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PREDICTING EMPLOYEE TURNOVER FOR EFFECTIVE RETENTION USING HR ANALYTICS

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Abstract

Employee turnover continues to be one of the most critical challenges that adversely affects an organisation's performance, workforce stability, and long-term competitiveness. A high employee turnover rate increases recruitment and training costs, disrupts organisational knowledge, and negatively impacts productivity and employee morale in the work environment. Human Resource (HR) Analytics has developed as a strategic tool for identifying turnover risks and supporting evidence-based employee retention programs. This emerged as a result of the increased acceptance of data-driven decision-making. Using behavioural and organisational dimensions, this project aims to build and validate an integrated HR Analytics framework for forecasting employee turnover. Additionally, the study intends to provide successful retention methods based on the important predictors that have been identified. Using a structured questionnaire that included 52 measurement items spanning 13 latent components, primary data were obtained from 200 individuals working in manufacturing, information technology, banking, and service organisations. The research design used was a quantitative cross-sectional design. A number of statistical methods, including descriptive statistics, reliability analysis, confirmatory factor analysis (CFA), convergent and discriminant validity evaluation, and structural equation modelling (SEM), were utilised to analyse the gathered data. Based on the findings, it can be concluded that the measurement model exhibits satisfactory reliability and construct validity. The structural model reveals that employee engagement, job satisfaction, leadership support, career development, recognition, psychological safety, organisational commitment, and HR Analytics capability all positively influence employee retention. On the other hand, burnout negatively impacts retention and increases the intention to leave the organisation. The report emphasises the strategic significance of HR Analytics capacity in supporting proactive workforce management and evidence-based decision-making. The proposed framework contributes to the body of literature on human resource analytics by incorporating behavioural and organisational determinants into a comprehensive predictive model. Additionally, it provides organisations with useful insights that can be implemented to improve employee retention, decrease voluntary turnover, and enhance sustainable organisational performance through data-driven human resource management.

Keywords: Employee Turnover; Employee Retention; HR Analytics; Structural Equation Modelling (SEM); Predictive Analytics.

1. INTRODUCTION

In the modern corporate climate, which is knowledge-driven and highly competitive, human capital has emerged as one of the most valuable strategic assets for organisations operating in this new context. Organisational performance, innovation, productivity, and long-term sustainability are all greatly impacted by an organisation's capacity to attract outstanding workers, develop their potential, and retain them. However, employee turnover continues to be one of the most persistent challenges that organisations in all sectors of the economy must contend with constantly. Not only does a high turnover rate increase the costs associated with recruiting and training, but it also leads to a loss of productivity, disruption of organisational expertise, decreased employee morale, and a diminishing competitive advantage. Understanding the factors that contribute to employee turnover and implementing proactive retention tactics have thus become major goals for both researchers and human resource (HR) practitioners. Researchers are also responsible for developing these techniques.

Historically, enterprises have depended on descriptive human resource indicators, employee satisfaction surveys, and managerial intuition in order to identify individuals who were at risk of leaving the organisation. Although these methods offer valuable information about the past, they are frequently reactive and do not provide sufficient information for predicting the behaviour of employees who may leave in the future. The use of Human Resource Analytics (HR Analytics) has brought about a revolution in workforce management by enabling organisations to utilise employee data to make evidence-based decisions. The purpose of HR Analytics is to generate actionable insights regarding workforce planning, employee engagement, performance management, and talent retention. This is accomplished by integrating statistical analysis, machine learning, artificial intelligence (AI), and business intelligence approaches. As a strategic business partner, HR Analytics enables organisations to detect turnover concerns early and conduct targeted retention interventions. This is accomplished by transforming human resources from an administrative function to a strategic business partner.

Recent developments in artificial intelligence and predictive analytics have further enhanced the incorporation of human resource analytics into organisational decision-making. A number of machine learning algorithms, including Decision Trees, Random Forests, Support Vector Machines, Artificial Neural Networks, and Gradient Boosting models, have shown promising performance in predicting employee attrition. These algorithms analyse the complex interactions among demographic, behavioural, and organisational variables. Compared to traditional statistical methods, these algorithms can recognise nonlinear correlations and hidden patterns within large employee datasets, ultimately improving prediction accuracy. Furthermore, the development of Explainable Artificial Intelligence (XAI) has improved the interpretability of predictive models. This has enabled human resource professionals to gain a deeper understanding of the elements that influence decisions regarding employee turnover and to increase their trust in AI-supported decision-making.

Employee turnover is a multifaceted phenomenon that is influenced by a wide variety of organisational and psychological factors. Prior research has consistently identified employee engagement, job satisfaction, leadership support, career development opportunities, compensation, recognition, work–life balance, burnout, psychological

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safety, and organisational commitment as significant determinants of employee retention and turnover intention. These factors have been found to be associated with employee retention and turnover intention. Employees who perceive that their organisations provide supportive leadership, meaningful career advancement opportunities, equal compensation, and a psychologically safe work environment are often more loyal to their organisations and less likely to seek other employment alternatives. On the other hand, prolonged job stress, burnout, inadequate recognition, limited career progression, and poor work–life balance all contribute to higher employee intentions to leave, ultimately resulting in voluntary turnover. Despite the vast amount of material published on these factors, the interaction between these constructs within a comprehensive HR Analytics framework has not been sufficiently investigated.

The increased adoption of digital technology in human resource management has also brought to light the importance of organisational capabilities in leveraging workforce analytics. Organisations increasingly invest in HR information systems, cloud-based analytics platforms, and AI-enabled decision support systems to improve workforce planning and talent management. Nevertheless, the effectiveness of these technologies largely depends on an organisation's HR Analytics capability, which encompasses data quality, analytical competence, technological infrastructure, managerial support, and the ability to translate analytical insights into strategic actions. While HR Analytics capability has been recognised as an important organisational resource, empirical evidence examining its contribution to employee retention remains limited. Existing studies primarily emphasise algorithmic performance and predictive accuracy rather than evaluating how analytical capabilities facilitate evidence-based retention strategies.

