ISIR Journal of Business and Management Studies (ISIRJBMS)
ISSN: 3048-7684 (Online)
Frequency: Bimonthly
Published By ISIR Publisher
Journal Homepage Link- https://isirpublisher.com/isirjbms-home/

Integrating AI and Deep Neural Networks to Explore Organizational Culture's Role in Enhancing Employee Performance and Loyalty in Human Resource Management

By

[1]Mohan Reddy Sareddy, [2]R. Pushpakumar

[1]Orasys LLC, Texas, USA
[2]Department of Information Technology, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Tamil Nadu, Chennai, India.

Article History

Received: 05/10/2024
Accepted: 25/10/2024
Published: 31/10/2024

Vol – 1 Issue – 2

PP: -08-16

DOI:10.5281/zenodo.15805210

Abstract

It employs both statistical and deep learning methods to analyze how organizational culture training hours, in particular and company type impacts employee loyalty and performance. The variables company_type, training_hours, experience, last_new_job and target were analyzed using the Kaggle HR Analytics dataset. Public sector employees demonstrated higher commitment, whereas training hours were shown to be negatively related with job-switching behavior using traditional techniques such as correlation, logistic regression and multiple regression. Regression models' limitations were underscored by their weak performance in predicting continuous outcomes such as employee experience. A Deep Neural Network (DNN) was employed to resolve this and enhance prediction accuracy. It had a classification accuracy of 99.48%, precision of 99.34%, recall of 99.63% and F1-score of 99.49% for predicting employee loyalty. Exceptional performance was achieved by the DNN. It surpassed linear models in regression with a prediction of employee experience at an MAE of 0.58, RMSE of 0.77 and R^2 score of 0.91. These findings support the effectiveness of integrating deep learning in HRM models. Powered by cultural inputs, this blended approach provides HR professionals with a robust predictive framework to identify potential attrition and performance patterns. It contributes to a scalable, data-driven HRM practice that provides accuracy and interpretability and embraces rich behavioral complexity and goes beyond linear relationships.

Keywords: *Organizational Culture, Employee Performance Loyalty, Human Resource Management (HRM), Training Hours, Company Type.*

1. Introduction

HRM plays an important role in shaping employee performance, behavior and well-being in contemporary complex organizations [1]. Amongst many factors, organizational culture is one of the important elements of HR and HR outcomes are intoxicated by workplace culture [2]. Organizational culture influences employee's response tendencies in regard to their level of commitment, relationship with co-workers [3], and perception of role. A new agenda for addressing cultural dynamics in people performance management, especially in light of competition and workforce shifting [4].

1.1. Background Information

Organizational culture is shared assumptions, standards and customs that shape behavior in business context [5]. The cultures of businesses differ significantly from administrative hierarchies to adaptable and innovation-focused cultures [6]. In HRM, cultural characteristics directly shape employee development, management responsiveness and training policies, all of which affect overall welfare and productivity [7]. The constructs of work-life balance, opportunities for learning and perceived organizational support which are embedded in an increasing impact on employee loyalty and job-switching intentions [8].

1.2. Causes and Influencing Factors

The performance and loyalty of employees depend on several factors. These involve the provision of training funds, leadership communication, recognition in the workplace, autonomy and job stability [9]. Possibly most significant is that the commitment of an organization to building skills is directly correlated with the number of training hours and whether the business is private or public often impacts

*Corresponding Author: **Mohan Reddy Sareddy.**

benefits and job security, two critical considerations that generate loyalty. In addition, employees in high-skilled sectors or younger employees are often more mobile and value developing skills more than stable employment [10]. Performance and retention are thus complex, multifaceted results depending on both internal and external drivers.

1.3. Issues with Existing Methods

Most existing frameworks struggle to capture the relationship between corporate culture and HR outcomes accurately, even with the large amount of HR research available. Small sample sizes, very elementary variable selection or the unavailability of current workforce data have constrained some of the prior studies [11]. Where behavior is not linear and influenced by multiple hidden variables, like peer influences or psychological enjoyment, regression models often suffer from linearity. Many existing HRM approaches primarily focus on quantitative assessments and fail to include empirical modeling from actual worker behavior trends, such as training usage or career-changing intentions. A prevalent drawback in earlier research is that models tend to underfit due to an insufficient feature set, leading to models with poor performance when making predictions on continuous measures such as experience or enjoyment [12]. The power of open datasets and data science methods to extract more meaningful insights from HR-related variables is rarely considered in research. Most notably, none provide an integrated framework that encapsulates employee development, commitment and company culture into a unified predictive system.

