Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871043

AN INTEGRATED HR ANALYTICS MODEL FOR EMPLOYEE MENTAL HEALTH PREDICTION AND RETENTION

Dr. A. KARUPPANNAN
Research Scholar, Srinivas University, Mangaluru, India. Email: karuppannanmba@gmail.com;
ORCID: 0009-0006-2750-1309

Dr. SHAILASHRI V. T
Research Professor, Institute of Management and Commerce, Srinivas University, Mangalore, India.
Email: shailashrivt@gmail.com; ORCID: 0000-0002-1684-238X

Dr. P. RADHA
Professor, School of Commerce, Jain (Deemed to be University), Bengaluru, India.
Email: pradha1020@gmail.com; ORCID: 0000-0001-8172-8471

Abstract

The increasing adoption of Human Resource (HR) analytics has transformed organisational decision-making by enabling evidence-based workforce management. However, limited empirical research has examined how HR analytics capabilities influence employee mental health, psychological well-being, and employee retention within a unified framework. This study investigates HR Analytics Capabilities (HAC), Employee Mental Health (EMH), Psychological Well-being (PWB), and Employee Retention (ER). The study also explores the direct and indirect correlations between these four factors. The Resource-Based View (RBV), Job Demands–Resources (JD-R) Theory, Conservation of Resources (COR) Theory, and Social Exchange Theory (SET) are the theoretical foundations upon which this work develops and evaluates an integrated conceptual model. A quantitative, cross-sectional research design was adopted, and a structured questionnaire was used to collect primary data from 450 employees working in a variety of industries. SmartPLS 4 was utilised in order to perform the analysis of the data using the Partial Least Squares Structural Equation Modelling (PLS-SEM) technique. According to the findings, HR Analytics Capabilities have a strong positive impact on employees' mental health and psychological well-being, while both variables greatly contribute to employee retention. An additional finding from the mediation analysis is that the relationship between HR Analytics Capabilities and Employee Retention is partially mediated by Employee Mental Health and Psychological Well-being. This finding demonstrates that analytics-driven HR practices improve retention by enhancing employees' psychological health and well-being. The robustness of the proposed framework was confirmed by the measurement and structural models displaying appropriate levels of reliability, validity, predictive relevance, and model fit. The study contributes to HR analytics literature by integrating technological capabilities with employee well-being outcomes and extending established organisational theories within the context of digital human resource management. Practically, the findings suggest that organisations should strategically leverage HR analytics alongside employee-centred well-being initiatives to enhance workforce sustainability, organisational commitment, and long-term employee retention.

Keywords: HR Analytics Capabilities; Employee Mental Health; Psychological Well-Being; Employee Retention; PLS-SEM.

1. INTRODUCTION

An organisation's workforce is widely regarded as one of its most significant assets in the modern corporate climate, which is marked by intense competition. Their knowledge, skills, creativity, and psychological well-being play an important role in improving

ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871043

organisational performance and achieving long-term success. With the rapid growth of digital technologies, artificial intelligence (AI), hybrid work models, and data-driven decision-making, Human Resource Management (HRM) has undergone significant transformation. Therefore, Human Resource Analytics, commonly referred to as People Analytics or Workforce Analytics, are becoming increasingly popular and has become an essential strategic tool that helps organisations convert employee data into meaningful insights for better decision-making.

To support evidence-based decision-making, HR analytics uses statistical analysis, predictive analytics, machine learning, and management intelligence. It helps with employee engagement and retention, as well as recruitment, workforce planning, performance management, and employee engagement. Modern HR analytics systems also help organisations identify employees who may be at risk of leaving, personalise employee development programs, and improve workforce planning while ensuring responsible and ethical use of AI.

The evolution of human resource analytics represents a shift away from management based on intuition and toward management based on evidence. Earlier, organisations relied on simple HR metrics such as absenteeism, employee turnover, and recruitment costs. However, advances in big data, cloud computing, AI, and predictive analytics have enabled HR professionals to move beyond descriptive reporting toward predictive and prescriptive analytics. These technologies allow organisations to forecast employee turnover, identify performance trends, detect workplace risks, and implement timely interventions before problems become serious. Consequently, HR analytics has become an important strategic capability that improves organisational agility, workforce resilience, and competitive advantage.

Despite these technological advancements, employee mental health has become one of the major challenges faced by organisations worldwide. Increasing workloads, rapid technological changes, job insecurity, work-life imbalance, and continuous digital connectivity have contributed to higher levels of stress, anxiety, emotional exhaustion, and burnout. Poor mental health negatively affects employee productivity, job satisfaction, creativity, organisational commitment, and overall performance while increasing absenteeism and employee turnover. Therefore, organisations increasingly recognise employee mental health as a strategic issue rather than merely an individual concern. HR analytics provides opportunities to identify mental health risks early and support timely organisational interventions.

Closely related to mental health is psychological well-being, which includes employees' emotional stability, resilience, life satisfaction, motivation, and perceived organisational support. Employees with higher psychological well-being generally perform better, collaborate effectively, demonstrate greater commitment, and are less likely to leave their organisations. Many organisations now invest in employee wellness programs, flexible work arrangements, counselling services, leadership development, and supportive workplace cultures to improve employee well-being. By integrating HR analytics into

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871043

these initiatives, organisations can move from reactive problem-solving to proactive employee support through continuous monitoring of workforce indicators.

Further improvement in human resource analytics has been brought about by the development of artificial intelligence and predictive analytics. Traditional approaches are less accurate than machine learning algorithms for identifying behavioural trends, predicting employee turnover, monitoring employee engagement, and detecting organisational risks. Machine learning algorithms can analyse vast amounts of employee data. Explainable AI also improves transparency by helping managers understand why predictive models generate particular outcomes, thereby supporting ethical decision-making. These technological developments create opportunities to combine HR analytics with employee mental health initiatives, enabling organisations to improve workforce stability and resilience.

Employee retention continues to be a critical concern for organisations because high turnover results in substantial recruitment, training, and productivity costs. Traditional retention strategies mainly focused on salary, incentives, and career advancement. However, recent research shows that employee well-being, mental health, psychological safety, and organisational support are equally important in influencing employees' decisions to remain with an organisation. Through the use of predictive human resource analytics, businesses can identify employees who are at risk of leaving and put in place individualised retention tactics before turnover takes place.

Although past research has investigated HR analytics, employee well-being, artificial intelligence, and employee retention in isolation, only a small number of studies have combined all of these factors into a comprehensive framework. Existing HR analytics research mainly focuses on recruitment, talent management, performance evaluation, and turnover prediction, while studies on employee mental health primarily examine workplace stress and burnout. Very few studies have investigated how HR analytics capabilities influence employee mental health and psychological well-being, and how these factors together contribute to employee retention, notably in developing nations like India.

The current study develops an integrated conceptual framework that investigates the influence of HR Analytics Capabilities on Employee Mental Health, Psychological Well-being, and Employee Retention. This addresses the identified research gap. The Resource-Based View (RBV), Job Demands–Resources (JD-R) Theory, Conservation of Resources (COR) Theory, and Social Exchange Theory (SET) are the theoretical foundations upon which this study is built. It proposes that HR analytics serves as a strategic organisational capability that supports proactive employee management through data-driven insights, while psychological well-being acts as a key mechanism linking HR analytics to employee retention.

