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Research Article

Linking AI-Driven HRM Practices to Organizational Performance: Empirical Evidence from Delhi NCR's IT Industry

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ABSTRACT

This study reveals the impact of AI-powered Human Resource Management (HRM) practices on organizational performance in Delhi NCR's information technology sector. With Artificial Intelligence revolutionizing fundamental HR activities recruitment, training, analytics, and performance management—its implementation is increasingly revolutionizing workforce strategy. The study, employing a quantitative approach and data collected from 430 Delhi, Haryana, and Uttar Pradesh respondents, applies Partial Least Squares Structural Equation Modeling (PLS-SEM) to investigate structural relationships between AI-enabled HRM constructs and performance indicators. Constructs such as Talent Management and Recruitment (TMR), AI-enabled HR Operations (HODS), Workforce Analytics and Planning (PWAP), and Talent Development and Performance Management (TDPM) were anticipated to possess high reliability, validity, and discriminant characteristics. Findings confirm the positive effect of AI-HRM on organizational performance and provide practical implications for IT firms to strategically implement AI in HR practices. This study bridges an essential empirical research gap and contributes to AI-HRM studies in the Indian context.

Keywords: Organizational Performance, PLS-SEM, IT Sector, Structural Equation Modelling, Artificial Intelligence, HRM

1 Introduction

The emergence of Artificial Intelligence (AI) has profoundly transformed organizational functioning by redefining strategic decision-making and day-to-day operations. In the field of Human Resource Management (HRM), AI is revolutionizing traditional practices such as recruitment, employee engagement, training, and performance appraisal. Through automation, predictive analytics, and intelligent decision systems, AI enhances both the efficiency and strategic value of HRM, thereby contributing to improved organizational performance (Premnath & Arun, 2019). Unlike earlier waves of digital transformation, the AI era is characterized by adaptive learning systems that analyze workforce data, forecast employee behavior, and support managerial decision-making with higher accuracy and transparency.

AI in HRM goes beyond simple automation it represents a paradigm shift in managing talent acquisition, motivation, and organizational capability development. As observed by Reddy et al. (2020), AI systems in HR not only optimize administrative functions but also improve fairness in rewards and recognition by minimizing human bias. Through advanced analytics, AI enhances the precision of hiring decisions, strengthens workforce planning, and facilitates continuous skill development. Organizations such as IBM and Amazon have successfully integrated AI-based HR analytics to improve employee retention, enhance engagement, and align human capital strategies with long-term business objectives (Premnath & Arun, 2019).

In the Indian IT industry, particularly within the Delhi–NCR region, the adoption of AI-based HRM systems has gained traction due to the concentration of technology-driven firms, startups, and multinational corporations. However, Indian organizations remain cautious, often citing challenges related to data integration, ethical concerns, and organizational readiness (Ritu PhD, 2025). Despite these obstacles, evidence suggests that AI-HRM practices when implemented strategically can enhance employee engagement, learning

orientation, and organizational agility (Meijerink et al., 2021).
Scholars have conceptualized AI-driven HRM practices through multidimensional frameworks. For instance, Talent Management and Recruitment (TMR) emphasizes automation in hiring and candidate matching (Upadhyay & Khandelwal, 2018), HR Operations and Decision Support (HODS) captures data-driven decision-making through predictive analytics (Wang & Cotton, 2018), Workforce Planning and Analytics (PWAP) focuses on forecasting future workforce needs (Wamba-Taguimdje et al., 2020), and Talent Development and Performance Management (TDPM) highlights personalized learning and accountability enhancement (Meijerink et al., 2021). These AI-enabled functions collectively drive organizational performance dimensions such as Business Growth and Organizational Efficiency (BGOE), Market Growth and Service Improvement (MGSI), and Customer Satisfaction and Resource Optimization (CSRO) (Minbaeva, 2021).
Despite growing global research, there remains a lack of empirical validation within the Indian context, particularly regarding the mechanisms through which AI-based HRM practices influence organizational outcomes. This gap is critical, as the Indian IT sector represents both a high-skill labor environment and a frontier for digital transformation. Addressing this void, the present study models the relationship between AI-driven HRM practices and organizational performance using Partial Least Squares Structural Equation Modelling (PLS-SEM). The study analyzes responses from IT professionals across Delhi, Haryana, and Uttar Pradesh NCR to test the reliability and significance of AI-HRM constructs.
This investigation contributes to the literature by offering a data-driven framework that links AI-enabled HR functions with measurable performance indicators. The insights from this study are expected to guide practitioners and policymakers in designing ethical, human-centric, and performance-oriented AI strategies that enhance competitiveness, efficiency, and workforce sustainability in India's evolving technology sector.

