Journal of Information Systems Engineering and Management
2025, 10(32s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Impact of Artificial Intelligence for Humanizing Retention Approach

Dr. Sakthi Kumaresh[1] , Dr. Latha D S[2], Huang Tianjiao[3], Dr. P. Vasantha Kumar[4]
[1] *M.O.P. Vaishnav College for Women (Autonomous), Chennai-34*
[2] *M.O.P. Vaishnav College for Women (Autonomous), Chennai-34*
[3] *Faculty of Education, Shinawatra University*
[4] *Assistant Professor (Selection Grade), School of Excellence in Law, The Tamil Nadu Dr. Ambedkar Law University, Taramani, Chennai – 600113, Tamil Nadu ,India.*

ARTICLE INFO

Received: 26 Dec 2024

Revised: 14 Feb 2025

Accepted: 22 Feb 2025

ABSTRACT

In modern digital era where everyone is battling for the same goal,managing star performers ispivotal to business milestone. The organization is facing acute challenges in maintaining member of workforce,the top management started relying on Artificial Intelligence (AI) to metamorphose human resource management and develop more effective retention plan. AI's potential to investigate the extensive information warrant HR teams to gain deep understanding into work place dynamics, preferences, and job satisfaction, facilitating the customization of retention process.Predictive analytics in AI has become a radical changein the workforceretention strategies, contributing to the business to visualize the talent in advance of any prospective challenges proliferate. Synchronizing statistical investigation and machine learning, predictive analytics determines the strategy that can predict the possibility of losing out an employee. This dynamic techniquemarks a notable shift from conventional receptive mechanism to cope the attrition. Instead of waiting for employees to resign or disengage, companies can be proactive to create a more supportive and engaging work environment.

This research aims to works ontwo-fold. Predictive analysis is done on both primary and secondary data. Key variables such as job satisfaction, engagement levels, and personal circumstances are analyzed on primary data to generate actionable insights. Sentiment analysis is carried out to analyze the employee feedback on the current work environment. Machine learning algorithms such as KNN & SVM are used on large employee dataset from Kaggle, andemployees who are likely to leave organization and the reason for their attrition are predicted. Both algorithms are implemented in python and it is found that accuracy of SVM algorithm is better than KNN. The Structural Equation Model was used to test the relationship between Employee Perception and its effect on Job satisfaction and Retention of employees and found that the fit indices fit the model well.From the Multiple Regression it was found that Job satisfaction was positively associated with employee retention.

Keywords: Artificial Intelligence, Predictive analytics, Machine Learning, Retention, Job satisfaction, Employee Engagement , Perception.

INTRODUCTION

In today's scenario, organizations experience extensive, challenges in maintaining crucial talent. Customary retention strategies are based on training and one model fitting all types of employees. Take good care of competent personnel is becoming more demanding for companies in today's robust yard. Due to artificial intelligence, there is a shift in the arena, pushing the businesses the potential to generate the information, personify the retention plans considering individual choice, work behavior, and path ways.

The adoption of Artificial Intelligence (AI) in Human Resource Management (HRM) has transformed talent retention and development strategies. The capability of AI in automating the processes, foresee the patterns, and personalize employee experiences,AI has become a foremost tool for the business advancing toimprove employee involvement,upholding,and employeeprogression. Employing predictive analytics supported by machine learning process and natural language processing (NLP), AI assist HR desk to single out the risk of attrition, enhancing employeemorale, and advance satisfaction in the job.

This research paper explains how AI-driven predictive analytics helps in framing an effective retention plan. Merging of AI and Machine Learning (ML), organizations can envision employeeleaving,modify careergrowth plans, and bring about enterprising intrusion for the employees likely to leave the organization. Newest AI models, along with Support Vector Machines, clustering algorithms, and sentiment analysis through NLP, are carried out in this research to explore employee retention.

Further this study portrays the present-day practice, advantages and threats of AI in Human Resource Management demonstrating the working of predictive analytics detecting behavioral patterns understanding the future turnover risk.

1.1 Objective

❖ Predictive analysis is done on primary data to generate insights and allow HR team to intervene with early personalized retention efforts

❖ Sentiment analysis is carried out on employee feedback to understand the rate of dissatisfaction

❖ Machine learning algorithms are used for employee attrition prediction to transform HR practices from reactive to strategic engagement.