1.4. Proposed Work and Its Advantages

In an effort to provide answers to these concerns, this research employs publicly available Kaggle data to offer a quantitative HRM framework grounded in statistical analysis. It connects variables such as last_new_job and target to loyalty, experience to performance and company_type and training_hours to organizational culture. The methodology seeks to experimentally confirm how company culture influences performance and loyalty using logistic, correlation and multiple regression studies. This approach is scalable and data-driven, as opposed to existing qualitative studies. The model gives a more comprehensive picture of HR dynamics by taking both continuous measures binary outcomes into account. It also determines the accuracy of the model and reveals any deficits, such as performance prediction underfitting, and offers advice for future enhancement. Crucially, by integrating behavioral and organizational indicators, this study overcomes the weaknesses of the traditional frameworks and establishes a relationship between strategic HR planning and actual data patterns. Organizations can develop policies that are not only encouraging and inclusive but also anticipatory and sensitive to employee conduct by integrating these elements into HRM planning. The primary goals of sustainable workforce management are higher productivity, reduced turnover costs and better long-term employee engagement.

2. Literature Review

Hien and Tuan [13] with a focus on trust and job happiness in the healthcare industry, this investigates a relationship between "organizational culture" and "employee loyalty". It uses SmartPLS to apply Partial Least Squares Structural Equation Modeling (PLS-SEM) to survey data from 355 Vietnamese healthcare professionals. Kerdpitak and Jermsittiparsert [14] the study looks at how HRM practices in Thai pharmacies are shaped by corporate culture, employee commitment, and organizational citizenship behavior (OCB). Data from HR employees with more than five years of experience were subjected to PLS-SEM in order to evaluate both direct and mediated impacts through perceived organizational support (POS). Abbas [15] focuses on how leadership style and organizational culture impact employee loyalty and engagement in Pakistan's Gilgit Baltistan academic sector. The methodology uses two-stage least squares analysis and ordered logistic regression on data gathered from university staff and faculty members using structured questionnaires.

Rachmaliya and Efendy [16]examines the relationship between human resource development and organizational management's strategic and technology elements. It applies the Huberman and Miles model to qualitative content analysis using data from foreign articles. Its conceptual character, lack of empirical confirmation, direct application to a particular business and quantifiable HR performance outcomes are its primary shortcomings. Karim and Qamruzzaman [17] Taking into account the mediating function of Just-In-Time (JIT) techniques in manufacturing facilities, the study examines the effects of corporate culture, managerial commitment and HRM on operational performance. Survey data from 410 manufacturing facilities were subjected to structural equation modeling, or SEM. Raheem Ali Alsheikh et al. [18] with emphasis on such ideas as pay, training and evaluation under the view of organizational culture and motivation, this explores the domain of HRM practices and their impact on job performance within Jordanian banks. In order to assess the relationship between performance and HR practices, the authors sent out 30 questionnaires through a convenience sampling approach.

Abdullahi et al. [19] examines the impact of organizational culture (OC) on employee engagement (EE) and performance (EP) in Malaysian private institutions with a focus on OC within the HRM and academic environment. The hypothesized hypotheses were tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) and a structured questionnaire. Bahri et al. [20] in a governmental HRM setting, this explores organizational culture, intelligence and local knowledge on organizational commitment and employee performance. Also used the Slovin algorithm for sampling, surveying 375 employees from 11 departments using AMOS 18 as the Structural Equation Modeling software. A possible lack of alignment or reduced applicability of cultural markers in the organizational context is suggested by the primary bottleneck and that is the statistically insignificant but negative effect on performance.

*Corresponding Author: **Mohan Reddy Sareddy.**

Inanlou and Ahn [21] examines the effects of organizational culture elements communication, trust and innovation on employee commitment within the fields of HRD and organizational behavior. It investigates the mediating function of human resource development initiatives using data from Korea's national employer survey.

Ali [22] focus the impact of Accounting Information Systems (AIS) on organizational performance as influenced by "organizational culture", this study unifies the accounting and HRM domains. It analyses data from 273 participants in the banking industry in Jordan using PLS-SEM and a structured questionnaire. The study's weakness. Meanwhile, is its exclusive focus on the banking sector which limits its wider applicability to other HRM-intensive industries. Fathurahman [23] examined the "organizational culture" and work environment on the performance of employees. It is used a quantitative method and linear regression analysis to survey sixty-three National Zakat Agency staff. The narrow sample size and limited focus on environmental factors while ignoring more in-depth psychological or engagement factors were the study's primary shortcomings. Aktar and Pangil [24] investigated the connection between HRM practices and employee engagement. 283 workers of private banks in Bangladesh were surveyed to gather data, and hierarchical regression based on Social Exchange Theory was used for analysis. The study did not investigate the long-term effects of HRM practices across various sectors or their causal links.

