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Human Resource Analytics and Employee Performance: A Data-Driven Approach to Talent Management

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ABSTRACT

The study explores the predictive capability of Human Resource Analytics (HR analytics) on employee performance through a data-driven approach to human resource management. The study uses a data set of 500 employee records to investigate the associations between demographic, job-related, and behavioral factors with employee performance, as measured by performance ratings. The study used a quantitative and exploratory research approach, which involved descriptive statistics, correlation analysis and multiple linear regression to determine the significant predictors and the effectiveness of the model. Results show that employee performance is centred at moderate levels, with low correlations found between performance and variables like work-life balance, salary, overtime, and age. The regression model showed weak predictive ability, with low explanatory power and negative R^2 values, suggesting that the HR variables considered are not sufficient to predict employee performance. These findings suggest the multifaceted nature of performance and the impact of other psychological, organisational and contextual factors not included in the data. Notwithstanding these limitations, the research highlights the potential of HR analytics to support talent management decisions. It shows how analytics can offer insights into workforce trends and inform HR strategies. The research adds to the body of knowledge on HR analytics by showcasing its use and limitations in predicting performance. It also highlights the importance of richer data and sophisticated analytical methods for enhancing performance prediction.

KEYWORDS: Workforce Analytics; Performance Prediction; HR Metrics; Organizational Performance; Regression Analysis

1. Introduction

Organizational success hinges on employee performance, which affects productivity, efficiency and competitiveness. In the rapidly evolving business landscape, organizations are increasingly adopting strategic human resource management to improve employee performance and drive long-term goals. Historically, human resource management has been more of an art than a science, with decisions primarily informed by intuition and management judgement; however, the increasing availability of data has seen a shift towards more scientific approaches (Margherita, 2022).

Human Resource Analytics (HR analytics) is a powerful approach that helps organizations to collect and analyse employee data to develop insights. It enables HR practitioners to shift from descriptive to predictive and prescriptive HR practices (Bibi & Ali, 2024). Research has demonstrated how HR analytics can boost employee performance, lower attrition rates and boost organisational performance by connecting human resource strategies to business objectives (Bottesch et al., 2025). Likewise, digital HR and data-driven practices have been shown to enhance performance by facilitating more effective and timely decision-making (Huynh Thi Thu et al., 2025).

The development of HR analytics is tied to the progress in information systems and workforce analytics. Previous studies have focused on the need for data to be used in HR decision-making to support strategy implementation and enhance organizational performance (Levenson, 2018). Recent research focuses on how analytics can make HR a strategic function in the organisation (Dubey, 2023). This marks a shift from traditional HR management to evidence-based talent management, where HR decisions are informed by data rather than intuition (Marler & Boudreau, 2017).

Additionally, the use of emerging technologies like artificial intelligence (AI) and digital transformation has sped up the adoption of HR analytics. AI-powered solutions allow companies to analyse vast amounts of employee data, uncover trends, and make predictions (Majumder et al., 2026). These innovations have broadened the application of HR analytics, which is now an integral part of contemporary talent management practices (O'Brien et al., 2025). While HR analytics is increasingly important, predicting employee performance remains a complex and challenging task for many organisations. Performance is affected by a myriad of demographic, behavioural and organisational factors, making it challenging to predict. Current HR practices are often based on limited data, which limits their effectiveness in predicting performance and making decisions.

Further, data-driven talent management practices are not widely adopted. Although HR analytics has received attention in both research and practice, its adoption is not uniform due to the absence of analytical skills and integration in HR systems (Ahuja et al., 2025). This suggests a need for more empirical research that shows how HR data can be effectively used for performance prediction. A further challenge is the need for predictive capabilities in HR. Companies need solutions that can predict employee performance, detect talent and aid in workforce planning. Predictive analytics has been proven to enhance employee engagement and lower attrition rate through proactive interventions (Mishra, 2024).

The research also seeks to assess the impact of HR analytics for talent management. Existing literature has shown that HR practices like employee engagement, job satisfaction and HR audits play a pivotal role in performance (Chaudary et al., 2025; Shaikh et al., 2025). The current study builds on these findings to explore how analytics practices can improve their effectiveness and inform HR decision-making.