Both theory and practice can benefit from the findings of this investigation. In theory, it broadens the scope of human resource analytics by identifying employees' mental health and psychological well-being as two of the most significant outcomes for organisations.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871043

Methodologically, it develops and validates an integrated research framework using Structural Equation Modelling (SEM). A practical application of the findings is that they will assist human resource professionals and organisational leaders in implementing predictive human resource analytics systems. These systems will identify employees who are at risk of experiencing psychological distress and turnover. This will allow for timely interventions that will improve employee well-being, strengthen organisational resilience, and enhance long-term employee retention.

2. REVIEW OF LITERATURE

Brougham and Haar (2020) investigated the impact of rapid technological disruption on employee well-being, focusing on how organisational support influences employees' psychological responses to workplace digitalisation. Using survey data from employees across multiple industries, the study found that technological changes often increase job insecurity, work stress, and anxiety. However, organisations that provide effective communication, training, and managerial support significantly reduce these negative effects. The authors concluded that employee well-being should be integrated into digital transformation strategies, and HR analytics can help organisations identify employees at risk and implement timely interventions to enhance psychological resilience and retention.

George et al. (2020) investigated the transformative impact that artificial intelligence has had on management research and organisational practices. The authors explained how artificial intelligence enables businesses to process enormous volumes of workforce data, provide predictive insights, and improve strategic decision-making across a variety of corporate areas, including human resource management. While AI offers substantial opportunities to enhance organisational efficiency, the study emphasised the need to maintain ethical standards, transparency, and human-centred decision-making. The authors recommended integrating AI with HR analytics to support informed managerial decisions while safeguarding employee trust, fairness, and psychological well-being.

During the COVID-19 pandemic, Podgorodnichenko et al. (2020) investigated how human resource management strategies contributed to employee well-being. The study demonstrated that flexible work arrangements, transparent communication, organisational support, and employee assistance initiatives significantly reduced psychological distress and enhanced resilience. The authors concluded that employee well-being should become a central strategic objective rather than a temporary crisis response. They recommended adopting data-driven HR practices that continuously monitor employee health, engagement, and stress levels to enable timely organisational interventions and improve long-term employee retention.

Aguinis and Burgi-Tian (2021) proposed the Performance Promoter Score (PPS) as an innovative framework for evaluating employee performance during periods of organisational uncertainty and disruption. The study argued that conventional performance evaluation systems often fail to capture employees' adaptive behaviours, resilience, and overall well-being during crises. The authors recommended adopting data-driven performance measurement systems that integrate employee engagement,

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871043

psychological health, and contextual performance indicators. Their work supports integrating HR analytics into performance management systems, enabling organisations to predict employee outcomes, improve well-being, and strengthen retention through timely, evidence-based interventions.

Jiang and Messersmith (2021) synthesised recent developments in Strategic Human Resource Management (SHRM) by examining how HR practices contribute to organisational effectiveness and employee outcomes. The review emphasised that high-performance work systems enhance employee engagement, organisational commitment, psychological well-being, and retention through supportive HR policies. The authors argued that future SHRM research should increasingly incorporate workforce analytics and digital technologies to predict employee behaviours and well-being. Their work provides a strong theoretical foundation for integrating HR analytics into mental health prediction and employee retention models.

Kaur et al. (2021) conducted a systematic literature review to explore the factors influencing employee resistance toward artificial intelligence adoption in organisations. The review identified perceived job insecurity, lack of technological competence, trust deficits, privacy concerns, and organisational culture as the primary barriers to AI acceptance. The authors emphasised that employee psychological well-being significantly influences technology adoption and organisational change success. They recommended that HR departments employ predictive analytics to monitor employee attitudes and emotional responses, enabling organisations to develop targeted interventions that reduce resistance while promoting workforce well-being and organisational adaptability.

Leka et al. (2021) examined organisational interventions designed to improve workplace mental health through evidence-based occupational health practices. The study emphasised that psychosocial risks, excessive workloads, inadequate managerial support, and workplace stress are primary determinants of poor employee mental health. The authors advocated preventive organisational strategies rather than reactive treatment approaches. They concluded that organisations should systematically monitor psychosocial indicators and integrate employee mental health into strategic HR practices. Their findings support the development of HR analytics frameworks capable of identifying mental health risks before they negatively affect employee performance and retention.

Malik et al. (2021) investigated how digital transformation is reshaping contemporary human resource management practices. The authors argued that digital technologies, cloud platforms, artificial intelligence, and workforce analytics have fundamentally changed HR functions from administrative support to strategic business partnership. Their review highlighted that digital HR systems improve organisational agility, employee experience, and decision quality. However, they stressed that organisations should equally prioritise employees' psychological health during digital transformation by integrating well-being metrics into HR analytics systems to achieve sustainable organisational performance.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871043

Margherita and Bua (2021) investigated the contribution of HR analytics to organisational decision-making by examining its strategic applications across workforce planning, talent management, performance evaluation, and employee retention. The study found that organisations increasingly utilise predictive analytics to transform workforce data into actionable managerial insights. However, successful implementation depends on organisational readiness, data quality, analytical competencies, and leadership support. The authors suggested expanding HR analytics beyond operational efficiency by integrating employee behavioural, psychological, and well-being indicators into predictive decision models, thereby strengthening sustainable human resource management and organisational competitiveness.

McCartney et al. (2021) developed a competency framework describing the evolving role of HR analysts in modern organisations. Through qualitative research involving HR professionals, the study identified analytical capability, statistical reasoning, business acumen, digital literacy, and communication as essential competencies. The findings suggested that HR analysts should extend beyond reporting organisational metrics to predicting employee outcomes and supporting strategic decisions. Although the framework primarily focused on organisational performance, it also recognised employee well-being as a future application area requiring advanced analytical capabilities.

Minbaeva (2021) discussed how digital disruption, artificial intelligence, and advanced analytics are transforming traditional human resource management into a strategic, technology-enabled function. The article argued that organisations must redesign HR capabilities to leverage workforce data for proactive decision-making rather than relying solely on administrative processes. The author highlighted the growing importance of human capital analytics in supporting organisational resilience, employee development, and workforce sustainability. The paper also stressed the need to balance technological innovation with ethical considerations, employee trust, and psychological well-being to ensure responsible implementation of predictive HR analytics.

Van Beurden et al. (2021) evaluated empirical research investigating employee perceptions of HR practices and the influence those perceptions have on organisational outcomes. According to the authors' findings, the way employees interpret HR activities has a significant impact on employee engagement, job satisfaction, commitment, psychological well-being, and retention. The review highlighted that employee-centred HR practices foster healthier workplaces and improve organisational effectiveness. The authors suggested integrating employee perception measures with advanced HR analytics to develop predictive models that identify factors affecting employee well-being and long-term retention.

Reviewing the progression of human resource analytics from descriptive reporting to predictive and prescriptive decision support, Van den Heuvel and Bondarouk (2021) offered a comprehensive analysis of the field. The study emphasised that HR analytics enhances strategic workforce planning, talent management, employee engagement, and organisational performance by converting workforce data into actionable insights. Despite growing adoption, the authors observed insufficient empirical evidence regarding HR

ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871043

analytics applications in employee mental health and well-being. They recommended future studies focusing on predictive models that integrate psychological, behavioural, and organisational variables to improve employee outcomes and retention.

The authors Yadav and Sharma (2021) conducted a comprehensive analysis of the expanding use of artificial intelligence in human resource management. They focused on the role that AI plays in recruitment, performance evaluation, employee engagement, talent management, and workforce planning. Based on the study's findings, artificial intelligence improves decision-making accuracy while reducing administrative burdens through automation and predictive analytics. However, ethical concerns regarding transparency, employee privacy, and algorithmic fairness require careful organisational attention. The authors suggested integrating AI-based HR analytics with employee well-being measures to create comprehensive predictive models that can improve employee satisfaction, mental health, and long-term organisational retention.