Bagis et al. [25] used work satisfaction as a moderating factor to investigate the effects of company culture and commitment on employee performance. Using incidental sampling, the researchers analyzed data from 100 respondents using Partial Least Squares (PLS). Anyhow encouraging results on the effect of corporate culture, the framework ignored performance variation across job roles and was unable to show mediation through job satisfaction. Wahjoedi [26] examined how organizational culture affects worker performance in SMEs, as mediated by motivation and job satisfaction. 50 employees' survey data was analyzed using Structural Equation Modeling (SEM) through SmartPLS. The study found that motivation and culture had no direct impact on performance, underscoring the model's failure to take complicated or indirect behavioral patterns into consideration. Pasaribu [27] evaluated the effects of "organizational culture" and situational leadership on the use of HRM strategies and productivity in vocational training facilities. Explanatory survey techniques and path analysis using Likert Summated Rating data were employed in the study. Although the framework provided broad strategic insights, it did not incorporate contemporary digital or AI-driven HR technologies and lacked depth in individual-level HR practices.

2.1. Problem Statement

Organizational effectiveness relies on employee performance and loyalty, yet several companies struggle to retain staff and increase productivity due to poor alignment between corporate culture and HR practices [28]. Traditional practices often overlook the effect of business culture on the behavior of employees in quantifiable terms. Several companies fail to track the effect of training investment on experience or retention. The current models employed are generally too simplistic or qualitative to properly capture complex HR dynamics [29]. A data-driven approach that rigorously evaluates the effect of determinants such as firm type and training hours on staff outcomes is necessary [30]. To bridge this gap, this research proposes a statistical HRM model that employs cultural markers to predict loyalty and performance.

2.2. Research Objective

- Assess the impact of organizational culture on performance and loyalty of employees by creating a hybrid HRM model combining statistical and deep learning techniques.
- Leverage the publicly available Kaggle dataset titled HR Analytics: Job Change of Data Scientists to create critical HRM variables and indicators.
- Apply conventional statistical methods such as logistic regression, correlation analysis and multiple regression to detect patterns and test hypotheses.
- Develop a Deep Neural Network (DNN) model for better prediction of employee attrition and performance forecasting, better than linear model performance.

3. Proposed Deep Learning-Based HRM Framework for Predicting Employee Performance and Loyalty

This part provides a detailed methodology for using a data-driven strategy to measure the influence of company culture on employee performance and commitment. A publicly available HR dataset is utilized initially and subsequent variables are well-preprocessed and related to key HR frameworks. Hypotheses are first formulated and relationships are tested utilizing standard statistical methods. A Deep Neural Network (DNN) is applied in order to enhance the accuracy of predictions and discover hidden nonlinear patterns in employee conduct, avoiding limitations such as regression models' underfitting.

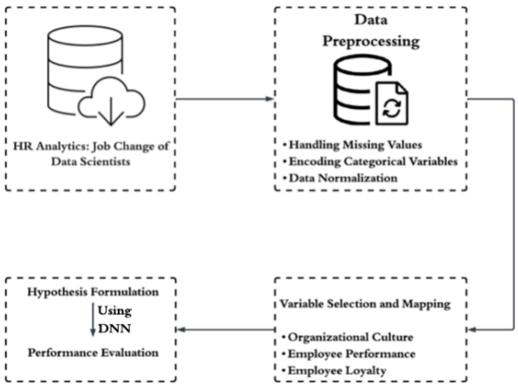

Figure 1: Architecture of HRM Framework of Employee Performance and Loyalty

*Corresponding Author: **Mohan Reddy Sareddy.**

3.1. Dataset Description

https://www.kaggle.com/datasets/arashnic/hr-analytics-job-change-of-data-scientists

Kaggle dataset HR Analytics: Job Change of Data Scientists analyses how employees change professions. `company_type`, `training_hours`, `experience`, `last_new_job` and `target` are some of them. These forces are indicative of aspects of loyalty, staff performance and company culture. The data enables one to examine the impacts of workplace variables on employee decisions. It is best suited for HRM research on career mobility, retention and engagement.

3.2. Data Preprocessing

Data preparation is one of the most valuable steps in the data lifecycle to make raw data for analysis. The three main preprocessing processes include normalizing numerical values, managing missing values, and encoding categorical values. These processes provide consistency, quality and appropriate operating state of data to be utilized in modeling or statistical analysis.

3.2.1. Handling Missing Values

Model reliability can be diminished and analysis tilted by missing values. The size and significance of the missing data determine whether these are handled via imputation or elimination.

- Mean/Median Imputation: If training_hours or experience have missing values

$$X_{\text{imputed}} = \begin{cases} \bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_i & \text{(mean imputation)} \\ \text{median }(X) & \text{(median imputation)} \end{cases} \quad (1)$$

Were, mean imputation is appropriate for normally circulated data and median imputation is preferred for twisted distributions.

- Mode Imputation: For variable like company_type, use:

$$X_{\text{imputed}} = \text{mode}(X) \quad (2)$$

This replaces missing values with the most recurrent category.