Theoretically, the research adds to the emerging literature on HR analytics by showcasing its use in predicting performance. With the growing adoption of digital and AI-based HR practices, the use of analytics in talent management is likely to increase (Jana et al., 2023; Mwita & Kitole, 2025). Moreover, there is a need to build analytical skills among HR practitioners to use these tools effectively (McCartney et al., 2021).

To address these issues, the current research seeks to investigate the role of HR analytics in performance prediction. In particular, the study aims to examine HR-related factors impacting employee performance and to build a predictive model using these factors. Through an analysis of the association between demographic, job-related and behavioural characteristics and employee performance, the study offers insights into human resource dynamics.

2. Methodology

2.1 Research Design

This current study adopts a quantitative, data-driven, and exploratory research design to explore the predictive power of Human Resource (HR) analytics for employee performance. In an era where data is increasingly used to inform decision-making in organisations, this study takes a predictive modeling approach to explore the influence of a range of factors related to employees on performance. This design is well-suited to uncovering statistical associations between variables and to provide evidence-based insights for organizations' talent management strategies.

2.2 Dataset Description

The study employs a structured data set of 500 employee records, which represent a diverse range of departments and positions within an organisation. The dataset encompasses a wide range of data, including demographic, job-related and behavioural factors. These attributes offer a holistic view of employee characteristics and workplace environment (Sayeeduddin, 2025). The study's main objective is to predict employee performance, represented by the variable PerformanceRating. This captures the general performance of employees, and is the variable to be predicted. The dataset is a good fit for HR analytics purposes because it combines several factors related to employee performance and organisational success.

2.3 Variables Used

The dependent variable in this study is employee performance, represented by PerformanceRating. This is the variable that the research seeks to explain using a series of independent variables. Independent variables represent a variety of factors that are theoretically and practically related to performance. Age is a demographic variable that offers insights into the age distribution of the workforce, whereas department and position are organisational variables that capture the structure of the organisation. Education-related variables include education level, which can affect employee skills and abilities. Financial data is captured through monthly salary, reflecting rewards. Several work and behavioural factors are also considered, such as overtime hours, number of leaves taken, and projects handled, which represent employee participation and workload. Hours of training reflect investment in employees, and customer satisfaction measures reflect the performance from an external perspective. Moreover, years at company reflect employee tenure and work-life balance score reflects subjective well-being, which are critical factors influencing productivity. AttritionRisk is used with caution as it may be related to performance. It could be affected by performance and using it in predictions might lead to bias or data leakage, so it is used with caution.

2.4 Data Preprocessing

Prior to analysis, the dataset is preprocessed to remove noise and make it suitable for statistical modeling. Irrelevant variables, such as employee IDs and contact information, are excluded to protect privacy and eliminate model noise. The data is checked for missing data points, and techniques like imputation or removal are employed as needed. Nominal variables, such as department, position, and educational background, are encoded to convert them into numerical data for statistical analysis. Also, continuous variables are checked for scale differences, and normalization or standardization techniques are applied, if needed, to enhance model performance and consistency. These data preprocessing actions improve the validity of the analysis.

2.5 Analytical Techniques

The study employs a combination of statistical techniques to explore relationships within the dataset and to develop a predictive model. First, descriptive analysis is conducted to provide a summary of the data and to give an overview of employee characteristics, such as measures of central tendency and dispersion. Then, correlation analysis is performed to assess the relationships between independent variables and employee performance. This allows for identification of significant predictors and patterns in the data.

In order to examine the impact of a group of variables, multiple linear regression is conducted. This allows for the assessment of the effect of each variable on the dependent variable (employee performance) while considering the effects of other variables. The regression model is used for prediction and interpretation. Moreover, classification methods, such as logistic regression or decision trees, may be used for additional analysis. These methods enable the classification of employee performance into categories, offering another view of prediction.

2.6 Model Evaluation

The model's predictive performance is assessed statistically. The coefficient of determination (R^2) is used to evaluate the variability in employee performance explained by the model. The closer to 1, the better the explanation.

The significance of predictors is assessed with p-values, which indicate the likelihood that observed associations are by chance. In classification-based models, the performance of the model is measured using accuracy metrics and confusion matrices, which help determine how well the model can classify different performance categories.