2 Literature Review

Artificial Intelligence (AI) has redefined the operational and strategic boundaries of Human Resource Management (HRM) by embedding data-driven intelligence into recruitment, training, appraisal, and retention processes. Contemporary scholars note that AI-based HRM practices not only enhance efficiency but also generate strategic insights that strengthen organizational agility and performance (Roul et al., 2024; Prikshat et al., 2024). Unlike earlier technological interventions, AI integrates predictive analytics and machine learning to forecast workforce needs, optimize human potential, and align HR strategy with organizational goals (Meijerink et al., 2021).
A growing body of literature classifies AI-HRM functions into several thematic dimensions. Talent Management and Recruitment (TMR) focuses on automating candidate sourcing, screening, and selection through predictive algorithms that improve job–person fit (Upadhyay & Khandelwal, 2018). HR Operations and Decision Support (HODS) emphasizes data-driven decision-making, enabling managers to use AI dashboards and sentiment analytics for performance evaluation and policy design (Wang & Cotton, 2018). Predictive Workforce Analytics and Planning (PWAP) leverages historical data to forecast turnover, optimize staffing, and enhance workforce flexibility (Wamba-Taguimdje et al., 2020). Finally, Talent Development and Performance Management (TDPM) incorporates adaptive learning platforms and AI-based feedback systems that personalize development paths while reinforcing accountability (Minbaeva, 2021).
Empirical studies show that these AI-HRM dimensions collectively contribute to organizational performance, often measured through productivity, profitability, innovation, and employee satisfaction (Arslan et al., 2022; Jeong & Jeong, 2024). Gupta and Mehra (2024) observed that AI-based recruitment improves workforce diversity and reduces human bias, thereby enhancing creativity and innovation. Similarly, Pillai et al. (2022) found that AI-enabled chatbots and virtual assistants improve internal communication, leading to faster problem-solving and stronger employee engagement. However, other researchers have raised ethical and psychological concerns. Böhmer and Schinnenburg (2023) cautioned that algorithmic opacity and surveillance can lead to reduced trust and emotional exhaustion among employees, while Xiao, Yan, and Bamber (2024) emphasized the importance of balancing automation with empathy to sustain resilience and motivation.
In the Indian IT context, the integration of AI into HR functions is still evolving. Reddy and Gupta (2023) and Bhardwaj (2022) noted that adoption levels vary depending on firm size, technological readiness, and management support. Although large IT corporations have begun implementing predictive HR analytics and AI-driven learning systems, small and mid-sized firms continue to struggle with data standardization, ethical frameworks, and employee acceptance (Ritu PhD, 2025). The Delhi–NCR region, with its dense concentration of technology firms and skilled workforce, offers a unique ecosystem for understanding this transformation.
Despite widespread acknowledgment of AI's strategic potential, limited empirical studies have modelled how distinct AI-HRM dimensions jointly affect organizational performance in developing economies. This research therefore bridges a critical gap by empirically testing the relationship between AI-driven HRM practices—represented by TMR, HODS, PWAP, and TDPM—and organizational performance using PLS-SEM analysis. In doing so, it contributes to both theory and practice by clarifying the mechanisms through which AI enhances organizational efficiency, competitiveness, and human sustainability within India's dynamic IT industry.