1.2 Conceptual Framework

The research work aims to understand the employee attrition using primary and secondary data. A Questionnaire containing information pertaining to Job satisfaction, Work life balance, Job security, work environment, Retention were collected from 50 employees from service and Manufacturing sectorand the reasons for attrition are found out using open ended question. To predict the employee attrition across various department, Employee attrition dataset from Kaggle.com is taken for analysis. Machine learning algorithms like KNN and SVM algorithms are implemented for employee attrition prediction. In order to understand perception from the employees, sentiment analysis is carried out on feedback data that is collected from questionnaire. Based on the results of the analysis, personalized retention strategies are framed in order to make proactive decision to retain employees.The entire process is depicted in the Fig.1

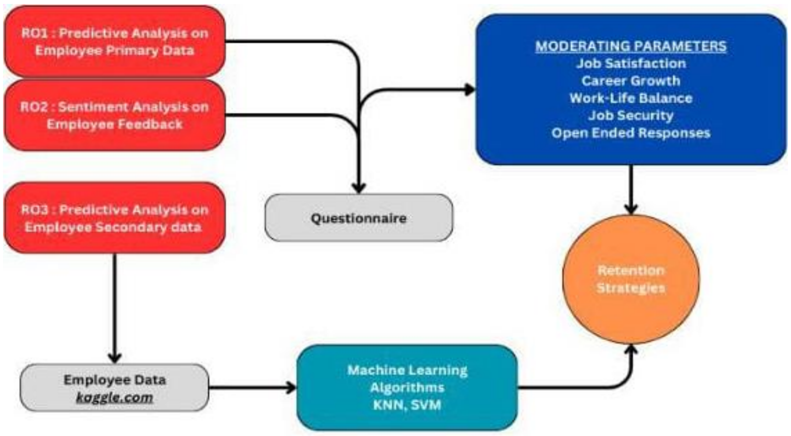


Fig 1: Conceptual Framework

1.3 Statement of the Problem

Personnel turnover is a serious battle forestablishments,directingto enhancedHiring, Learning and development costs, leading to low productivity, and low morale among the existingstaff. In spite of theprelavance of numerous retention strategies, organizations fightto effectively forecast and administer employee turnover. The collaboration of AI-driven predictive analytics offers a valuable solution to predict employee retention; however, itsadoption in HRM remains unnoticed and requires further investigation to understand itsfull impact on retention strategies.

LITERATURE REVIEW

❖ Sunil Basnet (2024) in his article "The Impact of AI-Driven Predictive Analytics on Employee Retention Strategies" provides a foundation for understanding the transformative potential of AI and ML in HRM, particularly in terms of enhancing employee retention strategies.

❖ Adjei et al. (2022) found that strategy to make the employee stay in the organization is to reward employees for their effective job performance, strengthening positive industrial relations, and maintain conservative and healthy work environment.

❖ Rožman et al. (2022) explained that Merging AI into talent management models can positively the leverage the acquisition and retention of potential workforce, enhance employee engagement, and increase the overall organization performance

❖ Noordin et al. (2021) found that job nested significantly affects employee retention, suggesting that employees who feel more involved totheir work and community are proneless to leave

❖ Dubisetty & K (2021) showed that effective HRM practices can reduce employee turnover and increase retention rates within organizations.

❖ Nishad Nawaz et al (2024) did their study on seven potential outcomes and did causal relationship between these variables. The research work revealed that accuracy, automation and real time saving has greater impact on outcome variable time and real time experience. The research sheds lights on the promising outcome using AI in HRM

❖ Ali Raza (2022) did predictive analytics using four machine learning algorithms and their study revealed that Extra tree classifier (ETC) achieved higher accuracy. Factors like Monthly income, job level, hourly rate and age are the key parameters for employee attrition according to their study

❖ Kiran Kumar Reddy Yanamala (2024) found that Leveraging AI for employee attrition prediction using logistic regression allowed for early identification of employees who are at the risk of leaving the organization, which enabled organizations to take timely decisions

❖ Salah AI-Darraji et al (2021) employed machine learning algorithm to predict attrition. Results revealed that overtime hours, job level and monthly income are the reasons for employee attrition. Their models were tested using accuracy, precision, recall and f-measure

❖ Qiong Jia et al (2018) suggested methods to leverage AI in every aspect of Human resource management. Authors came out with AI HRM that provides suggestions and decision to HRM team.