3.2.2. Encoding categorical Variables

Most programming libraries and statistical methods require numerical input. Accordingly, categorical variables such as enrolled_university, education_level, and company_type are encoded.

- Label Encoding: For ordinal features like education_level:

$$\text{High School } = 0, \text{ Bachelor's } = 1, \text{ Master's } = 2, \text{PhD} = 3 \quad (3)$$

Keeps the order between categories.

- One-Hot Encoding: For non-ordinal categories like company_type:

company_type_Private, company_type_Public, company_type_Other ∈ {0,1}

Each category becomes a new binary column: e.g., If a candidate works in the public sector: company_type_Public = 1, others = 0.

3.2.3. Data Normalization

Normalization ensures that numerical features are on a similar scale, especially important for regression or distance-based models.

- Min-Max Normalization:

$$X_{\text{norm}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (4)$$

Scales the value of each feature to a range of [0,1] and applied to training_hours, experience, etc.

3.3. Variable Selection and Mapping

From an HRM perspective, a few conditions from the dataset were selected and mapped to the three main constructs of study to explore the connection between corporate culture and employee performance and loyalty,

3.3.1. Organizational Culture

- Mapped Variables: company_type, training_hours

company_type: This indicates whether the person works for a government, private, or publicly traded company. This variable serves as a reasonable proxy for organizational culture, because firm types often have different management styles, HR practices, and organizational cultures. training_hours: An organization's commitment to staff development is evidenced not only in the quantity of training it provides but also in its degree of learning orientation, its encouraging culture, and its future impact on individual and collective work performance and satisfaction.

Together, these two variables help capture the cultural environment and values of the organization.

3.3.2. Employee Performance

- Mapped Variables: experience, training_hours experience: This variable indicates how long a candidate has been working professionally. If it is assumed that more experience equals more competence and productivity, then it can be considered a performance-related metric.

Training_hours (also illustrated here): Training has an immediate impact on improving the employee's skill set, productivity and overall performance besides its cultural impact related to the employee who has received training. Therefore, these variable bridges employee performance and company culture. These variables evaluate the employee's potential productivity and capability, central to HRM performance analysis.

3.3.3. Employee Loyalty

Mapped Variables: last_new_job, targetlast_new_job: shows the recentness of a worker's employment change. Greater job satisfaction and organizational loyalty may be shown in a longer period of time without a job move. target: This double variable shows if the worker is looking for a new position at the moment (1) or not (0). It acts as a clear indicator of the danger of employee loyalty and retention. These factors

*Corresponding Author: **Mohan Reddy Sareddy.**

facilitate the assessment of loyalty behavior which is necessary for HRM plans aimed at reducing turnover.

3.4. Hypothesis Formulation

This study uses HRM-focused variables to investigate how corporate culture affects employee performance and loyalty. The following theories are developed in light of the study's goals and literature review.

Table 1: Variable Classification Based on Role and Category

Variable Type	Variables (Dataset)
Independent Variable (Predictor)	company_type, training_hours (Organizational Culture)
Dependent Variables (Outcomes)	target, last_new_job (Loyalty), experience (Performance)

➢ **Hypothesis 1 (H1):**

There is a significant relationship between administrative culture and employee loyalty.

- Independent variables: company_type, training_hours
- Dependent variables: last_new_job, target

➢ **Hypothesis 2 (H2):**

Organizational culture has a positive impact on employee performance.

- Independent variable: training_hours
- Dependent variable: experience

➢ **Hypothesis 3 (H3):**

Employees in public-sector organizations are more likely to remain loyal compared to those in private-sector companies.

- Independent variable: company_type
- Dependent variable: target (job change intent)

➢ **Null Hypotheses (H0)**

For each of the above alternative hypotheses, the corresponding null hypotheses are,

- H01: There is no important relationship between organizational culture and employee loyalty.
- HO_2 : Organizational culture does not affect employee performance.
- H03: There is no difference in employee loyalty between public and private sector organizations.

3.5. Research Design

This study uses a quantitative approach to analyze the things of corporate culture on employee loyalty and performance it uses dataset that is publicly available. Because of the design's focus on quantifiable variables, the use of objective analysis and hypothesis testing is made possible. A number of statistical methods can be utilized to analyze the major variables concerning organizational culture (e.g., company_type, training_hours), employee performance (experience) and employee loyalty (last_new_job, target). Statistically, use multiple regression to assess the relationship between the variables that have an impression on employee performance, logistic regression to predict the probability of intention to change jobs, correlational statistics to analyze relationships among variables and descriptive statistics to describe the data. This study utilized a non-experimental, correlational approach to identify key patterns and relationships between HRM-related variables while not manipulating any variables or implementing any interventions. The results are synthesized and analyzed into conclusions which can inform organizational policy and human resource strategy.