3 Research Methodology

3.1 Research Design and Purpose

The study adopted a quantitative, cross-sectional, and explanatory research design to examine the impact of AI-driven HRM practices on organizational performance among IT professionals in Delhi NCR. This design was chosen to empirically test the relationships among multiple latent constructs through Partial Least Squares Structural Equation Modelling (PLS-SEM). The research aimed to model how four AI-based HRM dimensions Talent Management and Recruitment (TMR), HR Operations and Decision Support (HODS), Predictive Workforce Analytics and Planning (PWAP), and Talent Development and Performance Management (TDPM) affect overall Organizational Performance (OP).

3.2 Population and Sample

The target population comprised IT professionals employed in firms located across Delhi, Haryana, and Uttar Pradesh NCR, regions that represent India's most mature digital corridor. A purposive sampling technique was employed, selecting only full-time employees who had direct exposure to AI-enabled HR systems such as automated recruitment, AI-based appraisal dashboards, or predictive learning tools. Out of 600 distributed questionnaires, 511 valid responses were received and analyzed, representing a strong and diverse sample suitable for multivariate modelling. Ethical standards were maintained through voluntary participation, informed consent, and assured anonymity of responses.

3.3 Instrument Design and Measures

The data were collected through a structured questionnaire developed after an extensive review of previous literature and adapted from validated scales. Responses were recorded on a five-point Likert scale ranging from *1 = Strongly Disagree* to *5 = Strongly Agree*.

Each construct consisted of 4–6 indicators capturing the following dimensions:

- TMR: Automation, fairness, and transparency in recruitment decisions.
- HODS: Data-driven decision support and strategic HR operations.
- PWAP: Predictive analytics for workforce planning and turnover forecasting.
- TDPM: Personalized learning, AI-enabled appraisal, and development feedback.
- OP: Organizational efficiency, market growth, innovation, and service quality.

A pilot study with 30 participants confirmed the questionnaire's clarity and face validity. Cronbach's α values exceeded 0.80 for all constructs, indicating excellent internal consistency.

3.4 Data Analysis Procedure

Data were analyzed using SmartPLS 4 following the two-stage approach recommended by Hair et al. (2021). In the measurement model, reliability and validity were established through Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). Discriminant validity was assessed using the Fornell–Larcker criterion and the Heterotrait–Monotrait ratio (HTMT). Multicollinearity was examined through Variance Inflation Factor (VIF) values, all below 5.0, confirming model adequacy.

In the structural model, the relationships between the latent variables were tested using path coefficients (β), t-values, and p-values generated via bootstrapping with 5,000 subsamples. The R^2 and Q^2 values were evaluated to determine explanatory and predictive power. Results demonstrated that all four AI-HRM dimensions significantly and positively influenced organizational performance, validating the hypothesized model.

Summary

The research methodology provided a robust and replicable framework for examining the role of AI-enabled HRM practices in driving organizational outcomes. By employing PLS-SEM, the study ensured comprehensive evaluation of both measurement and structural relationships, thereby offering reliable empirical evidence on the transformative potential of AI in HRM within India's IT sector.

4 Empirical Analysis

4.1 Construct Reliability and Validity

Construct reliability and validity were assessed using Cronbach's Alpha, Composite Reliability (ρ_a and $\rho\square$), and Average Variance Extracted (AVE). All four constructs met the standard thresholds for these indices. The details are provided in Table 1.