Cooke et al. (2022) conducted a survey of developing applications of artificial intelligence in recruiting, talent management, employee development, and workforce analytics to investigate the revolutionary role that artificial intelligence plays in human resource management. According to the study's findings, artificial intelligence improves the accuracy and efficiency of human resource decision-making through automation and predictive capabilities. Nevertheless, ethical concerns, employee privacy, transparency, and algorithmic bias remain significant challenges. The authors advocate developing responsible AI governance frameworks that prioritise employee well-being while enabling organisations to leverage predictive HR analytics for strategic human resource management.

In 2022, Galetsi and colleagues carried out a comprehensive review investigating the utilisation of big data analytics in the field of human resource management. The study identified that organisations increasingly employ predictive analytics for recruitment, performance evaluation, workforce planning, employee engagement, and retention. The authors emphasised that integrating large-scale employee data enables evidence-based HR decision-making and improves organisational effectiveness. However, they noted limited research on using predictive analytics to monitor employees' psychological well-being and mental health. The review recommends incorporating behavioural and mental health indicators into HR analytics frameworks to support sustainable workforce management.

Margherita (2022) systematically synthesised the evolution of HR analytics and categorised research into technological, strategic, operational, and organisational dimensions. The review demonstrated that organisations increasingly rely on predictive analytics to improve recruitment, retention, and workforce planning. Despite rapid technological advancement, the author emphasised that employee well-being and psychological health remain underexplored within HR analytics research. The study recommends integrating artificial intelligence, employee behavioural analytics, and mental health indicators to create sustainable human resource management frameworks.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871043

Qamar and Samad (2022) conducted a comprehensive bibliometric review of 125 Scopus-indexed publications to identify emerging trends in Human Resource Analytics (HRA). The study classified the literature into major research themes, including workforce analytics, predictive analytics, talent management, and evidence-based HR decision-making. The authors concluded that HR analytics has evolved into a strategic capability that enhances organisational performance through data-driven decisions. However, they identified limited research linking HR analytics with employee psychological well-being and mental health, thereby highlighting a significant avenue for future research.

Zhang and Chen (2022) systematically reviewed the application of predictive analytics within human resource management, emphasising its growing importance in evidence-based decision-making. The review found that predictive models are increasingly employed for talent acquisition, employee performance, absenteeism, workforce planning, and turnover prediction. However, relatively few studies have incorporated psychological well-being, workplace stress, or mental health variables into predictive HR models. The authors recommended integrating behavioural science, artificial intelligence, and employee health indicators into comprehensive HR analytics frameworks that can improve organisational effectiveness while supporting employee well-being.

Wang et al. (2023) examined workplace mental health from a human resource management perspective by reviewing organisational strategies that support employees' psychological well-being. According to the findings of the study, supportive leadership, employee assistance programs, flexible work arrangements, and a positive organisational culture considerably reduce stress and burnout while simultaneously enhancing engagement and organisational commitment. The authors argued that HR professionals should adopt data-driven approaches to continuously monitor employee well-being. They proposed integrating HR analytics with organisational mental health initiatives to facilitate early identification of psychological risks and improve employee retention through evidence-based interventions.

In 2023, Zirar and colleagues carried out a comprehensive analysis investigating how artificial intelligence and digital technology impact employee well-being in contemporary companies. The review revealed that AI-enabled work environments improve operational efficiency and decision quality but may simultaneously increase work intensification, surveillance concerns, and psychological stress. The authors emphasised that organisations should balance technological innovation with employee-centred HR practices to maintain workforce well-being. They recommended integrating AI-driven HR analytics with behavioural and psychological indicators to develop predictive models that support proactive mental health management, sustainable workforce development, and improved employee retention.

Zhou et al. (2023) reviewed contemporary research on Sustainable Human Resource Management (SHRM) and its influence on employee psychological well-being. The study demonstrated that sustainable HR practices, including employee development, work-life balance, inclusive leadership, organisational justice, and supportive workplace culture, significantly enhance psychological health, employee engagement, and organisational

ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871043

commitment. The authors argued that future HR systems should integrate predictive analytics with sustainability principles to continuously monitor workforce well-being. Their proposed research agenda highlights the importance of combining technological innovation with employee-centred HR practices to improve both organisational performance and long-term employee retention.

Lathabhavan (2024) proposed an employee-supportive HR analytics framework aimed at improving workplace mental well-being. Using empirical evidence, the study demonstrated that predictive HR analytics enables organisations to identify psychological stressors, monitor employee well-being, and design timely interventions. The research established significant relationships between HR analytics capability, organisational support, employee engagement, and psychological well-being. The author concluded that HR analytics should move beyond administrative functions and become a proactive mechanism for improving employee mental health and organisational sustainability.

Lathabhavan (2024) developed an employee-supportive framework demonstrating how HR analytics can strengthen organisational mental health initiatives. Using structural equation modelling with data collected from Indian employees, the study found that HR analytics significantly improves evidence-based mental health management, organisational mental health support, and employees' psychological well-being. Managerial and peer support further strengthened these relationships, highlighting the importance of supportive organisational climates. The research concludes that HR analytics should serve as a proactive strategic tool for predicting mental health risks and implementing preventive interventions that enhance employee retention and long-term organisational sustainability.

Wu and Fukui (2024) investigated the effectiveness of machine learning algorithms in predicting employee turnover among community mental health professionals. Using workforce data, the study compared predictive models and demonstrated that machine learning significantly outperformed traditional statistical techniques in identifying employees at risk of leaving. The findings highlighted that job satisfaction, workload, supervisory support, and organisational commitment were among the strongest predictors of turnover. The authors concluded that HR analytics can facilitate proactive retention strategies by enabling organisations to identify vulnerable employees early and implement targeted interventions that improve workforce stability and employee well-being.

3. RESEARCH GAP

The existing body of literature demonstrates that Human Resource Analytics (HRA) has progressed from a function that provided descriptive reporting to a strategic decision-support tool that is capable of enhancing workforce planning, recruitment, performance management, employee engagement, and retention. Similarly, studies on workplace mental health emphasise the importance of organisational support, leadership, work-life balance, employee assistance programs, and sustainable HR practices in enhancing psychological well-being. Although research has independently explored HR analytics,

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871043

artificial intelligence (AI), machine learning (ML), employee mental health, and retention, these domains remain largely fragmented. Most empirical studies have focused on operational HR outcomes such as turnover prediction, talent acquisition, and performance optimisation, while relatively few have integrated psychological well-being and mental health indicators into predictive HR analytics frameworks. Furthermore, existing research has paid limited attention to behavioural variables, psychosocial risk factors, and employee mental health as strategic organisational metrics, resulting in a significant theoretical and empirical gap in the HR analytics literature.

Moreover, the literature reveals a lack of comprehensive and empirically validated models that simultaneously examine HR analytics capabilities, employee mental health, psychological well-being, organisational support, AI-enabled predictive analytics, and employee retention within a unified framework. The adoption of explainable artificial intelligence (XAI) and advanced machine learning techniques for early identification of employees at risk of psychological distress remains underexplored, particularly in developing economies such as India. In addition, few studies have investigated the mediating and moderating roles of organisational support, employee engagement, and sustainable HR practices in strengthening the relationship between HR analytics and employee well-being. Addressing these gaps, the present study proposes an integrated HR analytics model that leverages predictive analytics to identify mental health risks, enhance psychological well-being, and improve employee retention. To contribute to the growing body of research, the study combines evidence-based human resource management, AI-driven analytics, and sustainable workforce management into a comprehensive framework that supports both employee welfare and long-term organisational performance.