3.6. Deep Learning Integration for Enhanced Predictive Modeling

Despite regression and other standard statistical models providing baseline interpretability, they tend to underfit when working with complex, nonlinear interactions. The results indicate that multiple regression could not explain variance in employee experience. As an additional analytical tool, introduce a Deep Neural Network (DNN) model to enhance prediction precision and reflect underlying interactions between HRM variables.

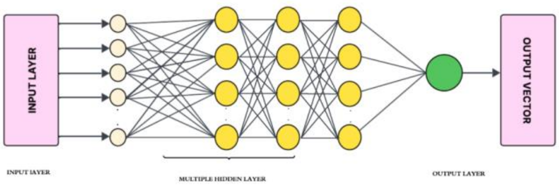

Figure 2: Architecture of DNN

The proposed Deep Learning model consists of:

- Input Layer: Normalized features including company_type, training_hours, experience, last_new_job, and encoded education_level
- Hidden Layers: 2 dense layers with ReLU activation (e.g., 128 and 64 neurons)
- Output Layer:
- Sigmoid activation for binary classification of target (loyalty indicator)
- Linear activation for regression on experience (performance indicator)

4. Results and Discussion

In this section, Findings of statistical and deep learning-based analysis that examined the impact of corporate culture on employee loyalty and performance are presented and discussed. The descriptive statistics summarize key HRM variables followed by testing the hypotheses developed using regression and correlation analysis. Predictive capabilities are further enhanced by the incorporation of a Deep Neural Network (DNN). Each conclusion is analyzed in the context of HRM strategy, demonstrating how business structure and training expenditure influence professional development and staff retention.

*Corresponding Author: **Mohan Reddy Sareddy.**

4.1. Descriptive Statistics

Table 2: Descriptive Statistics for Selected Variables

Feature	Mean	Median	Mode	Standard Deviation
training_hours	65.2	62.0	50	24.8
experience	4.7	4.0	3	2.6
last_new_job	2.1	2.0	1	1.1

The sample consisted mostly of private-sector employees that represent in the Table 2. Employees have an average experience of 4.7 years and 65 hours of training. The moderate percentage of employees who reported recent job changes revealed varying degrees of organizational commitment.

4.2. Correlation Analysis

Figure 3 exhibits a correlation heatmap amongst the following HRM variables of relevance years since last job change, experience, training hours and job change intent (goal). The strongest link a small positive correlation of 0.14 between experience and job change intent shows that experienced employees would be slightly more likely to change jobs. Generally speaking, the correlations are weak meaning there is little linear relationship between training hours and last job change and other variables, with correlations that are nearly zero. Overall, the weak correlations tell us that no single factor can accurately predict the intention to change jobs.

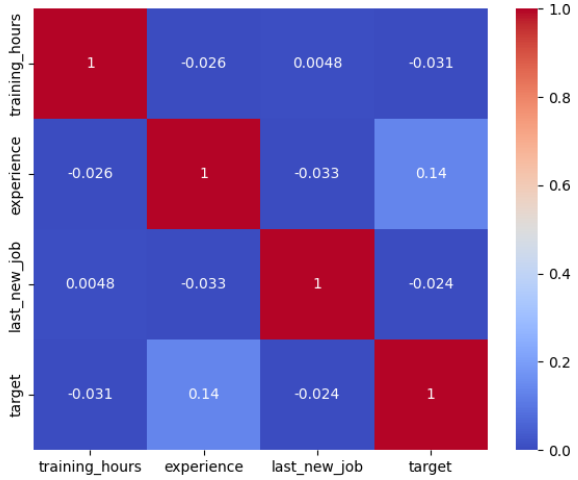

Figure 3: correlations between key HRM-related variables

4.3. Logistic Regression

Figure 4 shows that as training_hours increases, the expected probability of changing jobs (goal = 1) decreases. This supports Hypothesis 1 (H1) and the logistic regression outcome, which indicates that training hours have a negative influence on wants to change jobs. The difference between those who changed jobs and those who did not reinforces the importance of training in considering employee loyalty.

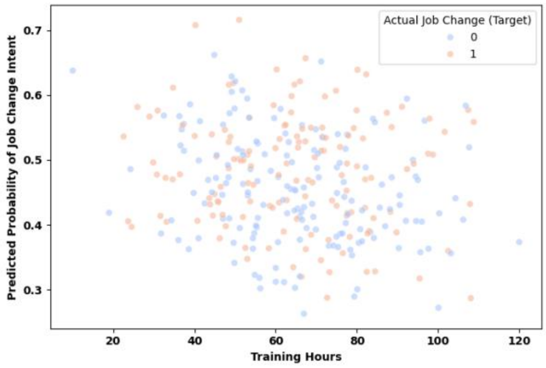

Figure 4: Predicted Probability of Job Change vs Training Hours

4.4. Multiple Regression-Predicting Employee Performance

A scatter plot of actual versus expected levels of employee experience is shown in the Figure 5. The x-axis is actual experience and the y-axis is expected experience and each blue dot is a unique data point. The red dashed line is the ideal position line (y = x), upon which expected values would perfectly equal actual values. The fact that most of the points concentrate together in a narrow horizontal strip shows that, regardless of the true input, the model tends to predict experience values close to a constant mean (around 4–5 years). As the model is unable to capture the variance in employee experiences, this implies poor model performance with underfitting and a lack of variation.