When possible, cross-validation is used to validate the model's performance. This involves training the model on various parts of the data to confirm its stability and predictive power. In summary, these approaches guarantee the validity and relevance of the analyses in HR analytics.

4. Results

The sample contained 500 employees with information on demographics, employment, behaviour and performance. PerformanceRating was the dependent variable used to assess employee performance. The performance ratings distribution revealed a large proportion of employees in the middle to upper-middle performance ratings, suggesting that the sample represents a group of employees with moderate performance. Table 1 shows the descriptive statistics of the key numerical variables. This gives an insight into the age, education, salary, overtime, leaves, projects, training, customer satisfaction, year of promotion, tenure, work-life balance, and performance rating of employees.

Table 1. Descriptive Statistics of Key Numerical Variables

Variable	Count	Mean	Std. Dev.	Min	25%	50%	75%	Max
Age	500.0	40.86	12.09	21.00	30.00	42.00	52.00	60.00
EducationLevel	500.0	3.02	1.42	1.00	2.00	3.00	4.00	5.00
MonthlySalary	500.0	103678.76	46043.11	30120.00	63717.50	103331.00	145391.50	179876.00
OvertimeHoursPerMonth	500.0	20.04	11.71	0.00	10.00	20.00	30.00	40.00
LeavesTaken	500.0	13.72	9.06	0.00	6.00	13.00	21.00	30.00
ProjectsHandled	500.0	8.07	4.32	1.00	4.00	8.00	12.00	15.00
TrainingHours	500.0	43.04	22.15	5.00	23.75	44.50	62.00	80.00

CustomerSatisfaction	181.0	5.21	2.86	1.00	3.00	5.00	8.00	10.00
LastPromotionYear	500.0	2020.42	3.27	2010.00	2019.00	2021.00	2023.00	2024.00
YearsAtCompany	500.0	8.09	4.08	2.00	4.00	8.00	12.00	15.00
WorkLifeBalanceScore	500.0	3.71	2.86	-2.83	1.56	3.95	5.93	9.83
PerformanceRating	500.0	3.26	0.94	1.00	3.00	3.00	4.00	5.00

The descriptive findings revealed the average age of the employees was 40.86 years, ranging from 21 to 60 years. The average education was 3.02, and the average monthly salary was 103,678.76. The average number of overtime hours per month was 20.04, the average number of leaves was 13.72, and the average number of projects was 8.07. The average number of training hours received was 43.04. The mean customer satisfaction was 5.21, but this variable had only 181 observations, suggesting there were missing data. The mean years of service was 8.09 and the mean work-life balance was 3.71. The mean employee performance rating was 3.26, on a scale from 1 to 5. The frequency distribution of employee performance ratings is shown in Figure 1. Most of the employees are rated as 3, followed by 4. This indicates that the employee performance distribution is centred around average to above average employee performance levels.