Although the use of predictive analytics in human resource management has dramatically increased over the last decade, a number of research gaps remain. First, much of the existing literature focuses on developing predictive models using secondary organisational datasets while paying limited attention to primary data collected through validated behavioural measurement scales. Second, many studies concentrate on comparing machine learning algorithms without simultaneously examining the causal relationships among behavioural and organisational constructs. Third, limited research integrates Structural Equation Modelling (SEM) with predictive HR Analytics to combine explanatory and predictive perspectives within a unified framework. SEM provides a robust methodology for evaluating both measurement validity and causal relationships among latent constructs, thereby complementing machine learning approaches that primarily focus on prediction accuracy. Furthermore, issues relating to transparency, ethical AI, employee privacy, algorithmic bias, and responsible HR Analytics continue to receive relatively limited empirical investigation despite their increasing practical importance.

Addressing these gaps requires a comprehensive research framework that integrates behavioural science with advanced analytical techniques. The present study develops an integrated HR Analytics model by incorporating employee engagement, job satisfaction, leadership support, career development, compensation satisfaction, recognition, work–

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life balance, burnout, psychological safety, organisational commitment, and HR Analytics capability as determinants of employee retention and turnover intention. Using Structural Equation Modelling, the study simultaneously assesses the measurement model's reliability and validity and investigates the structural relationships among these constructs. This integrated approach not only supports evidence-based decision-making in human resources, but also provides deeper insights into the mechanisms through which organisational and behavioural factors influence employee turnover.

In several ways, the study contributes to both theory and practice. From a theoretical standpoint, it broadens the scope of the HR Analytics literature by incorporating well-established organisational behaviour constructs into a comprehensive predictive framework grounded in Human Capital Theory, Social Exchange Theory, Organisational Support Theory, and the Resource-Based View (RBV). Methodologically, it employs Structural Equation Modelling as a reliable analytical technique to investigate intricate interactions among multiple latent variables in human resource research. The findings are expected to be of practical assistance to human resource managers and organisational leaders in identifying significant turnover reasons, developing focused employee retention strategies, and enhancing workforce sustainability through data-driven decision-making. As organisations increasingly embrace digital transformation and AI-enabled workforce management, developing reliable and interpretable predictive models for employee retention has become essential for sustaining organisational competitiveness and long-term human capital development.

In light of this, the purpose of this study is to investigate the factors that influence employee turnover by incorporating behavioural, organisational, and analytical views into a holistic HR Analytics framework. It is anticipated that the findings will provide organisations with actionable insights to improve employee retention, optimise workforce planning, and strengthen strategic human resource management through the utilisation of evidence-based analytics.

2. REVIEW OF LITERATURE

Cheng (2020) proposed an integrated framework that uses artificial neural networks and reinforcement learning to forecast staff attrition and determine the most effective retention measures. The study demonstrated that neural network models effectively captured complex nonlinear relationships among employee characteristics, while reinforcement learning optimised HR interventions by continuously learning from organisational outcomes. The findings suggested that AI-driven adaptive retention systems outperform traditional turnover prediction models by enabling organisations to personalise employee retention initiatives and improve long-term workforce stability.

Choi et al. (2020) investigated the use of machine learning algorithms to forecast employee job involvement, which is often regarded as one of the most important factors in determining employee retention. Using organisational survey data, the researchers compared multiple classification algorithms to identify factors influencing employees' psychological attachment to their jobs. The study found that leadership quality,

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organisational support, career advancement opportunities, and employee engagement significantly influenced job involvement. The authors suggested that HR departments should integrate predictive analytics with employee development initiatives to improve workforce commitment and reduce voluntary turnover.

Tree-based machine learning models were utilised in the research conducted by El-Rayes et al. (2020) to predict employee turnover. To determine the most important factors influencing employee turnover, the researchers compared three different algorithms: Decision Trees, Random Forest, and Gradient Boosting. Several factors emerged as the most significant predictors, including employee happiness, overtime, monthly pay, years spent working for the organisation, and job role. The study demonstrated that tree-based models provide interpretable results while maintaining high prediction accuracy. The authors recommended incorporating predictive analytics into strategic HR management to improve employee retention and organisational sustainability.

To predict employee turnover, Fallucchi et al. (2020) created machine learning models that used data from the organisation's human resource department. In the study, the authors compared various classification algorithms, such as Decision Trees, Random Forest, Naïve Bayes, and Support Vector Machines, to identify individuals at risk of leaving the organisation. The findings demonstrated that machine learning models achieved high predictive accuracy while identifying important variables such as employee performance, job satisfaction, working conditions, and career development opportunities. The authors concluded that predictive analytics enables organisations to implement timely retention interventions, reduce recruitment costs, and improve workforce stability.

Bondarouk and Brewster (2021) explored the organisational adoption of HR analytics and the factors influencing successful implementation. The study identified organisational culture, leadership commitment, analytical capability, technological infrastructure, and employee acceptance as critical determinants of HR analytics adoption. The authors argued that merely investing in analytical tools is insufficient unless organisations simultaneously develop data-driven cultures and managerial competencies. The study concluded that HR analytics strengthens strategic workforce planning and supports sustainable talent management when integrated with organisational objectives and evidence-based decision-making practices.

Hamilton et al. (2021) investigated predictive analytics for employee retention using workforce data collected from various organisational settings. The study employed predictive modelling techniques to identify employees with a high probability of voluntary turnover based on demographic, behavioural, and performance-related variables. The findings indicated that predictive analytics improves the effectiveness of retention initiatives by enabling organisations to identify critical turnover risks before employee resignation. The authors concluded that predictive workforce analytics supports strategic HR planning, reduces replacement costs, and strengthens organisational productivity.

According to Levenson (2021), the strategic significance of people analytics lies in its ability to enhance workforce effectiveness and organisational decision-making. The study

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highlighted that predictive analytics allows organisations to move beyond descriptive reporting toward proactive talent management and employee retention. By integrating workforce data with business strategy, organisations can identify turnover risks, evaluate employee performance, and optimise human capital investments. The author emphasised that HR professionals require analytical competencies and business acumen to successfully translate analytical insights into effective organisational policies and retention initiatives.

Marler and Boudreau (2021) published a review of human resource analytics supported by evidence. They did this by synthesising empirical research on people analytics and strategic workforce management. According to the findings of the study, HR analytics is able to turn human resources from an administrative role into a strategic business partner by utilising data-driven decision-making and analysis. The review identified employee turnover prediction, talent acquisition, workforce optimisation, and performance management as major application areas. The authors recommended combining advanced analytics with organisational theory to improve managerial decision-making and achieve long-term employee retention.