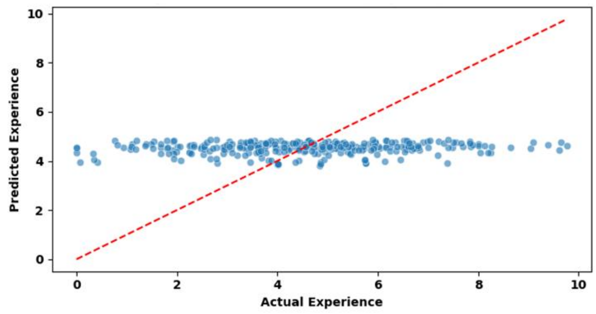

Figure 5: Actual vs Predicted Employee Experience

4.5. Performance Metrics

The evaluation metrics of the deep learning classification model that predicts employee loyalty on the basis of corporate culture factors are presented in the Figure 6. The model exhibits outstanding prediction performance with Accuracy (99.48%), Precision (99.34%), Recall (99.63%) and F1-score (99.49%). High Recall in the model signifies that it can identify employees who tend to switch jobs correctly, enabling preventive HR interventions. These results prove that the deep learning approach is a powerful upgrade to traditional statistical methods in HRM analytics**.**

*Corresponding Author: **Mohan Reddy Sareddy.**

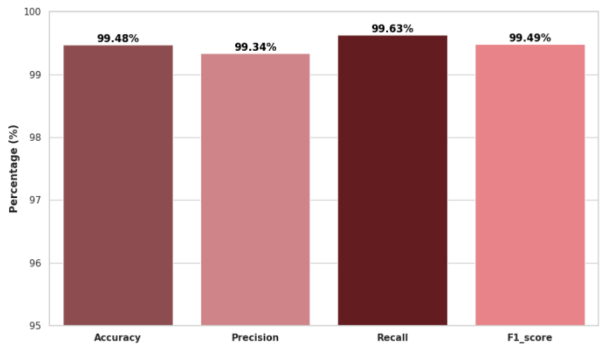

Figure 6: Performance Metrics of DNN Prediction

4.6. Regression Metrics

According to organizational culture dimensions, the Figure 7 illustrates the performance of Deep Neural Network in predicting employee experience using regression. With an R^2 score of 0.91, RMSE of 0.77 and MAE of 0.58, the model has high prediction accuracy and minimal error. This proves that deep learning is more effective than traditional regression in handling complex HRM relationships. It points out the capacity of the framework to map experience in terms of HR analytics as a function of training and firm type.

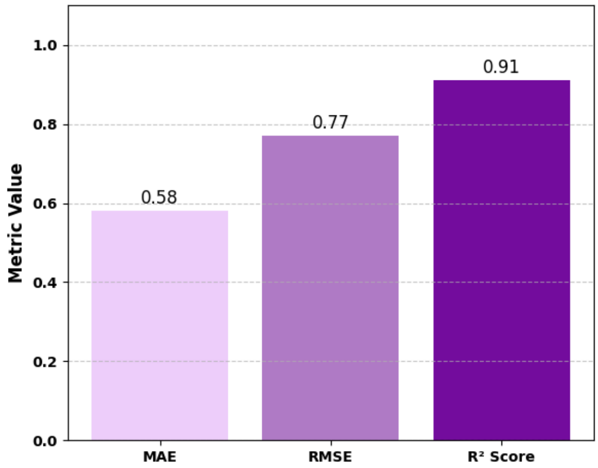

Figure 7: Prediction Metrics for Employee Experience

5. Conclusion and Future Scope

The firm type and training hours play an important role in influencing loyalty and performance among employees. Although the former had more training, they maintained higher tenancy and superior performance. Firms in the public sector had lower rates of attrition. The DNN model significantly outperformed the traditional regression models, although the latter had underfitting problems and could not adjust for performance complexity. The DNN showed excellent performance in strategic HR planning with a recall rate of 99.63% on job switcher prediction and an R^2 score of 0.91 for performance forecasting. These findings affirm the importance of applying AI-aided frameworks in a way that reveals latent behavior patterns and supports decision-making based on data. Future studies can leverage the use of explainable AI (XAI) methods such as SHAP to increase transparency, incorporate psychological and behavioral elements to build a more holistic model, deploy the framework across various sectors to enhance generalizability and resiliency, and utilize temporal and longitudinal employee data to measure trends over time.