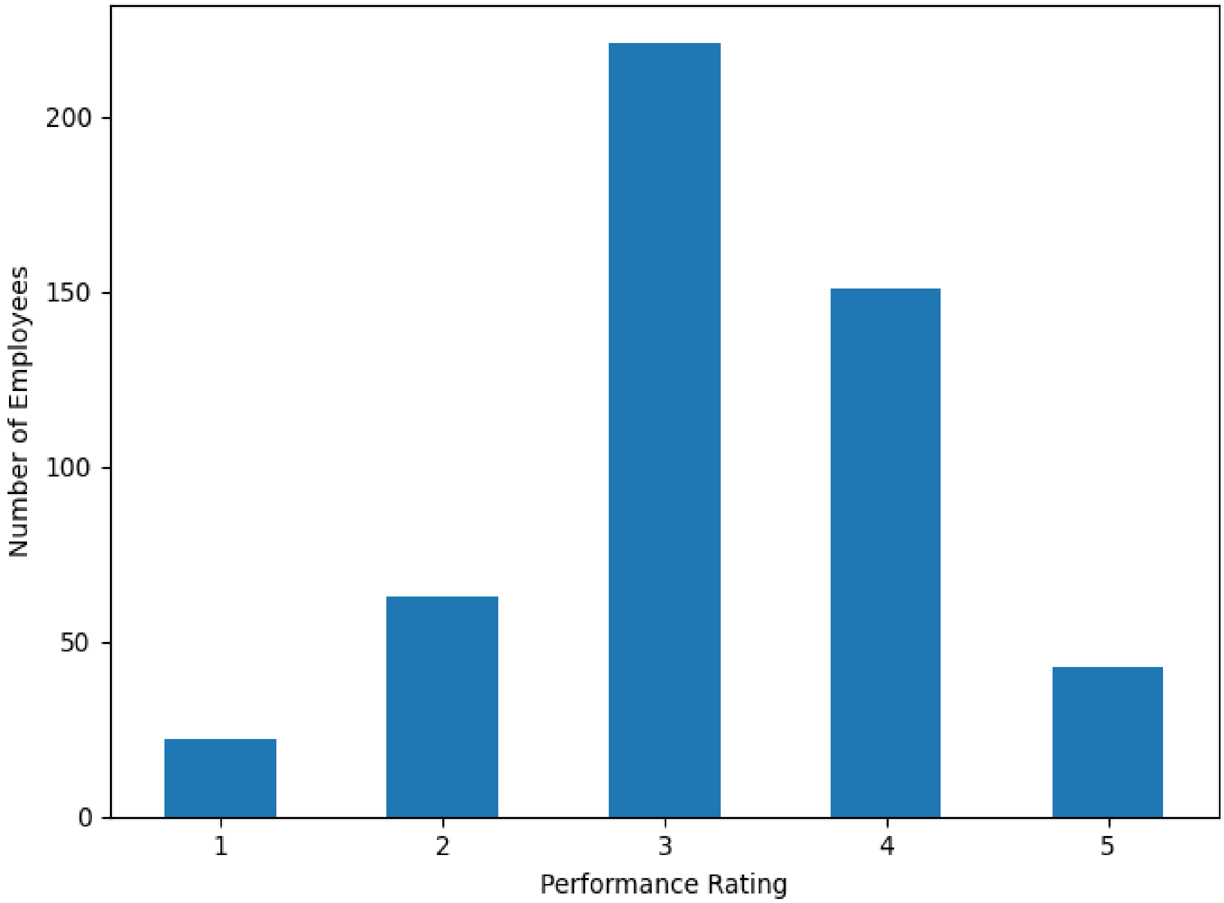

Figure 1. Distribution of Employee Performance Ratings

3.2 Correlation Results

A correlation analysis was carried out to understand the association between employee performance and selected numerical HR factors. This assisted in establishing which variables had positive and negative relationships with performance.The correlation between selected HR variables and performance is presented in Table 2. The greater the positive correlation coefficient, the stronger the positive relationship with performance; the greater the negative coefficient the stronger the negative relationship. The findings suggest that the selected numerical HR variables only had weak correlation with employee performance.

Table 2. Correlation between HR Variables and Employee Performance

Variable	Pearson Correlation with PerformanceRating	p-value

WorkLifeBalanceScore	0.083	0.0624
MonthlySalary	0.060	0.1800
EducationLevel	0.029	0.5246
LastPromotionYear	-0.002	0.9613
ProjectsHandled	-0.009	0.8378
CustomerSatisfaction	-0.009	0.9035
YearsAtCompany	-0.018	0.6896
LeavesTaken	-0.030	0.4968
TrainingHours	-0.044	0.3271
Age	-0.074	0.1003
OvertimeHoursPerMonth	-0.082	0.0656

The analysis reveals that the strongest positive correlation with performance was WorkLifeBalanceScore with a correlation coefficient of 0.083. The next strongest positive correlation was MonthlySalary with a coefficient of 0.060 and EducationLevel with a coefficient of 0.029. This shows that employees with higher work-life balance, salary and education level may have marginally higher performance.

Negative correlations were found for OvertimeHoursPerMonth with a coefficient of -0.082, Age with -0.074, TrainingHours with -0.044 and LeavesTaken with -0.030. These findings suggest that employees with higher overtime hours, age, training hours and leaves taken may have slightly lower performance ratings. But all the correlation values were weak and the p-values were above the commonly used significance level of 0.05. So, the associations need to be interpreted with caution. The correlation matrix of the selected numerical variables is shown in Figure 2. The heatmap illustrates the association between employee characteristics, behavioral indicators and performance rating. The figure also shows that most of the HR variables were weakly correlated with performance.