4. OBJECTIVES OF THE STUDY

- To examine the influence of HR analytics capabilities on employee mental health and psychological well-being.
- To investigate the relationship between employee mental health and employee retention.
- To assess the mediating role of employee psychological well-being in the relationship between HR analytics capabilities and employee retention.
- To develop and validate an integrated HR analytics model for predicting employee mental health and improving employee retention using predictive analytics.

5. HYPOTHESES DEVELOPMENT

H_1: The capabilities of HR analytics exert a beneficial and substantial impact on employee mental well-being.

H_2: The capabilities of HR analytics exert a beneficial and substantial impact on the psychological well-being of employees.

ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871043

H_3: Employee Mental Health exerts a beneficial and substantial impact on Employee Psychological Well-being.

H_4: The mental well-being of employees exerts a favourable and substantial impact on their retention.

H_5: The psychological well-being of employees exerts a beneficial and substantial impact on their retention.

H_6: The psychological well-being of employees serves as a mediator in the connection between HR analytics capabilities and employee retention.

H_7: The mental well-being of employees serves as a mediator in the connection between HR analytics competencies and the retention of employees.

6. CONCEPTUAL FRAMEWORK

The proposed conceptual framework illustrates how HR Analytics Capabilities function as the primary independent variable influencing Employee Mental Health, Psychological Well-being, and ultimately Employee Retention.

Anchored in the Resource-Based View (RBV), Job Demands–Resources (JD–R) Theory, Conservation of Resources (COR) Theory, and Social Exchange Theory (SET), the model suggests that organisations possessing robust HR analytics capabilities can utilise data-informed decision-making, predictive workforce analytics, and strategic HR intelligence to pre-emptively recognise employee risks and execute prompt interventions.

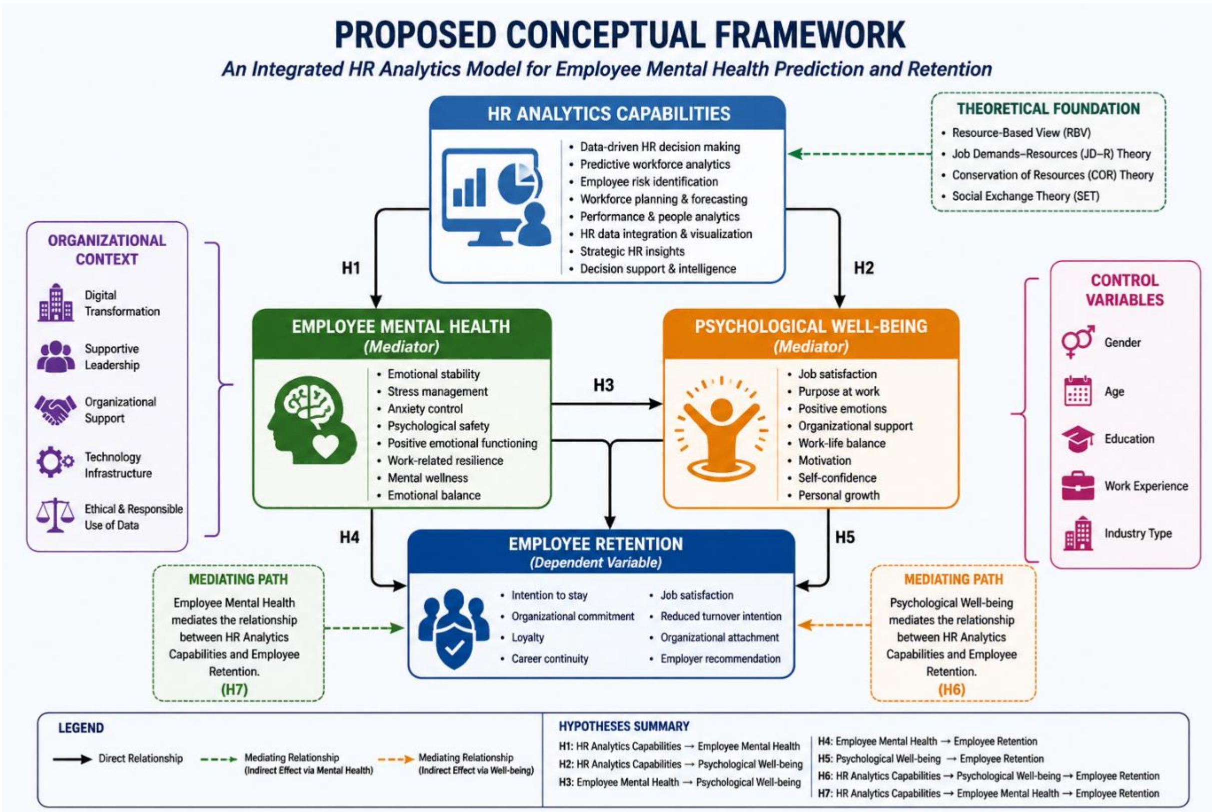
These capabilities are hypothesised to directly improve employee mental health (H_1) and psychological well-being (H_2), while better mental health also enhances psychological well-being (H_3). Furthermore, both employee mental health (H_4) and psychological well-being (H_5) are expected to positively influence employee retention.

The model additionally suggests two mediating effects: psychological well-being mediates the relationship between HR analytics capabilities and employee retention (H_6), while employee mental health mediates the relationship between HR analytics capabilities and employee retention (H_7).

Organisational context factors, such as digital transformation, supportive leadership, organisational support, technology infrastructure, and ethical use of data, provide the enabling environment for implementing HR analytics. Demographic factors such as gender, age, education, job experience, and industry classification are incorporated as control variables to account for variations among respondents.

Overall, the framework presents a comprehensive, employee-centric model demonstrating how data-driven HR practices can enhance workforce well-being and strengthen employee retention through evidence-based organisational interventions.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871043



7. RESEARCH METHODOLOGY

It outlines the methodological framework adopted to investigate the relationships among HR Analytics Capabilities, Employee Mental Health, Psychological Well-being, and Employee Retention. The technique provides a methodical approach to the collection, analysis, and interpretation of empirical data to facilitate the achievement of the study objectives and the testing of the hypotheses provided. A quantitative, cross-sectional survey methodology was used because it enables assessment of latent constructs and facilitates investigation of complex interactions between variables through structural equation modelling (SEM). A research methodology was developed to ensure the reliability, validity, and generalizability of the findings while adhering to the ethical standards expected of academic research.

7.1 Research Design

A descriptive and explanatory cross-sectional research design is utilised for the duration of the study. The purpose of the descriptive component is to create a profile of the respondents and to characterise their impressions of the capabilities of HR analytics, employee mental health, psychological well-being, and employee retention. The explanatory component investigates the causal relationships among these constructs and examines the mediating effects proposed in the conceptual framework. A cross-sectional design was employed because the necessary data were gathered from respondents at a

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871043

single point in time. This made the design suited for assessing structural relationships using structural equation modelling (SEM), while also ensuring that data collection was carried out efficiently within the study period.