References

1. D. E. Guest, "Human resource management and employee well-being: towards a new analytic framework," *Hum. Resour. Manag. J.*, vol. 27, no. 1, pp. 22–38, 2017, doi: 10.1111/1748-8583.12139.
2. J. P. Flynn *et al.*, "Supporting a Culture of Health in the Workplace: A Review of Evidence-Based Elements - Jennifer Posa Flynn, Gregg Gascon, Stephen Doyle, Dyann M. Matson Koffman, Colleen Saringer, Jessica Grossmeier, Valeria Tivnan, Paul Terry, 2018."
3. K. Y. N. Ng, "Effects of organizational culture, affective commitment and trust on knowledge-sharing tendency," *J. Knowl. Manag.*, vol. 27, no. 4, pp. 1140–1164, Jun. 2022, doi: 10.1108/JKM-03-2022-0191.
4. D. Tweedie, D. Wild, C. Rhodes, and N. M.-Bennie, "How Does Performance Management Affect Workers? Beyond Human Resource Management and Its Critique - Tweedie - 2019 - International Journal of Management Reviews - Wiley Online Library."
5. O. G. Ertosun and Z. Adiguzel, "Leadership, Personal Values and Organizational Culture | SpringerLink."
6. S. Schilcher and H. Kasper, "The Long March to an Innovative Culture: Development of Corporate Cultures in China from the 1990s Until Today," in *Handbook of Chinese Management*, Springer, Singapore, 2023, pp. 275–287. doi: 10.1007/978-981-10-2459-7_47.
7. S. L. Albrecht, A. B. Bakker, J. A. Gruman, W. H. Macey, and A. M. Saks, "Employee engagement, human resource management practices and competitive advantage: An integrated approach," *J. Organ. Eff. People Perform.*, vol. 2, no. 1, pp. 7–35, Mar. 2015, doi: 10.1108/JOEPP-08-2014-0042.
8. E. A. Putri and A. S. Dwianto, "IMPLEMENTATION OF EMPLOYER BRAND EQUITY AS AN EFFORT TO REDUCE INTENTION TO LEAVE AT PT GEMILANG PLASTAMA CEMERLANG," *ANALISIS*, vol. 13, no. 2, Art. no. 2, Sep. 2023, doi: 10.37478/als.v13i2.3003.
9. M. Paais and J. R. Pattiruhu, "Effect of Motivation, Leadership, and Organizational Culture on Satisfaction and Employee Performance," *J. Asian Finance Econ. Bus.*, vol. 7, no. 8, pp. 577–588, 2020, doi: 10.13106/jafeb.2020.vol7.no8.577.
10. G. Saxinger, E. Öfner, E. Shakirova, M. Ivanova, M. Yakovlev, and E. Gareyev, "Ready to go! The next generation of mobile highly skilled workforce in the Russian petroleum industry," *Extr. Ind. Soc.*, vol. 3, no. 3, pp. 627–639, Jul. 2016, doi: 10.1016/j.exis.2016.06.005.

