: **Building a Future-Ready India: The Role of Predictive HR Analytics in Employee Engagement and Job Satisfaction**

Author(s): Snigdha, Research Scholar, Manav Rachna University

- **Affiliation(s):** School of Business, Manav Rachna University, Faridabad, India
- Email: snigdha027@gmail.com
- **Supervisor:** Prof. (Dr.) Animesh Singh, *Manav Rachna University*
- **Affiliation(s):** School of Business, Manav Rachna University, Faridabad, India
- Email: animesh@mru.edu.in

2. Declaration of Originality

We, the undersigned author(s), hereby declare that:

- This manuscript is an original work and has not been published elsewhere, in part or in full.
- The manuscript is not under consideration for publication in any other journal or conference proceedings.
- Proper acknowledgment has been given to all sources of information used in the manuscript.

3.Authorship Contribution

- We confirm that all listed authors have made significant contributions to the research and writing of this manuscript. Each author has reviewed and approved the final version of the manuscript prior to submission.

4.Conflict of Interest

- We declare that there are no conflicts of interest, financial or otherwise, that could have influenced the outcomes of this research.

5.Ethical Compliance

- We confirm that the research complies with ethical standards, including proper treatment of data, participants, and source.

6. Copyright Transfer

Upon acceptance of the manuscript for publication, we agree to transfer copyright to the journal.

7.Fundings

We declare that this research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

8.Author Signatures

(Snigdha, Research Scholar, SOB, Manav Rachna University)

(Prof. (Dr.) Animesh Singh, SOB, Manav Rachna University)

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