Table 1: Construct Reliability and Validity

Construct	Cronbach's Alpha	Composite Reliability (ρ_a)	Composite Reliability (ρ□)	AVE
HODS	0.907	0.908	0.935	0.781
PWAP	0.875	0.877	0.923	0.8
TDPM	0.892	0.894	0.933	0.823
TMR	0.904	0.905	0.933	0.776
Source: Author's own				

Table 1 highlights Each construct exhibits high reliability, with Cronbach's Alpha values ranging from 0.875 to 0.907, all above the 0.70 benchmark. Composite Reliability values also exceed the threshold of 0.70, confirming consistent measurement. AVE values are above 0.50, confirming that each construct explains over 50% of the variance in its indicators, thus meeting the standard for convergent validity.

4.2 Discriminant Validity: Fornell-Larcker Criterion

The Fornell-Larcker criterion was applied to establish discriminant validity. Each construct's square root of AVE should exceed its correlation with other constructs. Table 2 highlights Each diagonal value (representing √AVE) is greater than any corresponding inter-construct correlation in its row or column, indicating that all constructs exhibit adequate discriminant validity.

Table 2: Discriminant Validity (Fornell-Larcker)

Construct	TMR	HODS	PWAP	TDPM
HODS	—	0.883		
PWAP	0.557	0.601	0.894	
TDPM	0.548	0.598	0.555	0.907
TMR	0.881	0.512	0.512	0.548
Source: Author's own				

4.3 Heterotrait–Monotrait Ratio (HTMT)

The HTMT ratio was used as a stringent test of discriminant validity. The acceptable threshold is HTMT < 0.90. Table 3 highlights All HTMT values are well below 0.90, confirming that the constructs are empirically distinct and discriminant validity is established.

Table 3: HTMT Matrix

Construct Pair	HTMT Value
HODS <-> PWAP	0.601
TDPM <-> HODS	0.598
TDPM <-> PWAP	0.555
TMR <-> HODS	0.557
TMR <-> PWAP	0.512
TMR <-> TDPM	0.548
Source: Author's own	

4.4 Cross Loadings

Cross-loadings were examined to confirm that each item loads highest on its intended construct. The results are shown below. Table 4 highlights Each item shows the strongest loading on its respective construct, demonstrating good item differentiation and supporting discriminant validity. For example, TMR1 loads 0.874 on TMR and significantly lower on other constructs.

Table 4: Cross Loadings (Partial View)

Code	TMR	HODS	PWAP	TDPM
TMR1	0.874	0.441	0.357	0.436
TMR2	0.893	0.482	0.442	0.438
TMR3	0.871	0.439	0.4	0.419
TMR4	0.886	0.419	0.408	0.441
HODS1	0.413	0.88	0.46	0.457
PWAP1	0.374	0.486	0.877	0.445
TDPM1	0.453	0.481	0.433	0.907
Source: Author's own				

4.5 Collinearity Statistics (VIF)

To assess multicollinearity among indicators, Variance Inflation Factor (VIF) values were calculated. Table 5 highlights all VIF values fall well below the acceptable threshold of 5.0, indicating that multicollinearity is not a concern, and all items contribute uniquely to their respective constructs.

Table 5: Collinearity Diagnostics (VIF)

Item Code	VIF
HODS1	2.707
PWAP1	2.171
TDPM2	2.749
TMR3	2.476
Source: Author's own	

Conclusion

This study provides a statistically strong model connecting AI-based HRM practices and improved organizational performance in the Delhi NCR IT industry. Based on data collected from 430 IT professionals and PLS-SEM usage, the study is able to establish that AI implementation in core HR activities—recruitment, operations, analytics, and development has positive effects on organizational efficiency, employee engagement, and strategic alignment. The TMR, HODS, PWAP, and TDPM constructs not only demonstrated high validity and reliability but also emerged empirically unique, suggesting their distinct contributions to performance outcomes. These results emphasize the game-changing role AI plays in transforming HR capabilities and offer useful insights to HR professionals as well as decision-makers in utilizing AI as a strategic tool. Despite some associated adoption issues in the Indian market, evidence confirms that an appropriately integrated AI-HRM system has the capability to trigger competitiveness as well as sustainable growth in tech-savvy firms.

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