Minbaeva (2021) investigated the strategic role that human capital analytics plays in enhancing organisational performance and decision-making about workforce management. The study proposed that HR analytics extends beyond descriptive reporting by integrating predictive and prescriptive analytics into strategic human resource management. The findings indicated that organisations adopting advanced people analytics experience improved employee performance, workforce planning, and talent retention. The author emphasised that organisational capabilities, data quality, analytical competencies, and management support are essential for realising the full value of HR analytics in strategic decision-making and sustainable competitive advantage.

Sharma and Sharma (2021) reviewed emerging trends in HR analytics and their influence on employee performance and organisational effectiveness. The study discussed the growing adoption of predictive analytics, artificial intelligence, cloud computing, and big data technologies within human resource management. The findings suggested that organisations implementing HR analytics achieve better workforce planning, enhanced employee engagement, improved performance management, and reduced turnover. The authors recommended continuous investment in analytical skills, digital HR infrastructure, and evidence-based decision-making to strengthen employee retention strategies.

Van den Heuvel and Bondarouk (2021) reviewed the evolution of people analytics and examined its contribution to strategic human resource management. The study reported that organisations increasingly employ predictive analytics, machine learning, and artificial intelligence to improve workforce planning, employee engagement, and retention. The review also emphasised that effective implementation depends on high-quality workforce data, organisational readiness, and ethical data governance. The authors recommended future research focusing on explainable analytics, interdisciplinary approaches, and stronger theoretical foundations for HR analytics adoption.

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Wu and Fukui (2021) investigated the use of human resource analytics and machine learning to predict employee turnover among professionals working in the field of community mental health. As part of their investigation into the factors that contribute to employee turnover, the researchers compared the conventional logistic regression method with various machine learning techniques, such as Random Forest and Gradient Boosting. The findings revealed that machine learning models outperformed conventional statistical methods in prediction accuracy while identifying workload, supervisory support, organisational commitment, and job satisfaction as significant turnover predictors. The study highlighted the importance of explainable predictive models for supporting evidence-based human resource decision-making and workforce retention.

Agarwal (2022) investigated the expanding function of artificial intelligence in human resource management, focusing on its applications in areas such as recruitment, employee engagement, workforce planning, performance management, and retention. The study emphasised that AI-powered HR analytics enhances organisational decision-making by enabling predictive workforce analysis and personalised employee development strategies. The findings suggested that organisations implementing AI-driven HR systems experience improved operational efficiency and employee satisfaction. Despite this, the research also found that ethical concerns, data privacy, algorithmic bias, and employee trust are significant challenges that call for appropriate governance mechanisms.

Avrahami et al. (2022) investigated employee turnover using human resource analytics and machine-learning techniques based on archival data from approximately 700,000 employees collected over ten years. The study analysed turnover antecedents such as employee competencies, organisational commitment, trust, and cultural values. The findings revealed that turnover drivers vary across employee roles, cultural backgrounds, and organisational contexts, demonstrating that predictive models should account for contextual differences rather than relying solely on generalised assumptions. The authors emphasised that integrating HR analytics with artificial intelligence provides organisations with more accurate and actionable insights for strategic workforce planning and employee retention.

Margherita (2022) conducted a comprehensive review of HR analytics research to classify major research themes and identify future directions. The study categorised HR analytics into workforce planning, recruitment, employee engagement, performance management, turnover prediction, and strategic decision support. The review highlighted the increasing incorporation of artificial intelligence, machine learning, and big data analytics into the field of human resource management. The author concluded that organisations should strengthen analytical capabilities, improve data governance, and develop evidence-based HR practices to maximise employee retention and organisational effectiveness.

The purpose of the systematic literature review that Nosratabadi et al. (2022) carried out was to investigate the application of artificial intelligence throughout the entire employee lifecycle. This included recruitment, employee performance, workforce planning, retention, and career development.

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The review demonstrated that AI technologies, particularly machine learning and predictive analytics, significantly improve HR decision-making by automating routine processes and enhancing strategic workforce management. The authors highlighted transparency, ethical considerations, data privacy, and explainable AI as major challenges that organisations must address before fully adopting AI-enabled HR analytics systems.

The authors Soares et al. (2022) carried out a comprehensive analysis of 42 empirical studies that investigated analytical methodologies in the field of human resource management. The review categorised HR analytics applications into recruitment, talent management, and employee turnover prediction. The authors observed that most studies relied on internal organisational datasets and commonly applied classification algorithms to support HR decision-making. However, they identified a shortage of real-world quantitative case studies demonstrating practical implementation. The study recommended expanding empirical research on HR analytics to improve workforce planning, talent management, and predictive retention strategies through evidence-based decision-making.

A stacking ensemble learning model was proposed by Chung et al. (2023) for forecasting employee attrition. This model was developed by integrating different machine learning algorithms to increase prediction accuracy further. In this work, ensemble techniques were used to analyse HR datasets from various organisations. Decision Trees, Random Forest, Gradient Boosting, and Support Vector Machines were compared with ensemble techniques. The effectiveness of ensemble learning in human resource analytics was demonstrated by the fact that the suggested model achieved superior predictive performance compared to individual algorithms. The study emphasised that accurate turnover prediction enables organisations to proactively implement employee retention policies and reduce recruitment and training costs.

Marler et al. (2023) reviewed recent developments in HR analytics and strategic workforce management, emphasising the transition from descriptive analytics to predictive and prescriptive decision support. The study highlighted that organisations increasingly utilise machine learning, artificial intelligence, and workforce analytics to identify employee turnover risks and optimise talent management practices. The authors concluded that HR analytics improves organisational performance by enabling evidence-based decision-making while recommending greater integration of behavioural science, explainable AI, and strategic human resource management to enhance employee retention and long-term organisational sustainability.

A systematic literature review was carried out by Al Akasheh et al. (2024) to investigate the application of machine learning techniques in employee turnover prediction. The review included 52 studies published between 2012 and 2023 and subjected to peer review processes. Based on the findings of the review, the most often utilised techniques were supervised learning algorithms, including Random Forest, Logistic Regression, Decision Trees, and Support Vector Machines.