RESEARCH METHODOLOGY

1.1 Research Design: This study employed both qualitative and quantitative research design using questionnaire to explore the use of AI, ML and Predictive analysis in HRM to enhance employee retention.

1.2 Data Collection: The Primary data was collected by circulating questionnaire through Google form to the employees working in manufacturing and service sector. Secondary data was analyzed through Kaggle.com

1.3 Steps for Data Collection

1. Literature Review: This study comprehensively reviewed the literature on the use of AI, ML in HRM, employee retention strategies, and predictive analytics.

2. Data Analysis:The Primary data was analyzed through Structural Equation Model and Multiple Regression and secondary data was analyzed through Machine learning algorithms like KNN and SVM. Sentiment analysis using DistilBert is carried out to analyze employee feedback data. The insights from the analysis were synthesized to draw conclusions and make recommendations.

RESULTS AND DISCUSSIONS

4.1 Predictive Analytics for Employee Retention

Steps for predictive analytics for employee retention using Machine Learning algorithm such as KNN & SVM.

1. **Import modules**: Import modules for data manipulation and visualization, such as pandas, NumPy, matplotlib, and seaborn
2. **Read data**: Read the analytics file and store the data in a dataframe
3. **Data Preprocessing& Cleansing: C**heck the data set for missing values
4. **Analyze data**: Use machine learning algorithms and statistical tools to analyze the data
5. **Build prediction models**: Use the analyzed data to build models that predict employee behavior

4.2 Applying K-Means Clustering

The K-Means algorithm is applied with n_clusters=2, categorizing employees into two groups: **Cluster 0 (Low Attrition Risk) and Cluster 1 (High Attrition Risk).** Each employee is assigned a cluster based on patterns in their data. This scatter plot in figure 2 represents employees in a 2D space after PCA transformation.

The color-coded clusters show two groups:

❖ **Blue (Cluster 0): Low Attrition Risk**

- **Red (Cluster 1): High Attrition Risk**

This visualization helps HR professionals identify at-risk employees based on their work and demographic attributes.

4.3Employee Feedback Analysis using NLP

Sentiment analysis is a critical tool for businesses, researchers, and organizations to understand public opinion and customer feedback. To analyse employee feedback from primary data, this research work employs DistilBERT-based sentiment analysis model. This model can classify text into positive, Negative or Neutral sentiments. DistilBERT model is employed in this research work to analyse the employee's sentiments towards the job and the job environment. The following steps are involved in DistilBERT-based sentiment analysis model.

Algorithmic Steps in Sentiment Analysis

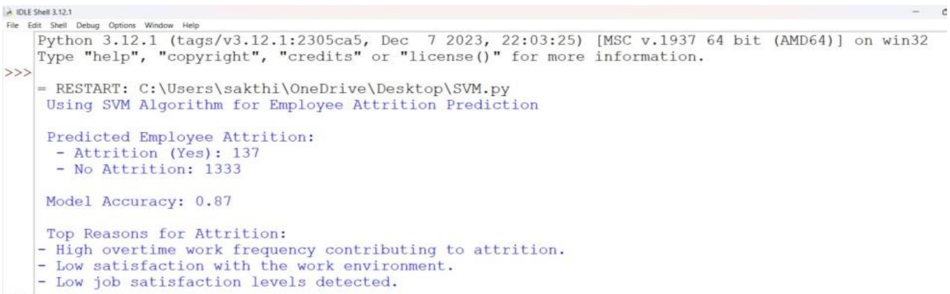
Step 1: Necessary Libraries files to be imported
Step 2: Load Pre trained data
Step 3: Sentiment Labels like Positive, Negative and Neutral are defined
Step 4: Sentiment Prediction for feedback data
Step 5: Identify Feedback Results through Manual Input and store in CSV
Step 6: Process CSV file for Sentiment Analysis