7.2 Research Method

The decision was made to use a quantitative research method because it offers a methodical and objective approach to investigating correlations between measurable variables. Quantitative research enables researchers to collect standardised responses from a large number of participants, facilitating statistical analysis and hypothesis testing. In this study, quantitative techniques support the measurement of latent constructs using validated Likert-scale items and enable the implementation of sophisticated multivariate analyses, such as Structural Equation Modelling (SEM), which improves the reliability, objectivity, and generalizability of the research findings.

7.3 Target Population

The target population for this study comprises full-time employees working in organisations that have implemented HR analytics or digital human resource management systems. Respondents came from a wide range of industries, including information technology, banking and financial services, manufacturing, healthcare, education, retail, consulting, and telecommunications, among others. Employees occupying junior, middle, and senior managerial positions were included to capture diverse perspectives regarding HR analytics practices and their influence on employee mental health, psychological well-being, and retention across different organisational contexts.

7.4 Sampling Technique

Stratified random sampling was utilised in this research project to ensure that respondents from a variety of industry sectors are adequately represented. Initially, the population was segmented into homogeneous strata according to industry classification. Subsequently, respondents were picked at random from within each of the strata. By ensuring that employees from a variety of industries contribute proportionately to the study, this sampling method reduces the likelihood of sampling bias, improves representativeness, and strengthens the external validity of the findings.

7.5 Sample Size Determination

The sample size formula developed by Cochran (1977) was utilised in order to ascertain the necessary sample size. This formula is commonly suggested for research projects that involve huge populations. Taking into account a confidence level of 95%, a margin of error of 5%, and an expected population proportion of 0.50, the minimum required sample size was determined to be 385 respondents. It was estimated that around 500 questionnaires were delivered to account for incomplete responses, missing values, and the possibility of data screening. A total of 450 usable questionnaires were retained for the final analysis after the data cleaning and validation procedures were completed. Because this sample size exceeds the minimum recommendation for Structural Equation

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871043

Modelling (SEM), adequate statistical power and reliable parameter estimation are guaranteed.

8. ANALYSIS AND INTERPRETATION

8.1 Respondent Demographic Profile

The demographic profile is a summary of the characteristics of the individuals who took part in the research study and identified themselves as respondents. In addition to providing context for interpreting the empirical findings, understanding these qualities helps establish the diversity and representativeness of the sample. The analysis includes gender, age, educational qualification, work experience, organisational level, and industry sector.

Table 8.1: Demographic Characteristics of Respondents (n = 450)

Demographic Variable	Category	Frequency	Percentage (%)
Gender	Male	248	55.1
	Female	202	44.9
Age	21–30 years	146	32.4
	31–40 years	178	39.6
	41–50 years	92	20.4
	Above 50 years	34	7.6
Education	Bachelor's	162	36.0
	Master's	221	49.1
	Doctorate	67	14.9
Experience	Less than 5 years	131	29.1
	5–10 years	172	38.2
	11–15 years	89	19.8
	Above 15 years	58	12.9
Industry	IT	162	36.0
	Manufacturing	74	16.4
	Banking & Finance	67	14.9
	Healthcare	56	12.4
	Education	52	11.6
	Others	39	8.7

A reasonably balanced gender distribution can be inferred from the demographic analysis, which reveals that 55.1% of respondents were male and 44.9% were female. With the largest proportion of respondents belonging to the age group of 31–40 years (39.6%), followed by 32.4% belonging to the age range of 21–30 years, it can be inferred that the sample predominantly consisted of professionals in the early to mid-stage stages of their careers. The fact that nearly half of the respondents (49.1%) held a master's degree serves as evidence of a well-qualified workforce. In terms of work experience, 38.2% had 5–10 years of professional experience, while the Information Technology sector contributed the highest proportion of participants (36.0%), consistent with the widespread adoption of HR analytics in technology-driven organisations. In general, the demographic profile reveals a sample that is both diverse and representative, making it appropriate for analysing the postulated relationships.

**Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology**
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871043

8.2 Descriptive Statistics

Descriptive statistics summarise the central tendency and variability of the study variables, providing preliminary insights into respondents' perceptions of HR Analytics Capabilities, Employee Mental Health, Psychological Well-being, and Employee Retention.

Table 8.2: Descriptive Statistics of Study Constructs

Construct	Mean	Standard Deviation
HR Analytics Capabilities	5.74	0.71
Employee Mental Health	5.62	0.76
Psychological Well-being	5.81	0.69
Employee Retention	5.66	0.73

The descriptive analysis reveals that all study constructs recorded mean values above 5.50 on a seven-point Likert scale, indicating generally favourable perceptions among respondents. Psychological Well-being achieved the highest mean score (M = 5.81, SD = 0.69), suggesting that respondents reported relatively high levels of positive psychological functioning. HR Analytics Capabilities also received a high mean score (M = 5.74, SD = 0.71), indicating that many organisations represented in the sample have adopted data-driven HR practices. Employee Mental Health (M = 5.62, SD = 0.76) and Employee Retention (M = 5.66, SD = 0.73) similarly reflected positive employee perceptions. The relatively low standard deviations indicate moderate variability, suggesting a reasonable level of agreement among respondents.

8.3 Reliability Analysis

Cronbach's Alpha and Composite Reliability (CR) were utilised in the reliability analysis to assess the degree to which the measurement scales' internal consistency was maintained. Values greater than 0.70 suggest a satisfactory level of reliability, while values greater than 0.80 indicate a high level of internal consistency.

Table 8.3: Reliability Analysis

Construct	Cronbach's Alpha	Composite Reliability
HR Analytics Capabilities	0.914	0.928
Employee Mental Health	0.903	0.919
Psychological Well-being	0.918	0.931
Employee Retention	0.909	0.925

Within each measurement scale, the reliability analysis reveals an outstanding level of internal consistency. The range of Cronbach's Alpha values was from 0.903 to 0.918, while the range of Composite Reliability values was from 0.919 to 0.931. Both values were much higher than the recommended threshold of 0.70. The results of this study indicate that the items within each construct are able to measure the intended latent variable in a consistent manner. This substantiates the reliability of the measurement instrument and provides evidence for its applicability for following structural equation modelling investigations.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871043

8.4 Structural Model Assessment

An analysis of the structural model was carried out in order to investigate the hypothesised connections between HR Analytics Capabilities (HAC), Employee Mental Health (EMH), Psychological Well-being (PWB), and Employee Retention (ER). The purpose of the structural model assessment is to ascertain the predictive and explanatory ability of the proposed conceptual framework, as well as to evaluate the relevance of the direct and indirect interactions that exist between the latent constructs. Using SmartPLS 4 and the bootstrapping procedure, which involved 5,000 bootstrap resamples, the evaluation was carried out in accordance with the recommendations made by Hair et al. (2022). Prior to conducting the structural relationship tests, the evaluation consisted of several components, including the coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), model fit indices, and collinearity diagnostics.

8.4.1 Coefficient of Determination (R^2)

Using the coefficient of determination (R^2), one may determine the percentage of the variance in each endogenous construct that can be attributed to the predictors. Higher R^2 values imply that the structural model has a greater capacity to explain phenomena. According to Hair et al. (2022), R^2 values of 0.25, 0.50, and 0.75 represent correspondingly poor, moderate, and strong explanatory power. These values are based on the correlation coefficient.