*Corresponding Author: **Mohan Reddy Sareddy.**

11. F. L. Forcino, L. R. Leighton, P. Twerdy, and J. F. Cahill, "Reexamining Sample Size Requirements for Multivariate, Abundance-Based Community Research: When Resources are Limited, the Research Does Not Have to Be," *PLOS ONE*, vol. 10, no. 6, p. e0128379, Jun. 2015, doi: 10.1371/journal.pone.0128379.
12. C. G. Bampis, Z. Li, I. Katsavounidis, and A. C. Bovik, "Recurrent and Dynamic Models for Predicting Streaming Video Quality of Experience," *IEEE Trans. Image Process.*, vol. 27, no. 7, pp. 3316–3331, Jul. 2018, doi: 10.1109/TIP.2018.2815842.
13. P. H. Hien and T. T. Tuan, "Strengthening the link between organizational culture and employee loyalty: Exploring the mediating effects of employee trust and job satisfaction," *Glob. Bus. Finance Rev. GBFR*, vol. 28, no. 3, pp. 68–84, 2023, doi: 10.17549/gbfr.2023.28.3.68.
14. C. Kerdpitak and K. Jermsittiparsert, "The Influence of Organizational Culture, Employee Commitment and Organization Citizen Behaviour on the HRM Practices: Mediating Role of Perceived Organization Support," vol. 11, no. 1, 2020.
15. M. Abbas, "THE EFFECT OF ORGANIZATIONAL CULTURE AND LEADERSHIP STYLE TOWARDS EMPLOYEE ENGAGEMENT AND THEIR IMPACT TOWARDS EMPLOYEE LOYALTY," vol. 07, no. 02, 2017.
16. N. S. Rachmaliya and H. Efendy, "Analysis of Employee Performance, Organization Culture, Work Satisfaction and Organization Commitment," *Hum. Resour. Res.*, vol. 1, no. 1, p. 41, Sep. 2017, doi: 10.5296/hrr.v1i1.11740.
17. S. Karim and M. D. and Qamruzzaman, "Corporate culture, management commitment, and HRM effect on operation performance: The mediating role of just-in-time," *Cogent Bus. Manag.*, vol. 7, no. 1, p. 1786316, Jan. 2020, doi: 10.1080/23311975.2020.1786316.
18. G. A. R. Raheem Ali Alsheikh, E. A. Theeb Alnawafleh, M. S. B. Abd Halim, and A. M. B. A. A Tambi, "The Impact of Human Resource Management Practices, Organizational Culture, Motivation and Knowledge Management on Job Performance with Leadership Style as Moderating Variable in the Jordanian Commercial Banks Sector," *J. Rev. Glob. Econ.*, vol. 6, pp. 477–488, Jan. 2018, doi: 10.6000/1929-7092.2017.06.48.
19. M. Abdullahi, K. Raman, and S. Solarin, "Effect of Organizational Culture on Employee Performance: A Mediating Role of Employee Engagement in Malaysia Educational Sector," *Int. J. Supply Oper. Manag.*, vol. 8, no. 3, Aug. 2021, doi: 10.22034/IJSOM.2021.3.1.
20. S. Bahri, M. Ramly, A. Gani, and S. Sukmawati, "Organizational Commitment and Civil Servants Performance: The Contribution of Intelligence, Local Wisdom and Organizational Culture," *Eur. J. Bus. Manag. Res.*, vol. 6, no. 1, Art. no. 1, Feb. 2021, doi: 10.24018/ejbmr.2021.6.1.720.
21. Z. Inanlou and J.-Y. Ahn, "The Effect Of Organizational Culture On Employee Commitment: A Mediating Role Of Human Resource Development In Korean Firms," *J. Appl. Bus. Res. JABR*, vol. 33, no. 1, pp. 87–94, Dec. 2016, doi: 10.19030/jabr.v33i1.9869.
22. B. J. A. Ali, "ACCOUNTING INFORMATION SYSTEM (AIS) AND ORGANIZATIONAL PERFORMANCE: MODERATING EFFECT OF ORGANIZATIONAL CULTURE," vol. IV, no. 4, 2016.
23. M. Fathurahman, "Path Analysis Between Job Satisfaction And Loyalty With Work Environment And Culture As Explanatory Variables," vol. 1, no. 1, 2022.
24. A. Aktar and F. Pangil, "The Relationship between Human Resource Management Practices and Employee Engagement: the Moderating Role of Organizational Culture," *Empl. Engagem.*.
25. F. Bagis, U. I. Kusumo, and A. Hidayah, "JOB SATISFACTION AS A MEDIATION VARIABLES ON THE EFFECT OF ORGANIZATIONAL CULTURE AND ORGANIZATIONAL COMMITMENT TO EMPLOYEE PERFORMANCE | International Journal of Economics, Business and Accounting Research (IJEBAR)."
26. T. Wahjoedi, "The effect of organizational culture on employee performance mediated by job satisfaction and work motivation: Evident from SMEs in Indonesia," *Eff. Organ. Cult. Empl. Perform. Mediat. Job Satisf. Work Motiv. Evident SMEs Indones.*, vol. 11, no. 7, Art. no. 7, 2021.
27. F. Pasaribu, "The Situational Leadership Behavior, Organizational Culture and Human Resources Management Strategy in Increasing Productivity of Private Training Institutions," *Inf. Manag. Bus. Rev.*, vol. 7, no. 3, pp. 65–79, Jun. 2015, doi: 10.22610/imbr.v7i3.1155.
28. T. Harrison and J. D. Bazzy, "Aligning organizational culture and strategic human resource management," *J. Manag. Dev.*, vol. 36, no. 10, pp. 1260–1269, Nov. 2017, doi: 10.1108/JMD-12-2016-0335.
29. K. U. S. Somarathna, "An agent-based approach for modeling and simulation of human resource management as a complex system: Management strategy evaluation," *Simul. Model. Pract. Theory*, vol. 104, p. 102118, Nov. 2020, doi: 10.1016/j.simpat.2020.102118.
30. S. K. Parker and G. Grote, "Automation, Algorithms, and Beyond: Why Work Design Matters More Than Ever in a Digital World - Parker

*Corresponding Author: **Mohan Reddy Sareddy.**

- 2022 - Applied Psychology - Wiley Online Library."