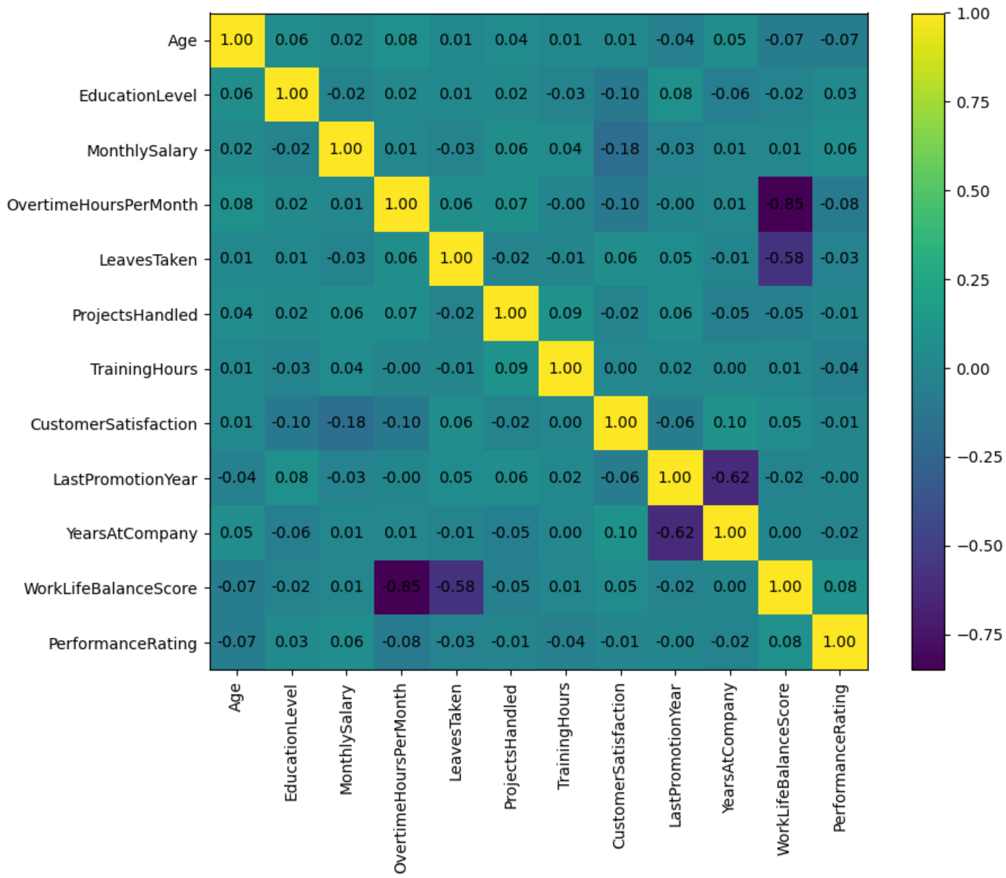

Figure 2. Correlation Matrix of HR Variables and Employee Performance

3.3 Predictive Model Results

Employee performance was predicted using multiple linear regression with a range of demographic, job-related, and behavioral HR variables. Prior to building the model, unnecessary personal information (employee ID, name, and phone) were excluded. The variable AttritionRisk was removed from the main model as it might be related to performance and may cause data leakage. The results of the multiple linear regression model are shown in Table 3. This suggests that the HR analytics variables were not sufficient to predict employee performance. While the model shows how predictive analytics can be used in HR, the model was weak in explanatory power.