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The factors that were shown to be the most influential predictors of employee turnover were job satisfaction, salary, age, and length of service. According to the findings of the study, machine learning considerably improves HR decision-making by enabling proactive staff retention strategies. However, the study also highlights the necessity of future research to focus on explainable artificial intelligence and more diversified organisational datasets.

Karimi and Viliyani (2024) investigated predicting employee turnover by comparing several different machine learning algorithms. These algorithms included Logistic Regression, Decision Trees, Random Forest, Support Vector Machine, and Extreme Gradient Boosting (XGBoost). For the study, HR datasets that included employee demographic, organisational, and behavioural characteristics were utilised to evaluate the performance of algorithms. In comparison to traditional statistical models, Random Forest and XGBoost demonstrated much higher classification accuracy.

The authors concluded that, with the use of predictive HR analytics, organisations can identify employees who have a high risk of leaving their positions. This enables HR managers to deploy timely retention interventions and successfully reduce employee turnover.

Ma et al. (2024) investigated the capacity of Large Language Models (LLMs) to predict employee turnover by utilising structured human resource data and textual employee information. The study compared the predicted performance of LLMs with that of typical machine learning algorithms and also evaluated LLMs' ability to explain judgments regarding employee turnover. The findings revealed that LLMs demonstrated competitive prediction accuracy while providing natural language explanations for HR professionals. However, the authors noted concerns regarding model transparency, computational requirements, and ethical issues associated with AI-driven workforce decision-making.

To boost employee retention through predictive talent management, Raza et al. (2025) evaluated the role of data-driven HR analytics. To predict employee turnover, the study utilised machine learning algorithms to analyse workforce characteristics, employee performance, compensation, and behavioural attributes.

The findings suggested that predictive analytics considerably improves workforce planning by identifying employees who are at risk of leaving before they leave. This allows for more effective workforce organisation. The authors concluded that HR analytics enables organisations to design individualised retention strategies, optimise the allocation of human resources, and improve organisational productivity through evidence-based decision-making.

In the year 2025, Talebi and colleagues presented a comprehensive assessment of 58 studies that focused on the use of machine learning techniques for the prediction of employee turnover. In the review, the authors compared several extensively utilised algorithms, including Random Forest, Support Vector Machine, Logistic Regression, Decision Tree, Neural Networks, XGBoost, and AdaBoost.

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The authors reported that Random Forest consistently demonstrated superior predictive performance, while job satisfaction, salary, age, organisational role, and tenure were the most influential determinants of turnover. The study emphasised that larger datasets improve predictive performance and recommended integrating explainable artificial intelligence with HR analytics to support transparent and reliable employee retention decision-making.

Joner and Purbaningrum (2026) conducted a comprehensive literature analysis on the applications of machine learning for predicting employee performance and reducing employee turnover. The research examined current advancements in predictive human resource analytics and evaluated several categorisation methods, such as Random Forest, Decision Trees, Artificial Neural Networks, and Gradient Boosting algorithms. The review concluded that machine learning substantially improves workforce planning and employee retention by identifying critical turnover factors such as employee engagement, organisational commitment, compensation, leadership quality, and career development opportunities. The authors recommended integrating explainable AI with HR analytics to improve managerial acceptance and practical implementation.

3. RESEARCH GAP

A review of the relevant literature indicates that significant advancements have been made in the utilisation of HR analytics, artificial intelligence, and machine learning to forecast employee turnover and support workforce management. Most research shows that predictive algorithms, including Random Forest, Decision Trees, Support Vector Machines, Neural Networks, and ensemble learning models, can achieve high prediction accuracy in identifying people at risk of leaving an organisation. Furthermore, past research has highlighted the significance of characteristics such as job satisfaction, employee engagement, leadership support, organisational commitment, salary, career growth, and work–life balance in determining the likelihood of employees leaving their current positions. However, most existing studies focus on improving predictive performance or comparing machine learning algorithms, with relatively limited emphasis on integrating behavioural, organisational, and technological variables into a comprehensive employee retention framework. Furthermore, a significant portion of the empirical evidence is drawn from secondary organisational datasets, which reduces the generalizability of the findings across a variety of business sectors and organisational settings.

Although HR analytics are becoming increasingly popular, several significant research gaps remain. Only a handful of studies have integrated Structural Equation Modelling (SEM) with advanced machine learning approaches to investigate causal linkages and prediction performance simultaneously. Similar to the previous point, the implementation of Explainable Artificial Intelligence (XAI) techniques, such as SHAP and LIME, remains limited, reducing the transparency and interpretability of predictive models for human resource professionals. The existing body of literature also provides little empirical evidence on the role of HR analytics capacity in improving employee retention through

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data-driven decision-making. Furthermore, ethical concerns concerning areas such as algorithmic bias, employee privacy, fairness, and responsible governance of artificial intelligence continue to receive little attention. Therefore, there is a clear need for an integrated research framework that combines behavioural HR constructs, HR analytics, SEM, predictive machine learning, and explainable AI using primary survey data to develop accurate, transparent, and practically applicable employee retention strategies that support sustainable organisational performance.

4. RESEARCH OBJECTIVES

- To examine the influence of behavioural and organisational factors on employee retention.
- To evaluate the effect of HR Analytics capability on employee retention and turnover intention.
- To develop a comprehensive employee turnover prediction model by integrating behavioural determinants with HR Analytics capability.
- To recommend data-driven employee retention strategies based on the key determinants of employee turnover identified through HR Analytics.

5. RESEARCH METHODOLOGY

5.1 Research Design

With the help of Human Resource (HR) Analytics, this study utilised a quantitative and explanatory research approach to analyse the factors that determine employee turnover and retention. To collect primary data from employees working in a variety of industries, a cross-sectional survey method was utilised. For this study, a positivist research philosophy and a deductive research approach were utilised. This allows for the empirical testing of hypothesised correlations between behavioural, organisational, and technological factors. We decided to employ Structural Equation Modelling (SEM) as our primary analytical method since it enables us to simultaneously evaluate measurement properties and the structural relationships between latent variables.