Sample Data for Sentiment Analysis

Sample Code:

```
model_path = "saved_model"
tokenizer = DistilBertTokenizer.from_pretrained(model_path)
model =
DistilBertForSequenceClassification.from_pretrained(model_path)
model.eval()
sentiment_labels = {0: "Positive", 1: "Negative", 2: "Neutral"}
def predit_sentiment(text):
   inputs = tokenizer(text, return_tensors="pt", truncation=True,
padding="max_length", max_length=128)
   with torch.no_grad():
      outputs = model(**inputs)
   logits = outputs.logits
   probs = F.softmax(logits, dim=1)
   confidence, predicted_class = torch.max(probs, dim=1)
   sentiment = sentiment_labels[predicted_class.item()]
   confidence_score = int(confidence.item() * 100)
   return sentiment, confidence_score
```

Screenshot: Employee Attrition Prediction using SVM Algorithm


```
IDLE Shell 3.12.1
File Edit Shell Debug Options Window Help
Python 3.12.1 (tags/v3.12.1:2305ca5, Dec  7 2023, 22:03:25) [MSC v.1937 64 bit (AMD64)] on win32
Type "help", "copyright", "credits" or "license()" for more information.
>>>
= RESTART: C:\Users\sakthi\OneDrive\Desktop\SVM.py
 Using SVM Algorithm for Employee Attrition Prediction

 Predicted Employee Attrition:
  - Attrition (Yes): 137
  - No Attrition: 1333

 Model Accuracy: 0.87

 Top Reasons for Attrition:
- High overtime work frequency contributing to attrition.
- Low satisfaction with the work environment.
- Low job satisfaction levels detected.
```

Table 1: Analysis results of Machine Learning Algorithms

Algorithm Used	Precision	Recall	f-score	Accuracy	Attrition - Yes	Attrition - No	Reasons for Attrition
SVM	0.66	0,40	0.50	0.87	137	1333	High Overtime work Low Job Satisfaction level detected
KNN	0.30	0.06	0.11	0,83	74	1396	Poor Work life balance Fewer total working years compared to average Low satisfaction with work environment