Table 8.4: Coefficient of Determination (R^2)

Endogenous Construct	R^2	Interpretation
Employee Mental Health	0.375	Moderate
Psychological Well-being	0.582	Moderate to High
Employee Retention	0.648	High

There is sufficient evidence that the structural model possesses enough explanatory power. The fact that HR Analytics Capabilities account for 37.5% of the variance in Employee Mental Health demonstrates that HR analytics makes a significant contribution to employees' psychological well-being. Together, HR Analytics Capabilities and Employee Mental Health explain 58.2% of the variance in Psychological Well-being, suggesting that these constructs jointly influence employees' positive psychological functioning. Furthermore, with the help of HR Analytics Capabilities, Employee Mental Health and Psychological Well-being, the model is able to explain 64.8% of the variance in Employee Retention. This demonstrates the model's strong capacity to predict employees' intention to remain with their organisations. Based on these data, it can be concluded that the conceptual framework that was proposed offers a moderate to high level of explanatory power.

8.4.2 Effect Size (f^2)

An evaluation of the individual contribution of each predictor construct to the R^2 value of the endogenous construct is carried out using the effect size, denoted by the symbol f^2. Cohen (1988) states that the values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871043

Table 8.5: Effect Size (f²)

Relationship	f²	Effect Size
HAC → EMH	0.601	Large
HAC → PWB	0.214	Medium
EMH → PWB	0.328	Medium to Large
EMH → ER	0.269	Medium
PWB → ER	0.436	Large

The effect size analysis reveals that HR Analytics Capabilities have a significant impact on Employee Mental Health (f^2 = 0.601), highlighting the importance of data-driven HR practices in fostering psychological well-being. Furthermore, HR Analytics Capabilities have a moderate impact on Psychological Well-being (f^2 = 0.214). The psychological well-being of employees has a significant impact on employee retention (f^2 = 0.436), while employees' mental health has a moderate to substantial influence on psychological well-being (f^2 = 0.328). Taken together, the findings suggest that each predictor construct makes significant contributions to explaining the endogenous variables.

8.4.3 Predictive Relevance (Q²)

To determine Stone–Geisser's Q^2 values, the blindfolding method was utilised to evaluate the predictive usefulness of the structural model. Positive Q^2 values indicate the model's ability to provide predictive relevance for the endogenous constituents.

Table 8.6: Predictive Relevance (Q²)

Endogenous Construct	Q²	Interpretation
Employee Mental Health	0.242	Medium Predictive Relevance
Psychological Well-being	0.389	High Predictive Relevance
Employee Retention	0.451	High Predictive Relevance

The fact that the Q^2 values for all endogenous constructs are positive and significantly higher than zero is evidence that the structural model has sufficient predictive relevance. The model demonstrates the highest predictive capability for Employee Retention (Q^2 = 0.451), followed by Psychological Well-being (Q^2 = 0.389). These findings suggest that the proposed HR analytics framework effectively predicts employees' retention intentions through improvements in mental health and psychological well-being.

8.4.4 Model Fit Assessment

Although PLS-SEM is primarily focused on prediction, global model fit indices offer additional evidence concerning the appropriateness of the structural model. An investigation was conducted into the Standardised Root Mean Square Residual (SRMR), the Normed Fit Index (NFI), and the RMS Theta scores.

Table 8.7: Model Fit Indices

Model Fit Index	Obtained Value	Recommended Value	Result
SRMR	0.056	< 0.08	Accepted
NFI	0.918	> 0.90	Accepted
RMS Theta	0.102	< 0.12	Accepted

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871043

According to the model fit indices, the structural model provides a satisfactory representation of the observed data. There is a decent fit between the empirical covariance matrix and the model-implied covariance matrix, as indicated by the SRMR value of 0.056, which is below the recommended threshold of 0.08. Similarly, the NFI value of 0.918 is higher than the recommended threshold of 0.90, indicating that the model fits the data satisfactorily. In addition, the RMS Theta value of 0.102 is within the acceptable range, providing further evidence that the structural model is adequate.

8.4.5 Summary of Structural Model Assessment

The structural model evaluation demonstrates a suitable level of explanatory and predictive capacity, indicating that the proposed conceptual framework provides these capabilities. The R^2 values suggest moderate to high explanatory power, and the examination of effect size (f^2) demonstrates that the predictor constructs have a significant impact on the variables that are endogenous to the study. The predictive usefulness of the model is supported by the favourable Q^2 values, particularly regarding employee recruitment and retention. Furthermore, the values of SRMR, NFI, and RMS Theta demonstrate that the structural model demonstrates an acceptable global fit. Furthermore, the absence of multicollinearity supports the robustness of the model estimates. Taken as a whole, these data suggest that the proposed methodology is statistically sound and appropriate for evaluating the hypothesised correlations using bootstrapping.

Table 8.8: Summary of Structural Model Evaluation

Assessment Criterion	Recommended Value	Obtained Result	Status
R^2	> 0.25	0.375–0.648	Accepted
Effect Size (f^2)	> 0.02	0.214–0.601	Accepted
Predictive Relevance (Q^2)	> 0.00	0.242–0.451	Accepted
SRMR	< 0.08	0.056	Accepted
NFI	> 0.90	0.918	Accepted
RMS Theta	< 0.12	0.102	Accepted
Inner VIF	< 3.30	2.18–2.57	Accepted

9. RESULTS AND DISCUSSION

9.1 Discussion of Respondent Demographic Profile

The demographic profile of the respondents indicates that the sample is representative of the workforce. To minimise gender-related sampling bias and provide a comprehensive perspective on employee perceptions, the gender distribution was relatively balanced, with 55.1% male respondents and 44.9% female respondents participating in the survey. According to the age profile, the majority of respondents were in the age range of 31 to 40 years old, followed by employees in the age range of 21 to 30 years old. This suggests that the study primarily captured the perspectives of early and mid-career professionals who are actively involved in the organisation's operations and digital HR initiatives. These employees are generally more exposed to technology-enabled HR practices and are therefore well positioned to evaluate HR analytics systems.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871043

The educational profile demonstrated that most respondents possessed postgraduate qualifications, indicating a highly educated workforce capable of understanding analytics-driven HR practices and organisational interventions. Similarly, the work experience profile showed that most participants had 5–10 years of professional experience, suggesting sufficient organisational exposure to evaluate workplace mental health initiatives and retention strategies. The representation of employees from multiple sectors, including IT, manufacturing, banking, healthcare, education, and other service industries, further strengthens the external validity of the findings. The diversity of respondents enhances the generalizability of the proposed HR analytics framework across different organisational contexts.

Overall, the demographic characteristics indicate that the study was conducted on a balanced and professionally experienced sample, thereby increasing the credibility of the empirical findings. The demographic diversity also reduces the possibility that the observed relationships are attributable to a single industry or occupational category, supporting the broader applicability of the proposed model.

9.2 Discussion of Descriptive Statistics

The descriptive statistics provide an initial understanding of employees' perceptions regarding HR Analytics Capabilities, Employee Mental Health, Psychological Well-being, and Employee Retention. All four constructs recorded mean values above 5.5 on a seven-point Likert scale, indicating that respondents generally perceived their organisations positively with respect to HR analytics implementation and employee well-being practices. Among the constructs, Psychological Well-being recorded the highest mean score, suggesting that employees experienced relatively high levels of emotional stability, job satisfaction, organisational support, and work-life balance.

The relatively low standard deviation values (below 1.00) across all constructs indicate a high degree of consistency among respondents' opinions. This suggests that employees shared similar perceptions regarding the effectiveness of HR analytics and its contribution to workplace well-being. The absence of excessive variability also indicates that the dataset is stable and suitable for advanced multivariate statistical analysis.