Table 3. Predictive Model Evaluation Results

Model Evaluation Metric	**Value**

R^2 Score	-0.180
Mean Absolute Error	0.840
Root Mean Squared Error	1.017
5-Fold Cross-Validation Mean R^2	-0.105

The R^2 value of the predictive model was -0.180, which suggests that the model was not better than a naive predictor in explaining employee performance. The Mean Absolute Error was 0.840, which means that the model's prediction of the employee performance rating was off by about 0.84 points on average. The Root Mean Squared Error was 1.017, suggesting moderate prediction errors. The mean R^2 of 5-fold cross-validation was -0.105, which indicates poor stability of predictions across different folds of the data. Figure 3 shows predicted employee performance ratings versus the actual employee performance ratings. The closer the points are to the diagonal line the better the prediction. But note that the pattern is not diagonal, meaning that the model was not very accurate in predicting employee performance ratings.

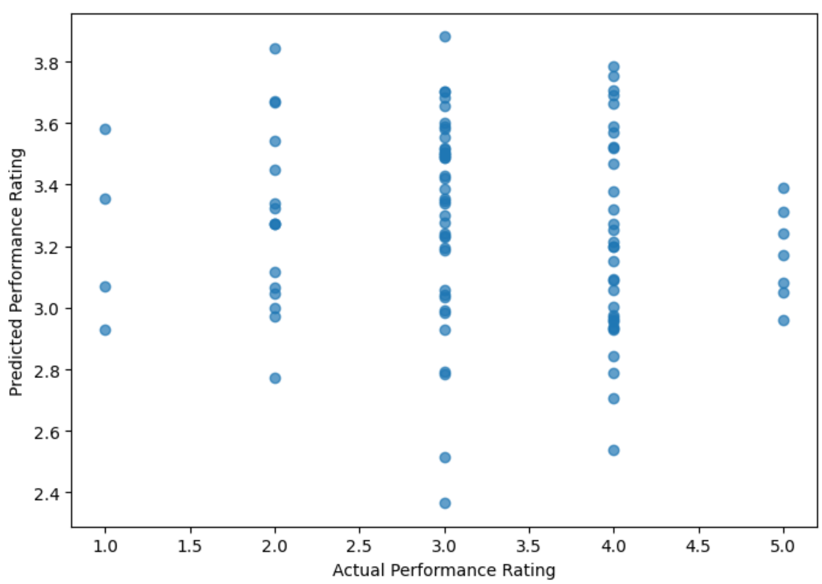

Figure 3. Actual versus Predicted Employee Performance Ratings

3.4 Predictive Model Findings

The results of the predictive model demonstrate that employee performance could not be significantly predicted with the variables in the dataset. The low correlation values and negative

R^2 indicate that the data set may not have strong predictors of employee performance. This suggests that there are other organizational, psychological and contextual factors that impact employee performance and are not captured in the dataset.

Potentially missing predictors could be employee motivation, job satisfaction, leadership quality, team support, role clarity, organisational culture, employee engagement, and manager feedback. The lack of these predictors may contribute to the low predictive power of the model.

Although this model was not able to predict employee performance, the analysis is valuable as it shows how HR analytics can be used to determine whether employee data are appropriate for predicting employee performance. The results indicate that companies should focus on enhancing HR data before using predictive models for talent management.

3.5 Key Insights

The findings have a number of implications for HR analytics and talent management. First, the performance ratings of employees were mostly centred on average and above-average levels, suggesting that the overall performance of employees was moderate. Second, work-life balance and monthly salary had the highest positive relationships with performance (albeit weak). This could indicate that well-being and salary may be related to performance.

Third, there were weak negative relationships between performance and overtime hours and age. This could suggest that high workload and age differences may have minimal impact on employee performance (but the association was weak). Finally, the regression equation was not a strong predictor, indicating that the independent variables were not enough to predict employee performance. In conclusion, the results suggest that HR analytics can be used to inform evidence-based talent management, but also that more data on employees is needed. To improve prediction, future HR analytics models need to take into account additional variables such as employee engagement, satisfaction, motivation, leadership, training and organisational culture.

4. Discussion

This study showed that the chosen HR indicators were only weakly related to employee performance and the model explaining performance outcomes had low predictability. While variables like work-life balance and salary demonstrated weak positive relationships with employee performance, overtime and age demonstrated weak negative relationships. But these associations were not statistically significant, indicating that the factors affecting employee performance are more complex and multifaceted. This study is in line with the literature, which suggests that employee performance can't be accurately predicted by individual HR variables. For example, research has demonstrated that complex analytics and AI models are needed to uncover hidden patterns in the data (Biradar et al., 2025; Sun, 2025). Likewise, research in the field of business analytics highlights that performance is determined by the interactions between organisational, behavioural and technological factors in a dynamic environment (Alyusef, 2025). Hence, the low predictive power of the model in this study is consistent with other research showing that simple HR data may not explain all the factors affecting employee performance.