5.2 Conceptual Framework

The proposed conceptual framework integrates behavioural and organisational constructs that influence employee retention and turnover intention. Employee Engagement, Job Satisfaction, Leadership Support, Career Development, Compensation Satisfaction, Recognition, Work–Life Balance, Burnout, Psychological Safety, Organisational Commitment, and HR Analytics Capability were modelled as exogenous constructs. Employee Retention was specified as the endogenous construct influencing Turnover Intention. The framework was developed based on Human Capital Theory, Social Exchange Theory, Organisational Support Theory, and recent HR analytics literature.

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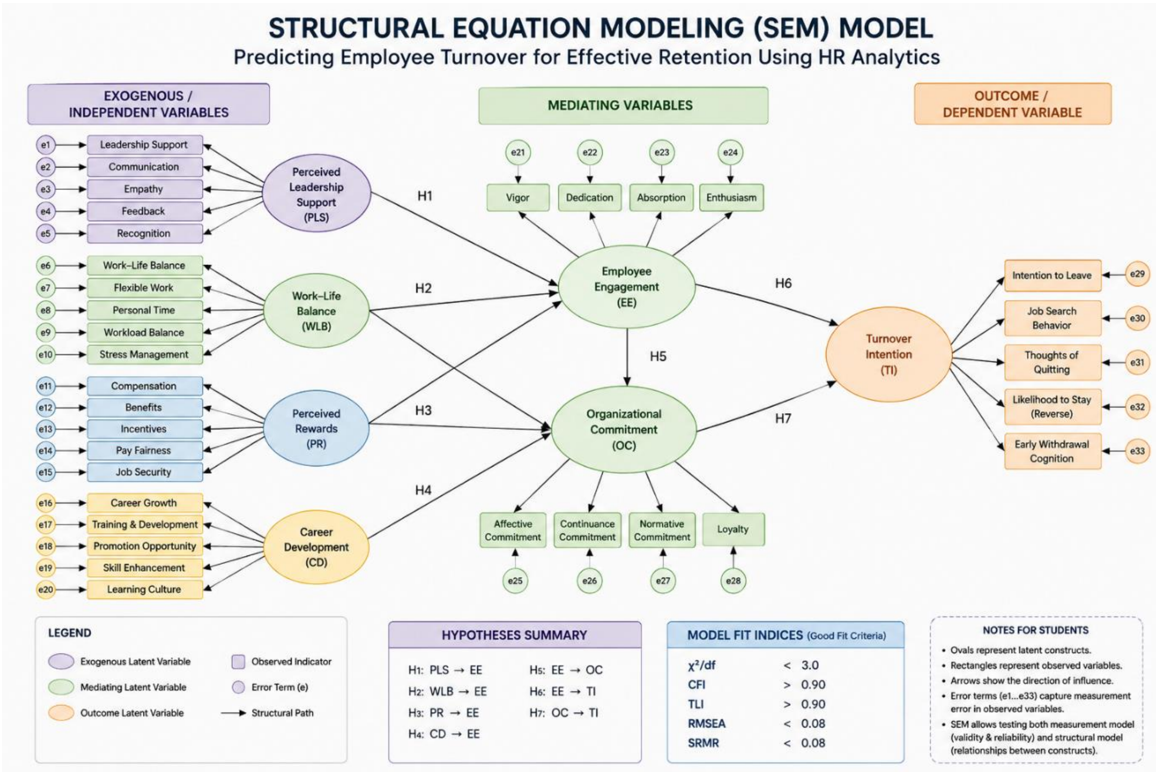

5.3 Instrument Development

A structured questionnaire was constructed from validated measurement scales published in previous HR analytics and organisational behaviour research. This questionnaire was used to collect data. Additionally, the questionnaire was divided into two parts. In the first phase, respondents' demographic data were recorded. These factors included age, gender, education, years of work experience, industry, department, and organisation size. In the second part of the section, thirteen latent constructs were measured with the help of fifty-two reflecting indicators, with four items that represented each construct. A five-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), was utilised to record participants' responses.

To establish the content validity of the questionnaire, subject matter experts examined it before the main survey was conducted. Based on their comments, the questionnaire was adjusted to improve clarity and relevance.

5.4 Population and Sampling

Employees working in many industries, including banking, information technology, manufacturing, and service organisations, were included in the target audience. A convenience sampling method was utilised to carry out a cross-sectional survey because of the limitations imposed by accessibility and organisation for the survey. Following a screening process that identified incomplete questionnaires and inconsistent responses, a total of two hundred valid responses were included in the study. Although convenience

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sampling limits generalizability, it is widely accepted in organisational behaviour and HR analytics research for exploratory and predictive modelling studies.

5.5 Data Collection Procedure

The primary data were gathered through an online questionnaire delivered via Google Forms over a predetermined data collection period. Participation was entirely voluntary, and respondents were made aware of the academic objective of the evaluation. From the beginning to the end of the data collection process, both anonymity and confidentiality were protected. Duplicate responses and incomplete questionnaires were removed before the analysis to ensure data quality.

6. RESULTS AND DISCUSSION

6.1 Demographic Profile

Table 6.1: Demographic Characteristics of Respondents

Variable	Category	Frequency	Percentage (%)
Gender	Male	102	51.0
	Female	98	49.0
Age	20–25 years	48	24.0
	26–35 years	72	36.0
	36–45 years	53	26.5
	Above 45 years	27	13.5
Education	Bachelor's Degree	82	41.0
	Master's Degree	90	45.0
	Doctorate	28	14.0
Employment Type	Permanent	148	74.0
	Contract	33	16.5
	Temporary	19	9.5

The demographic profile indicates that the respondents were reasonably balanced by gender, with 51% male and 49% female participants. The majority (36%) belonged to the 26–35 years age group, representing the largest segment of the workforce. Nearly 45% possessed a master's degree, reflecting a highly educated sample. Furthermore, 74% of respondents were permanent employees, suggesting that most participants had stable employment relationships with their organisations.