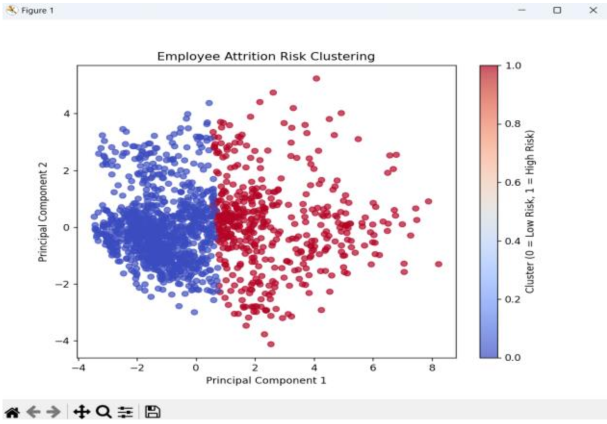


Fig 2: Employee Attrition Risk clustering using K means clustering

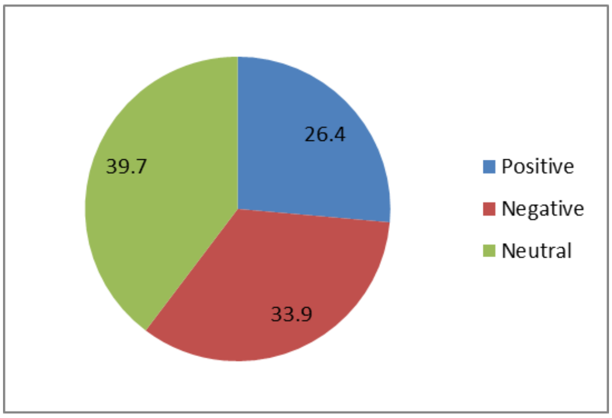


Fig 3: Sentiment Analysis on Employee feedback

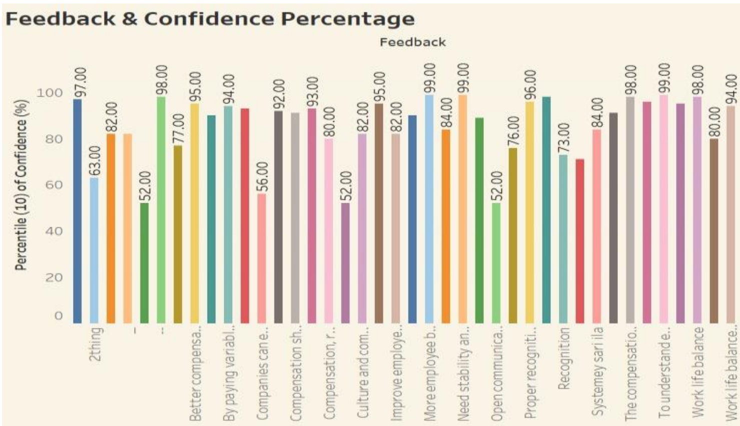


Fig 4: DistilBert Confidence Level in Prediction

Interpretation

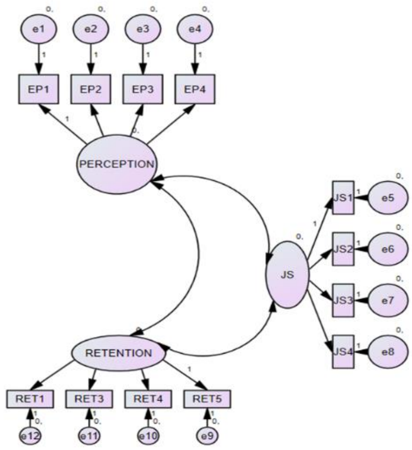
Employee attrition dataset from kaggle.com is used as secondary source of data to predict employee attrition. The dataset contains 1481 data with more than 20 parameters. Data cleansing is done on the dataset. SVM & KNN algorithms are implemented in *python*. The analysis result of SVM is shown in screenshot 1. The performance of ML algorithms indicates that SVM has more accuracy than KNN, both algorithms indicates the factors influencing attrition, which enables HR team to take proactive action. Analysis results are shown in Table 1. K means clustering algorithm is implemented in Employee attrition dataset to understand the employee attrition. Figure 2 depicts implementation result of the algorithm. Sentiment analysis is carried out on primary data to know the employee feedback. Results reveal that 26% have shown positive responses while 39.7% and 33.9% have shown negative and neutral responses (Fig 3.), hence proactive decision and personalised retention strategies can be adopted to make this neutral & negative response into a positive one.

AI BASED RETENTION STRATEGIES

Reason for Employee Attrition	**AI Based Retention Strategies**	**AI Tools Recommended**
High Overtime work & Less Pay	**AI-Enabled Workload Optimization** ✓ Implement an AI-based workload balancer that tracks employee work hours and redistributes tasks to prevent burnout. ✓ Use predictive analytics to forecast peak work periods and recommend proactive hiring or task automation. ✓ Deploy an AI-powered chatbot to remind managers when employees exceed healthy working hours	Workforce Analytics (e.g., SAP SuccessFactors, Workday) Task Automation (e.g., RPA, Zapier, UIPath)
Low Job Satisfaction level	**AI-Driven Employee Sentiment Analysis** ✓ Use NLP-based AI models to analyze emails, Slack messages, and surveys for early signs of dissatisfaction. ✓ Implement AI-powered pulse surveys to continuously gather feedback and suggest personalized engagement plans. ✓ Provide AI-driven career path recommendations to keep employees motivated with internal growth opportunities.	Sentiment Analysis (e.g., IBM Watson, MonkeyLearn) HR Chatbots for Career Growth (e.g., Pymetrics, HireVue)
Poor Work life balance	**AI-Backed Work-Life Balance Monitoring** ✓ **Use AI-powered scheduling tools that optimize work hours and suggest flexible shifts based on productivity patterns.** ✓ **Deploy mental wellness chatbots that provide stress-relief tips and meditation exercises.**	AI-Backed Work-Life Balance Monitoring
Fewer total working years compared to average	**AI-Based Career Progression Tracking** ✓ **Implement AI-driven career growth dashboards that provide insights on skill development and promotion timelines.** ✓ **Use AI mentors that recommend training courses based on performance analytics.** ✓ **Deploy predictive retention AI to flag employees at risk of leaving and offer tailored incentives.**	Learning & Development AI (e.g., Coursera for Business, LinkedIn Learning AI) Predictive Retention Models (e.g., Eightfold.ai)
Low satisfaction with work environment	**AI-Powered Workplace Satisfaction Enhancements** ✓ **Utilize AI-based surveys to identify workplace satisfaction drivers and suggest targeted improvements.** ✓ **Implement smart office solutions, such as AI-driven noise control and ergonomic workstation recommendations.**	Employee Engagement AI (e.g., Culture Amp, TINYpulse) Smart Office AI (e.g., Google Nest for workplace comfort)