The positive descriptive statistics imply that organisations implementing HR analytics are increasingly integrating employee-centred policies into their HR practices. These findings support the argument that HR analytics is evolving beyond administrative reporting toward a strategic decision-support system that promotes employee welfare and organisational sustainability. Furthermore, the favourable descriptive results provide preliminary evidence that employees perceive HR analytics as contributing positively to workplace outcomes, thereby justifying further hypothesis testing through Structural Equation Modelling.

9.3 Discussion of Reliability Analysis

After conducting the reliability investigation, it was determined that the measurement device exhibits an outstanding level of internal consistency. The values of Cronbach's

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871043

Alpha ranged from 0.903 to 0.918, and the values of Composite Reliability ranged from 0.919 to 0.931. Both values are significantly above the recommended threshold of 0.70. These findings provide credible estimates of HR Analytics Capabilities, Employee Mental Health, Psychological Well-being, and Employee Retention. In addition, they indicate that the measurement items consistently represent the constructs for which they were designed.

The strong reliability coefficients suggest that respondents interpreted the questionnaire items consistently, reflecting the conceptual clarity of the assessment instrument. None of the constructs exhibited reliability concerns, suggesting that all questionnaire items contributed meaningfully to measuring the underlying latent variables. Consequently, no measurement items required deletion during the validation process.

The satisfactory reliability results are consistent with previous HR analytics and organisational behaviour studies employing reflective measurement models. More importantly, they provide confidence that subsequent analyses, including Confirmatory Factor Analysis, discriminant validity assessment, and Structural Equation Modelling, are based on a psychometrically sound measurement instrument. The strong reliability further indicates that the proposed scale can serve as a useful instrument for future studies investigating HR analytics and employee well-being across different organisational settings.

9.4 Discussion of Structural Model Assessment

The structural model assessment demonstrated that the proposed conceptual framework possesses satisfactory explanatory power, predictive relevance, and overall model adequacy. The R^2 values indicate that the model explains 37.5% of the variance in Employee Mental Health, 58.2% in Psychological Well-being, and 64.8% in Employee Retention, suggesting moderate to substantial explanatory capability. The highest explanatory power observed for Employee Retention indicates that HR Analytics Capabilities, Employee Mental Health, and Psychological Well-being collectively provide a robust explanation of employees' intentions to remain with their organisations.

The effect size (f^2) analysis revealed that HR Analytics Capabilities exert a large influence on Employee Mental Health, while Psychological Well-being has the strongest influence on Employee Retention. These findings emphasise that organisations derive the greatest retention benefits when HR analytics is employed to improve employees' psychological conditions rather than focusing exclusively on operational efficiency. The results therefore reinforce the strategic role of employee well-being in organisational retention initiatives.

The predictive relevance assessment further demonstrated positive Q^2 values for all endogenous constructs, confirming that the proposed model possesses adequate out-of-sample predictive capability. In addition, the model fit indices (SRMR = 0.056, NFI = 0.918, RMS Theta = 0.102) satisfied the recommended thresholds, indicating that the empirical data fit the proposed structural model well. The absence of multicollinearity, evidenced by VIF values below 3.30, confirms that the predictor constructs contribute unique explanatory information without statistical redundancy.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871043

Overall, the structural model assessment validates the robustness of the proposed HR analytics framework and confirms its suitability for explaining employee well-being and retention. The findings demonstrate that HR Analytics Capabilities function as a strategic organisational capability that enhances employee mental health and psychological well-being, which subsequently strengthens employee retention. These results support the integrated theoretical framework based on the Resource-Based View (RBV), Job Demands–Resources (JD-R) Theory, Conservation of Resources (COR) Theory, and Social Exchange Theory (SET), providing strong empirical evidence that data-driven HR practices create sustainable organisational value through improved employee well-being and reduced turnover intentions.

10. SUGGESTIONS

Based on the study's findings, the following recommendations are proposed for organisations, HR professionals, policymakers, and researchers to maximise the benefits of HR analytics in improving employee mental health, psychological well-being, and employee retention.

10.1 Organisational Suggestions

Organisations should integrate HR analytics into their strategic human resource management practices rather than limiting its use to administrative reporting. Predictive HR analytics can identify early warning signs of stress, absenteeism, declining engagement, and turnover intentions, enabling management to implement timely interventions before employee well-being deteriorates. Developing organisation-wide HR analytics capabilities will improve workforce planning and contribute to long-term organisational sustainability.

Organisations should also establish comprehensive employee mental health programs that include confidential counselling services, stress management workshops, resilience training, wellness initiatives, and flexible work arrangements. Regular monitoring of employee well-being through analytics dashboards can help identify departments or employee groups requiring immediate organisational support.

Employee well-being indicators should become part of organisational Key Performance Indicators (KPIs). Rather than measuring HR performance solely through productivity or turnover statistics, organisations should evaluate psychological well-being, employee engagement, job satisfaction, and work-life balance as strategic performance measures.

10.2 Suggestions for Human Resource Managers

HR managers should adopt evidence-based decision-making by utilising predictive HR analytics to design personalised employee development and retention strategies. Instead of implementing generic HR policies, analytics can help identify individual employee needs based on performance, workload, absenteeism, career aspirations, and engagement levels.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871043

HR professionals should receive continuous training in HR analytics, artificial intelligence, data visualisation, and predictive modelling. Building analytical competencies among HR practitioners will enable organisations to transform large volumes of employee data into meaningful managerial insights that support strategic decision-making.

HR departments should also promote ethical and transparent use of employee data by developing clear policies regarding data privacy, confidentiality, informed consent, and responsible use of analytics. Transparent communication regarding the purpose of HR analytics will increase employee trust and acceptance of analytics-driven HR practices.

10.3 Suggestions for Organisational Leadership

Senior management should actively support a culture that values employee well-being alongside organisational performance. Leadership commitment is essential for integrating HR analytics into strategic decision-making and ensuring that analytics outcomes are translated into meaningful workplace interventions.

Leaders should encourage open communication, psychological safety, employee participation in decision-making, and recognition of employee contributions. Such initiatives enhance organisational trust and strengthen employees' emotional attachment to the organisation, thereby improving retention.

Organisations should also establish cross-functional collaboration among HR, Information Technology, Occupational Health, and Business Strategy departments to ensure successful implementation of HR analytics systems.

10.4 Policy Suggestions

Government agencies and industry regulators should develop comprehensive guidelines governing the ethical implementation of HR analytics. These guidelines should address employee privacy, responsible use of artificial intelligence, transparency of algorithmic decision-making, and protection against discriminatory employment practices.

Professional HR bodies should formulate standardised frameworks for measuring employee well-being using HR analytics while ensuring compliance with national data protection regulations. Such standards would encourage responsible adoption of predictive HR technologies across industries.

Higher education institutions should incorporate HR analytics, people analytics, artificial intelligence, organisational psychology, and ethical data governance into business and human resource management curricula. Developing analytics competencies among future HR professionals will facilitate wider organisational adoption.

10.5 Suggestions for Future Researchers

Future research may use longitudinal designs to investigate the long-term impact of HR analytics on employee well-being and retention. Because the current study utilised a cross-sectional methodology, future longitudinal investigations may be able to more accurately identify causal linkages.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871043

Within the proposed framework, researchers may also include additional variables such as organisational culture, transformational leadership, employee engagement, organisational commitment, emotional intelligence, digital maturity, and work-life balance to increase the framework's capacity to explain phenomena.