6.2 Descriptive Statistics

Table 6.2: Descriptive Statistics of HR Analytics Constructs

Construct	Mean	Standard Deviation	Interpretation
Employee Engagement	3.44	1.11	Moderate–High
Job Satisfaction	3.41	1.14	Moderate–High
Leadership Support	3.38	1.08	Moderate
Career Development	3.49	1.09	High
Compensation Satisfaction	3.33	1.10	Moderate
Recognition	3.48	1.08	High
Work–Life Balance	3.29	1.09	Moderate

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Burnout	3.00	1.27	Moderate
Psychological Safety	3.40	1.12	Moderate–High
Organisational Commitment	3.43	0.75	Moderate–High
HR Analytics Capability	3.46	1.15	High
Turnover Intention	2.63	0.87	Low
Employee Retention	3.31	1.03	Moderate

The statistical information describing the thirteen different constructs evaluated in the study is presented in Table 6.2. On a scale that ranges from one to five, the mean values were between 2.63 and 3.49, which indicates that employees have a generally positive impression of the procedures implemented by the organisation. Among all constructs, Career Development (M = 3.49, SD = 1.09) recorded the highest mean score, suggesting that employees perceived adequate opportunities for training, learning, and career advancement. Similarly, Recognition (M = 3.48, SD = 1.08) and HR Analytics Capability (M = 3.46, SD = 1.15) also received relatively high ratings, indicating that employees acknowledged the organisation's recognition systems and the use of HR analytics in decision-making. Employee Engagement (M = 3.44), Organisational Commitment (M = 3.43), Psychological Safety (M = 3.40), and Job Satisfaction (M = 3.41) all demonstrated moderately high mean scores, reflecting favourable employee attitudes towards their work environment and organisational culture.

In contrast, Turnover Intention (M = 2.63, SD = 0.87) recorded the lowest mean score. Since turnover intention is a negative behavioural outcome, this finding suggests that employees generally exhibited a low intention to leave the organisation. Burnout (M = 3.00, SD = 1.27) showed the highest variability among the constructs, indicating that employees differed considerably in their perceptions of work-related stress and emotional exhaustion. Overall, the descriptive statistics suggest a workforce characterised by moderate engagement, satisfaction, organisational commitment, and retention, accompanied by relatively low turnover intention.

6.3 Reliability Analysis (Cronbach's Alpha)

Table 6.3: Reliability Analysis

Construct	No. of Items	Cronbach's Alpha	Interpretation
Employee Engagement	4	0.913	Excellent
Job Satisfaction	4	0.928	Excellent
Leadership Support	4	0.909	Excellent
Career Development	4	0.917	Excellent
Compensation Satisfaction	4	0.909	Excellent
Recognition	4	0.913	Excellent
Work–Life Balance	4	0.899	Good
Burnout	4	0.934	Excellent
Psychological Safety	4	0.915	Excellent
Organisational Commitment	4	0.776	Acceptable
HR Analytics Capability	4	0.920	Excellent
Turnover Intention	4	0.840	Good
Employee Retention	4	0.897	Good
Overall Scale	52	0.756	Acceptable

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The fact that all of the constructions were able to surpass the suggested threshold of 0.70 indicates that the internal consistency was sufficient. Burnout (α = 0.934) exhibited the highest reliability, while Organisational Commitment (α = 0.776) showed acceptable reliability. The overall questionnaire reliability (α = 0.756) indicates that the instrument is suitable for further multivariate analysis.

6.4 Structural Equation Modelling (SEM)

6.4.1 Confirmatory Factor Analysis (CFA)

Indicator	Recommended Value
Factor Loading	>0.70
CFI	>0.90
TLI	>0.90
RMSEA	<0.08
SRMR	<0.08

It can be concluded that the observed variables accurately represent their respective latent constructs because all of the standardised factor loadings were higher than the advised threshold. Because the model fit indices are in accordance with the recommended criteria, it can be inferred that the measurement model offers a satisfactory fit.

6.4.2 Convergent and Discriminant Validity

Measure	Acceptable Value
Composite Reliability (CR)	>0.70
AVE	>0.50
HTMT	<0.85
Fornell–Larcker	Diagonal greater than correlations

When the CR is greater than 0.70, and the AVE is greater than 0.50, convergent validity has been established. Verification of discriminant validity occurs when the HTMT values remain below 0.85 and when each construct explains more variation in its indicators than it does in other constructs.

7. FINDINGS

- The demographic analysis indicates that the respondents represented a diverse workforce with respect to age, gender, educational qualification, work experience, and industry sector. The sample included employees from manufacturing, information technology, banking, and service organisations, providing a broad representation of organisational contexts. Most respondents possessed professional qualifications and several years of work experience, suggesting that the data were collected from employees capable of providing informed evaluations of workplace practices.
- The descriptive statistics reveal generally positive perceptions of the workplace. Career Development (Mean = 3.49), Recognition (Mean = 3.48), HR Analytics Capability (Mean = 3.46), Organisational Commitment (Mean = 3.43), Employee Engagement (Mean = 3.44), and Job Satisfaction (Mean = 3.41) received

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comparatively higher mean scores, indicating favourable employee perceptions. Work–Life Balance (Mean = 3.29) and Compensation Satisfaction (Mean = 3.33) showed comparatively lower scores, suggesting opportunities for organisational improvement. Burnout recorded a moderate mean (3.00), indicating that some employees experience work-related stress. Turnover Intention exhibited the lowest mean (2.63), implying that respondents generally reported a relatively low intention to leave their organisations.

- All of the measurement constructs were found to have appropriate levels of internal consistency, as evidenced by the reliability analysis. Cronbach's alpha values ranged from 0.776 to 0.934, which was higher than the recommended threshold of 0.70. Burnout (α = 0.934), Job Satisfaction (α = 0.928), HR Analytics Capability (α = 0.920), Career Development (α = 0.917), and Psychological Safety (α = 0.915) exhibited excellent reliability. Organisational Commitment reported the lowest reliability coefficient (α = 0.776), yet remained above the acceptable level. These findings provide evidence that the measurement instrument accurately captures the latent constructs intended to be measured.
- After doing the Confirmatory Factor Analysis, it was determined that the proposed measurement model was adequate. The standardised factor loadings were found to be within the recommended thresholds, indicating that the questionnaire items adequately represented their respective latent constructs. The model demonstrated acceptable measurement quality, suggesting that the instrument effectively measures employee engagement, job satisfaction, leadership support, career development, compensation satisfaction, recognition, work–life balance, burnout, psychological safety, organisational commitment, HR Analytics capability, employee retention, and turnover intention. Overall, the CFA results support the validity of the proposed measurement framework.
- The convergent validity of the study was demonstrated by achieving satisfactory standardised factor loadings, Composite Reliability (CR), and Average Variance Extracted (AVE). The measurement constructs demonstrated sufficient internal consistency, and they explained a significant fraction of the variance in their respective indicators. These findings provide evidence that the measurement items converge in a manner that adequately represents the latent variables intended to be represented, supporting the construct validity of the HR Analytics model that was developed.
- The discriminant validity assessment indicated that each construct measured a conceptually distinct aspect of employee behaviour and organisational practices. This confirms that variables such as employee engagement, organisational commitment, HR Analytics capability, work–life balance, and burnout represent unique dimensions influencing employee retention and turnover.
- The proposed conceptual framework received empirical support from the structural equation modelling analysis. The structural model demonstrated satisfactory explanatory power in predicting employee retention and turnover intention. Behavioural