4.4 Structural Equation Model

The Relationship Between Employee Perception And Its Effect On Job Satisfaction And Retention Of Employees



MODEL FIT INDICES FOR THE STRUCTURAL MODEL

CMIN	Df	CCMIN/Df	AGFI	NFI	CFI	RMSEA
2.846	1	2.846	0.96	0.969	0.910	0.669

INTERPRETATION

To test the fit of the data to the model, multiple fit indices have to be calculated. The goodness of fit indices like Adjusted goodness of fit (AGFI) should be greater than or equal to 0.95, and Root mean square of approximation (RMSEA) should be between 0.6 and 0.8. Comparative fit indices like the Normed fit index (NFI) should be greater than or equal to 0.95, and the Tucker Lewis index (TLI) should be greater than or equal to 0.95. The fit indices show that the data fit the model well.

PATH ESTIMATES FOR THE SAMPLE

Constructsandmeasures	Coefficients Standardized	Coefficients Unstandardized	S.E.	P
Perception<---Job satisfaction	0.372	0.354	0.048	***
Feeling secured<---Likely Stay in organization	0.056	0.055	0.05	0.272
Feeling engaged<--- Job clarity	-0.155	-0.364	0.12	0.002
Job satisfaction<--- Retention	0.383	0.392	0.051	***
Jobsatisfaction<--- employee diversity	0.201	0.268	0.066	***
Retention<--- Perception	0.225	0.33	0.072	***
Team collaboration<--- work life balance	0.27	0.264	0.048	***
Jobclarity<---job satisfaction	0.425	0.541	0.063	***
Retention<---job clarity	0.445	0.624	0.068	***
Job satisfaction<--- perception	-0.092	-0.092	0.047	0.047
Jobsatisfaction<---team collaboration	-0.162	-0.212	0.061	***
Work life balance<--- retention	-0.06	-0.086	0.066	0.192
Team collaboration<--- Job clarity	-0.054	-0.131	0.113	0.247
Jobsatisfaction<---work life balance	-0.047	-0.149	0.147	0.311

INTERPRETATION

The model consists of one exogenous variable (perception), two covariates (job satisfaction), and endogenous variable (retention).Perceptionhasapositive and significant direct impact on job satisfaction ($\beta = 0.35$, $p < 0.00$), job satisfaction($\beta = 0.42$, $p < 0.00$), retention ($\beta= 0.27$, $p < 0.00$) <0.00).Theresultsshowthatthereisasignificantindirecteffectofperception onjobsatisfaction(β=0.09,p<0.00),job satisfaction(β=0.14,p<0.00) and employee retention($\beta = 0.12$, p<0.00). Hence,the SEM Modelshowsthatthedatalargelysupportshypothesesthat have been proposed in the research.

4.5 MULTIPLE REGRESSION

Regressionfor Job Satisfaction on Employee Retention

Independentvariable	**Dependentvariable: Job Satisfaction**	
	Step1	**Step2**
Block1		
EMPLOYEE ENGAGEMENT	-0.16**	-0.15**
PERCEPTION	-0.06	-0.07
Block2		
EMPLOYEE RETENTION		0.50**
Modelstatistic		
R^2	0.034	0.28
AdjustedR^2	0.03	0.277
Model$F$	5.8**	43.21**
ChangeinR^2		0.25
Fforchange inR^2		113.99**

INTERPRETATION

Employee engagement and perception were entered as control variables in the first step, and in the second step, job satisfaction was regressed on the variable employee retention. The results show that employee retention explains 27% of the variance in job satisfaction (Model F = 43.21, p < 0.001). Job satisfaction was positively associated with employee retention (β = 0.50, p<0.001)

5.RECOMMENDATIONS:

- The organizations should provide appropriate training and development in the areas of power BI, AI tools used for the various HR policies.
- Personalized flexi working system should be provided to the employees to balance their work and life
- The organization should foster inclusion mutual respect and recognition.
- the work environment should be toxic free ,providing security and focusing on the well being of the employees.