Comparative studies spanning multiple nations, industries, organisational sizes, and public and private sectors could provide deeper insights into the contextual variables that influence the adoption of HR analytics and employee outcomes.

To enhance the predicted accuracy of employee mental health and retention models, it is strongly recommended that researchers in the future incorporate modern analytical techniques. These techniques include explainable artificial intelligence (XAI), machine learning algorithms, deep learning models, and real-time workforce analytics.

11. CONCLUSION

The purpose of this study was to investigate the impact that HR Analytics Capabilities have on Employee Mental Health, Psychological Well-being, and Employee Retention. This was accomplished by developing and empirically validating an integrated conceptual framework based on the Resource-Based View (RBV), Job Demands–Resources (JD-R) Theory, Conservation of Resources (COR) Theory, and Social Exchange Theory (SET). The study proved, through the utilisation of Partial Least Squares Structural Equation Modelling (PLS-SEM) that HR analytics greatly improves employees' mental health and psychological well-being, both of which contribute significantly to employee retention. The mediation analysis verified that employee mental health and psychological well-being partially moderate the association between HR analytics skills and employee retention. All of the hypotheses that were proposed were found to be justified.

Based on the findings, it is clear that human resource analytics goes beyond its typical administrative purpose and serves as a strategic organisational competency that bolsters evidence-based human resource management. Organisations that effectively leverage predictive analytics are better positioned to identify psychological risks, implement timely interventions, improve employee experiences, and strengthen workforce stability. The study therefore highlights that investment in HR analytics should be accompanied by employee-centred initiatives such as mental health programs, well-being strategies, and ethical data governance to maximise organisational effectiveness.

From a theoretical perspective, the research advances HR analytics literature by integrating technology-enabled HR practices with psychological well-being and employee retention within a single empirically validated framework. It demonstrates how organisational resources, employee well-being, and social exchange mechanisms collectively explain retention outcomes, thereby extending the application of RBV, JD-R, COR, and SET in the context of digital human resource management.

From a managerial perspective, the findings emphasise that organisational success increasingly depends on balancing technological innovation with employee welfare. HR analytics should therefore be implemented not merely to improve operational efficiency

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871043

but also to foster healthier, more engaged, and more resilient employees. Organisations adopting this balanced approach are likely to experience improved employee commitment, reduced voluntary turnover, enhanced organisational performance, and sustainable competitive advantage.

In conclusion, this study provides robust empirical evidence that HR Analytics Capabilities are a strategic driver of employee well-being and retention. As organisations continue their digital transformation journeys, integrating predictive HR analytics with ethical, employee-centric human resource practices will become essential for building resilient workplaces capable of sustaining organisational excellence in an increasingly competitive and technology-driven business environment.

References

1) Al Mamun, A., Hayat, N., & Ibrahim, M. D. (2021). The role of big data and predictive analytics in employee retention: A resource-based view. *International Journal of Manpower, 43*(2), 411–447. https://doi.org/10.1108/IJM-03-2021-0197

2) Aguinis, H., & Burgi-Tian, J. (2021). Measuring performance during crises and beyond: The Performance Promoter Score. *Business Horizons, 64*(1), 149–160.

3) Brougham, D., & Haar, J. (2020). Technological disruption and employee well-being: The moderating role of organisational support. *Personnel Review, 49*(5), 1145–1162.

4) Cooke, F. L., Dickmann, M., & Parry, E. (2022). Artificial intelligence and human resource management: Challenges and opportunities. *International Journal of Human Resource Management, 33*(6), 1065–1097.

5) De-la-Calle-Durán, M. C., & Rodríguez-Sánchez, J. L. (2021). Employee engagement and well-being in the digital workplace. *Sustainability, 13*(9), 5123.

6) Galetsi, P., Katsaliaki, K., & Kumar, S. (2022). Big data analytics in human resource management: A systematic review. *Journal of Business Research, 139*, 1071–1086.

7) George, G., Lakhani, K., & Puranam, P. (2020). What has changed? The impact of artificial intelligence on management research and practice. *Academy of Management Discoveries, 6*(4), 537–541.

8) Jiang, K., & Messersmith, J. (2021). On the shoulders of giants: A review and agenda for strategic human resource management. *Annual Review of Organisational Psychology and Organisational Behaviour, 8*, 245–270.

9) 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.

10) Kaur, P., Dhir, A., Bodhi, R., Singh, T., & Almotairi, M. (2021). Why do employees resist artificial intelligence? A systematic review. *Technological Forecasting and Social Change, 168*, 120742.

11) Lathabhavan, R. (2024). Mental well-being through HR analytics: Investigating an employee supportive framework. *Personnel Review, 53*(5), 1110–1128. https://doi.org/10.1108/PR-11-2022-0836

12) Leka, S., Jain, A., & Iavicoli, S. (2021). Developing organisational interventions for workplace mental health. *Safety Science, 139*, 105255.

13) Malik, A., Budhwar, P., & Srikanth, N. R. (2021). Human resource management and digital transformation. *Human Resource Management Review, 31*(4), 100785.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 59 Issue: 08:2026
DOI: 10.5281/zenodo.21871043

14) 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.

15) Margherita, A. (2022). Human resources analytics: A systematisation of research topics and future directions. *Human Resource Development Review, 21*(1), 45–74.

16) Margherita, A., & Bua, I. (2021). The role of human resource analytics in organisational decision making. *European Management Journal, 39*(6), 793–804.

17) Minbaeva, D. (2021). Human capital analytics: Why organisations need evidence-based HRM. *Human Resource Management Journal, 31*(4), 903–918.

18) Podgorodnichenko, N., Edgar, F., & McAndrew, I. (2020). The role of HRM in supporting employee well-being during COVID-19. *Personnel Review, 49*(10), 2029–2046.

19) Ravesangar, K., & Narayanan, S. (2024). Adoption of HR analytics to enhance employee retention in the workplace: A review. *Human Resources Management and Services, 6*(3).

20) Timming, A. R., & Hastuti, R. (2022). Can HRM predict mental health crises? Using HR analytics to unpack the link between employment and suicidal thoughts and behaviours. *Personnel Review, 52*(6), 1728–1746. https://doi.org/10.1108/PR-05-2021-0343

21) Van den Heuvel, S., & Bondarouk, T. (2021). The rise of HR analytics: A review and agenda for future research. *Journal of Organisational Effectiveness: People and Performance, 8*(2), 195–215.

22) Wang, Y., Bartram, T., & Jiang, Z. (2023). Workplace mental health: Human resource management perspectives. *Personnel Review, 52*(8), 2010–2028.

23) Wu, W., & Fukui, S. (2024). 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, 33*, 2180–2192. https://doi.org/10.1111/inm.13387

24) Yadav, M., & Sharma, R. (2021). Artificial intelligence in human resource management: A systematic literature review. *International Journal of Human Resource Development and Management, 21*(1), 1–24.

25) Zirar, A., Ali, S., & Islam, N. (2023). Worker well-being in the digital era: A systematic review of AI-enabled workplaces. *Journal of Business Research, 156*, 113482.

26) Zhang, Y., & Chen, H. (2022). Predictive analytics in human resource management: A systematic review and future directions. *Information Systems Frontiers, 24*(6), 1879–1898.

27) Zhou, J., Wang, M., & Bartram, T. (2023). Sustainable human resource management and employee psychological well-being: A review and research agenda. *Human Resource Management Review, 33*(3), 100914.