The findings of this study offer valuable insights for talent management. While the predictive model was not highly accurate, it highlights the value of HR analytics for decision making. By adopting similar analytical methods, organisations can identify patterns in employee data and gain insights for workforce management.

For example, in employee development, HR analytics can be used to identify training needs and skill gaps, allowing organizations to create development initiatives. In the performance evaluation domain, analytics can help ensure more objective and fair assessments. Moreover, predictive analytics can help in predicting which employees might underperform or leave the company, enabling retention measures.

Moreover, the use of analytics in HR is also beneficial for sustainable talent management through better recruitment, retention, and workforce planning (Kapoor et al., 2025). Moreover, organizational learning theories underline the value of using data to improve long-term performance and resilience (Almunawar et al., 2025). Therefore, while HR analytics may not be highly predictive, it offers insights that can improve talent management practices. Theoretically, this research adds to the existing literature on HR analytics and data-driven HRM. The results support the perspective that HR analytics must be seen as an additional, rather than a sole approach to performance prediction. The weak predictive power found in the study reinforces the view that business outcomes are shaped by environmental factors.

The latest developments in strategic HRM highlight the importance of taking into account external shocks, like technological advancements and global crises, in workforce analysis (Minbaeva & Navrbjerg, 2023). Likewise, modern HRM models also point to the growing complexity of work settings and the need for integrated analyses (Holland et al., 2022). This study highlights the need to move beyond simple predictive models, and embrace more integrated theoretical perspectives in HR analytics research.

The study's implications for practice include the need for organisations to improve their HR data analytics and analytical skills. They should adopt sophisticated analytical tools and technologies to enhance HR analyses. The future of HR practice is in the use of data analytics, artificial intelligence (AI), and digital platforms to inform HR strategy (Stone et al., 2025). Further, studies indicate that companies need to build strong data infrastructure and maintain data quality to reap the benefits of HR analytics (Castaño et al., 2024). The research highlights the need for HR managers to integrate data analytics with human judgement. Decision-making should not be solely based on predictions, but rather analytics should be used to complement human-centred HR practices (Ayorinde & Idyorough, 2024).

The limitation is potential data bias. While the variable AttritionRisk was removed from the model to prevent data leakage, its inclusion raises the possibility of variable overlap with performance indicators. The lack of psychological and behavioural variables, such as motivation and job satisfaction, may also have impacted the poor performance prediction. Researchers should consider these limitations, and use real data to include more variables in future studies. Psychological, behavioral and other organizational variables, such as employee engagement, leadership and culture, may enhance the predictive power of HR analytics models.

Finally, studies on emerging technologies indicate that the use of advanced analytics tools can enhance the decision-making processes in organizations. In general, future research should focus on building more advanced and integrated HR analytics models that incorporate data-driven and theoretical methods to better understand and predict employee

5. Conclusion

This research explored the role of Human Resource (HR) analytics and data-driven decision-making methods to predict employee performance. The results showed that while the data set offered valuable insights into employee attributes and behaviours, the predictive model had low explanatory power. The low correlations and negative R^2 values suggest that the HR variables used in the analysis were not able to explain employee performance. Nonetheless, the study underscores the potential of HR analytics in facilitating data-driven HR decision making. The findings indicate that work-life balance and compensation might have positive, albeit weak, effects on performance, while overtime and age might have negative effects. These findings can help HR managers to make inferences about the workforce. The research highlights that performance cannot be explained by a simple set of HR factors; rather, it's a complex interplay of organisational, psychological and contextual variables. Thus, using only structured HR data may not provide good predictions. Overall, HR analytics has the potential to improve talent management, but it requires access to high-quality HR data. Future research should explore the use of new analytical methods and the inclusion of other factors, such as engagement, motivation, and culture, to enhance predictive power and inform HR strategies.

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