CONCLUSION

This research provides a foundation for understanding the transformative potential of AI and ML in HRM, particularly in terms of predicting employee attrition and devising retention strategies. However, the identified limitations and future research directions explain the need for ongoing investigation and adaptation to fully realize the benefits of AI-driven HR practices. By addressing these areas, future studies can contribute to more effective, ethical, and innovative HRM solutions

REFERENCES:

[1] Abba, M. and Babanmairam, M. (2021). Does learning opportunity matters in employee retention? Journal of Humanities Arts and Social Science, 5(2), 231-248. https://doi.org/10.26855/jhass.2021.07.007

[2] Adjei, B. F., Boateng, V., Anim, J., Agyemang, O. O., & Buabeng, B. (2022). Employee satisfaction and retention of Stanbic Bank head office in Accra, Ghana. Journal of Corporate Finance Management and Banking System, 22, 11-21.

[3] Agnihotri, A. (2023). Artificial intelligence shaping talent intelligence and talent acquisition for smart employee management. Eai Endorsed Transactions on Internet of Things, 10. https://doi.org/10.4108/eetiot.4642.

[4] Ahad, A., Khan, M., & Rahman, M. (2020). Hr retention strategies for enhanced job satisfaction in a highly competitive job market: a study with private banking sector in bangladesh. International Journal of Social Sciences Perspectives, 6(1), 53-58. https://doi.org/10.33094/7.2017.2020.61.53.5

[5] Antony, D. (2023). Disentangling the relationships between talent management, organizational commitment and turnover intention: evidence from higher educational institutions in india. Global Business and Organizational Excellence, 43(2), 176-201. https://doi.org/10.1002/joe.22231

[6] Avrahami, D., Pessach, D., Singer, G., & Ben- Gal, H. (2022). A human resources analytics and machine-learning examination of turnover: implications for theory and practice. International Journal of Manpower, 43(6), 1405-1424. https://doi.org/10.1108/ijm-12- 2020-0548.

[7] Basnet, S. (2024). Navigating the ethical landscape: considerations in implementing AIML systems in human resources. International Journal of Research Publication and Reviews, 5(3), 3436-3447. https://doi.org/10.55248/gengpi.5.0324.0755

[8] Ersoy, A. and Ehtíyar, R. (2023). The impact of artificial intelligence on hospitality employees' work outcomes. Advances in Hospitality and Tourism Research (Ahtr), 11(4), 505-526. https://doi.org/10.30519/ahtr.1264966

[9] IBM. (2022). IBM's Predictive Attrition Program Helps Retain Employees [Case Study]. Retrieved from https://www.ibm.com/case-studies/ibmpredictive-attrition-program

[10] Masood, D. (2024). Strategies for employee retention in high turnover sectors: an empirical investigation. International Journal of Research in Human Resource Management, 6(1), 33-41. https://doi.org/10.33545/26633213.2024.v6.i1 a.167.

[11] Nishad Nawaz a, Hemalatha Arunachalam b, Barani Kumari Pathi c, Vijayakumar Gajenderan d (2024) The adoption of artificial intelligence in human resources management practices., International Journal of Information Management Data Insights, Available online 20 Volume 4, Issue 1, January 2024, https://doi.org/10.1016/j.jjimei.2023.100208

[12] Ali Raza 1 , Kashif Munir 2, Mubarak Almutairi 3,, Faizan Younas 1 and Mian Muhammad Sadiq Fareed (2022) Predicting Employee Attrition Using Machine Learning Approaches, Appl. Sci. 2022, 12, 6424. https://doi.org/10.3390/ app12136424

[13] Kiran Kumar Reddy Yanamala (2024) Artificial Intelligence in Talent Development for Proactive Retention Strategies, Journal of Advanced Computing Systems (JACS), Vol. 4(8), pp. 13-21, August 2024, www.scipublication.com.

[14] Salah Al-Darraji 1, , Dhafer G. Honi, Francesca Fallucchi , Ayad I. Abdulsada 1 , Romeo Giuliano and Husam A. Abdulmalik, Employee Attrition Prediction Using Deep Neural Networks, Computers, 2021, 10, 141. https://doi.org/ 10.3390/computers10110141

[15] Qiong Jia., Guo Y., Li R., Li Y.R., & Chen Y.W. (2018). A conceptual artificial intelligence application framework in human resource management. In Proceedings of The 18th International Conference on Electronic Business (pp. 106- 114). ICEB, Guilin, China, December 2-6.