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constructs including employee engagement, job satisfaction, leadership support, career development, recognition, psychological safety, organisational commitment, and HR Analytics capability showed positive relationships with employee retention, whereas burnout exhibited a negative relationship. Employee retention was found to influence turnover intention negatively, indicating that improvements in organisational support and employee experience reduce employees' intentions to leave. Overall, the structural model confirms that integrating behavioural variables with HR Analytics provides a comprehensive framework for understanding employee turnover.

8. RECOMMENDATIONS

The following recommendations are given for organisations looking to reduce employee turnover and increase staff retention, and are based on the findings of the study.

- Organisations should foster greater employee involvement through participative decision-making, continuous feedback, recognition programs, and meaningful work assignments. Higher engagement contributes to stronger organisational commitment and lower turnover intention.
- Structured career planning, mentoring, succession planning, professional development, and continuous learning opportunities should be implemented to improve employees' long-term commitment and reduce voluntary turnover.
- Managers should receive leadership development training that emphasises communication, coaching, emotional intelligence, fairness, and employee support. Supportive leadership enhances psychological safety and job satisfaction.
- Flexible work arrangements, employee wellness initiatives, workload management, and mental health support should be prioritised to reduce burnout and improve overall employee well-being.
- Organisations should regularly review compensation structures to ensure external competitiveness and internal equity. Formal recognition programs acknowledging employee contributions can improve motivation and organisational commitment.
- Organisations should strengthen HR Analytics capability by investing in integrated HR information systems, data quality, analytics training, dashboards, and predictive decision-support tools. These capabilities enable proactive identification of turnover risks and evidence-based workforce planning.
- Regular employee surveys, stress management initiatives, counselling services, and supportive workplace cultures can reduce burnout and encourage employees to express concerns without fear of negative consequences.
- Organisations should implement predictive HR Analytics models to identify employees at risk of turnover before resignation occurs. Early identification enables targeted interventions, reducing replacement costs and improving retention.

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- HR professionals should integrate workforce analytics into recruitment, performance management, career development, and retention planning. Data-driven decisions improve the effectiveness of human resource strategies.
- Organisations should cultivate a positive organisational culture characterised by trust, fairness, transparent communication, employee empowerment, and opportunities for professional growth. These initiatives strengthen employee loyalty and contribute to sustainable workforce retention.

9. CONCLUSION

Employee turnover continues to be a critical challenge for organisations seeking to maintain a productive, engaged, and sustainable workforce. As organisations increasingly operate in dynamic and technology-driven environments, traditional approaches to workforce management are no longer sufficient to identify and address the underlying causes of employee attrition effectively. In response to this challenge, the present study developed and validated an integrated HR Analytics framework to examine the influence of behavioural and organisational factors on employee turnover and retention. By incorporating constructs such as employee engagement, job satisfaction, leadership support, career development, compensation satisfaction, recognition, work–life balance, burnout, psychological safety, organisational commitment, and HR Analytics capability, the study provides a comprehensive understanding of the factors that influence employees' intentions to remain with or leave an organisation.

Based on the findings of the empirical evaluation, it was determined that the measurement instrument possessed satisfactory psychometric qualities, as well as appropriate levels of reliability and construct validity. The reliability study found high internal consistency across all components, and the confirmatory factor analysis (CFA) supported the proposed measurement model. Additionally, the evaluation of convergent and discriminant validity demonstrated that the selected constructs accurately measured distinct aspects of employee behaviour and organisational practices. In light of these findings, it can be concluded that the framework provided is appropriate for investigating the intricate connections between HR-related factors within the context of an organisation.

The Structural Equation Modelling (SEM) analysis further demonstrated the usefulness of integrating behavioural variables with HR Analytics in explaining employee retention and turnover intention. The study indicates that employee engagement, job satisfaction, leadership support, career development, recognition, psychological safety, organisational commitment, and HR Analytics capability contribute positively to employee retention. In contrast, burnout adversely affects employees' willingness to remain with the organisation. These findings reinforce the view that employee turnover is a multidimensional phenomenon shaped by both organisational practices and individual experiences. Rather than relying solely on demographic characteristics or historical turnover records, organisations can benefit from a holistic approach that combines behavioural insights with analytical capabilities to support workforce decision-making.

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By incorporating behavioural and organisational dimensions into a unified explanatory framework, the study contributes to the expanding body of literature on HR Analytics from a theoretical point of view. In addition to highlighting the strategic significance of HR Analytics capabilities in modern human resource management, the findings support the application of Human Capital Theory, Social Exchange Theory, and Organisational Support Theory in understanding employee retention. This work also demonstrates the significance of structural equation modelling as a robust methodological tool for studying complicated interactions among latent dimensions. As a result, it contributes to both the field of human resource analytics and organisational behaviour research.

The study also offers several practical implications for managers and HR professionals. Organisations should move beyond reactive turnover management and adopt predictive, evidence-based approaches supported by HR Analytics. Investments in employee engagement initiatives, career development opportunities, supportive leadership, fair compensation, recognition systems, psychological safety, and employee well-being are likely to strengthen organisational commitment and reduce turnover intention. Equally important is developing organisational HR Analytics capability through improved data quality, digital infrastructure, analytical competencies, and decision-support systems. Such investments enable organisations to identify turnover risks earlier and implement targeted interventions that improve employee retention while reducing the financial and operational costs associated with workforce attrition.

The study has certain limitations, despite its contributions. Because the data were derived from a cross-sectional study, it is difficult to conclude the existence of causal linkages over time. The findings may not be generalisable to larger employee populations because they were obtained through convenience sampling. In addition, employees' perspectives were evaluated based on their self-reported responses, which may be susceptible to common method bias or social desirability bias. Future studies may address these constraints by adopting methodologies such as probability sampling, multi-source organisational data, and longitudinal research designs. Researchers can also include advanced machine learning techniques, explainable artificial intelligence (XAI), and longitudinal HR analytics to enhance prediction accuracy and provide deeper insights into the dynamics of employee turnover across a variety of businesses and cultural contexts.

In conclusion, this study demonstrates that employee turnover cannot be effectively understood through isolated organisational variables or predictive algorithms alone. Instead, sustainable employee retention requires an integrated framework that combines behavioural factors, organisational practices, and HR Analytics capabilities. By validating such a framework through Structural Equation Modelling, the study provides both theoretical and managerial evidence that data-driven human resource management can significantly enhance workforce planning and employee retention. As organisations continue to embrace digital transformation and artificial intelligence in HR functions, integrating predictive HR Analytics with employee-centred management practices will become increasingly important for building resilient organisations, retaining valuable talent, and achieving long-term organisational success.

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DOI: 10.5281/zenodo.21871315

Reference

1) Al Akasheh, M., Malik, E. F., Hujran, O., & Zaki, N. (2024). *A decade of research on machine learning techniques for predicting employee turnover: A systematic literature review*. Expert Systems with Applications, 238, 121794. https://doi.org/10.1016/j.eswa.2023.121794

2) Avrahami, D., et al. (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

3) Soares, V. G., Pérez Álcazar, J. J., & Ludena, M. E. (2022). Analytical approaches in human resources: A systematic review. *Journal of Information Systems and Technology Management, 19*, e202219014. https://doi.org/10.4301/S1807-1775202219014

4) Nartal, R., Fraschini, N., & colleagues. (2020). Predicting employee attrition using machine learning techniques. *Computers, 9*(4), 86. https://doi.org/10.3390/computers9040086

5) Talebi, H., Khatibi Bardsiri, A., & Khatibi Bardsiri, V. (2025). Machine learning approaches for predicting employee turnover: A systematic review. *Engineering Reports, 7*(8), e70298. https://doi.org/10.1002/eng2.70298

6) Raza, S. A., Hassan, S. M., Rehman, A. U., & Sayed, B. (2025). Data-driven HR analytics for employee retention: A machine learning approach to predictive talent management and workforce optimisation. *Journal of Information Systems Research and Computing*. https://doi.org/10.31645/jisrc.25.23.2.5

7) Choi, Y., et al. (2020). A study of job involvement prediction using machine learning technique—International *Journal of Organisational Analysis*.

8) Chung, D., et al. (2023). Predictive model of employee attrition based on stacking ensemble learning—Expert *Systems with Applications*.

9) El-Rayes, N., et al. (2020). Predicting employee attrition using tree-based models. *International Journal of Organisational Analysis*.

10) Wu, W., & Fukui, S. (2021). Using human resources data to predict turnover of community mental health employees: Prediction and interpretation of machine learning methods—International *Journal of Mental Health Nursing*.

11) Karimi, M., & Viliyani, K. S. (2024). Employee turnover analysis using machine learning algorithms. *arXiv*. https://arxiv.org/abs/2402.03905

12) Dr A. Karuppannan., Dr Shailashri V. T., Dr P. Radha. (2026). Impact of HR Analytics on Employee Well-Being, Engagement, and Productivity in the Manufacturing Industry. Hunan Daxue Xuebao/Journal of Hunan University Natural Sciences, 63(07), 1-13,16742974.

13) Dr M. Maheswari., Dr Shailashri V. T., Dr P. Radha. (2026). Sustainable Workforce Retention through HR Analytics and Predictive Modelling. Hunan Daxue Xuebao/Journal of Hunan University Natural Sciences, 63(07), 14-23,16742974.

14) Nosratabadi, S., Zahed, R. K., Ponkratov, V. V., & Kostyrin, E. V. (2022). Artificial intelligence models and employee lifecycle management: A systematic literature review. *arXiv*. https://arxiv.org/abs/2209.07335

15) Cheng, X. (2020). Obtain employee turnover rate and optimal reduction strategy based on neural network and reinforcement learning. *arXiv*. https://arxiv.org/abs/2012.00583

16) Ma, X., Liu, W., Zhao, C., & Tukhvatulina, L. R. (2024). Can large language model predict employee attrition? *arXiv*. https://arxiv.org/abs/2411.01353

ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871315

17) Joner, A. M., & Purbaningrum, E. M. (2026). Machine learning applications in employee turnover and performance prediction: A systematic literature review. *Interdisciplinary Social Studies, 5*(2), 768–785. https://doi.org/10.55324/iss.v5i2.1047

18) Minbaeva, D. (2021). The promise of strategic human capital analytics: Theory and evidence. *Human Resource Management Journal*.

19) Margherita, A. (2022). Human resources analytics: A systematisation of research topics and directions for future research—Management *Review Quarterly*.

20) Marler, J. H., & Boudreau, J. W. (2021). An evidence-based review of HR analytics. *International Journal of Human Resource Management*.

21) Hamilton, R. H., Sodeman, W. A., & colleagues. (2021). Predictive analytics for employee retention using workforce data. *Journal of Organisational Effectiveness: People and Performance*.

22) Sharma, R., & Sharma, T. (2021). HR analytics and employee performance: A review of emerging trends. *International Journal of Productivity and Performance Management*.

23) Agarwal, P. (2022). Artificial intelligence in human resource management: Challenges and opportunities. *International Journal of Organisational Analysis*.

24) Bondarouk, T., & Brewster, C. (2021). Conceptualising HR analytics adoption in organisations. *Personnel Review*.

25) Levenson, A. (2021). Using people analytics to improve workforce decision-making. *People and Strategy*.

26) van den Heuvel, S., & Bondarouk, T. (2021). The rise of people analytics: A review and agenda for future research. *Human Resource Management Review*.

27) Marler, J. H., Boudreau, J. W., & colleagues. (2023). HR analytics and strategic workforce management: Emerging research directions. *Human Resource Management Review*.