ARTIFICIAL INTELLIGENCE INTEGRATION IN HRM AS A MEDIATING MECHANISM: A STUDY OF THE HRM–AI–ATTRITION NEXUS IN IT INDUSTRY

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ABSTRACT
This paper aims to examine the correlation between Human Resource Management (HRM) practices, the integration of Artificial Intelligence (AI) and employee attrition in the IT industry of India. The study proposes the mediating construct of AI Integration in HRM Practice (AIIHRMP) and empirically validates the structural model by using primary data from HR professionals of the IT organisations in Chennai with the help of Confirmatory Factor Analysis (CFA). The results support the hypothesis that better HRM practices have a significant positive effect on the integration of AI in HRM practice, which in turn has a significant negative impact on employee attrition, making AIIHRMP a real mediator in the relationship between HRM and employee attrition. Interestingly, the results show that this retention effect of HRM practice quality is significantly strengthened by the integration of AI by about 29.7%, indicating that the integration of AI has a meaningful second-order effect on the power of HRM systems to retain talent. The findings of this study can be considered theoretical, as it offers the first empirical validation of the incorporation of AI as a mediating mechanism in the HRM-attrition structural relations within the Indian IT context. It is also developed a practical framework for the development of AI-augmented HRM strategies to proactively mitigate the risk of human resource talent attrition in the Indian IT sector.

Keywords: AI in HRM, Employee Attrition, Confirmatory Factor Analysis, Mediation Analysis, IT Industry, DHRMP, AIIHRMP, DEAW.
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1. Introduction

One of the most impactful technological developments in the current practice of organisations is the rapid incorporation of Artificial Intelligence (AI) into Human Resource Management (HRM). The role of AI in HRM and its impact on the traditional understanding of the link between HRM and employee attrition is particularly relevant in the IT sector of India, where employee turnover rates consistently hover between 17 and 25 percent annually (Chandar et al., 2024; Kargeti & Sharma, 2023). The results of this research work resulted in the four-factor structure of HRM Practice Determinants (DHRMP) as well as confirming that the four factors explain 68 per cent of the variance in employee attrition outcomes (R2 = 0.680; F = 227.461, $p < 0.001$). The fundamental theoretical claim is that better HRM practices directly lead to more and higher quality integration of AI in the HR function (DHRMP to AIIHRMP), and that the integration of AI in the HR function, in its own right, leads to a lower propensity to quit (AIIHRMP to DEAW). This mediation pathway has not been modelled in the Indian IT context before. This paper offers the first empirical test and validation of this structural mediation hypothesis with 650 HR professionals, as well as a thorough analysis of the downstream workplace consequences of employee attrition on the remaining employees.

Bharadwaj (2024) presented an overview of AI in HRM, highlighting the ability of workforce analytics platforms to handle continuous streams of employee data that allow HR professionals to move from reactive turnover management to proactive retention management, preventing potential turnover decisions before they even solidify. The study ultimately reinforces the current research's placement of the use of AI as a mechanism to strengthen HRM's ability to retain. In this study, Basnet (2024) examined the use of AI for predictive analytics and employee retention measures, highlighting that AI models can accurately predict which employees are at risk of leaving, and do so significantly earlier than conventional HR monitoring, based on multi-dimensional employee data such as performance, pay, engagement scores, and promotion rate. This substantiates the argument of the study that the AI enhances the effectiveness of HRM systems

Gryncewicz, W and et.al. (2023) used a case-study example of a large IT company to explore how the use of AI to enhance HRM practices (in the form of recruitment, performance management and personalised training) could lower turnover rates by improving job-person fit and early identification of at-risk employees, offering direct empirical precedent to the mediation relationship investigated in this study. Hiring for candidate-job fit (Zawada, 2024) and continuously monitoring job satisfaction during the employment relationship (Zawada, 2024) represents a fundamental advancement over periodic HR review processes, which can be seen as a continuous, proactive retention capability of AI.

The study highlights the need for transparency in AI deployment, as organisations must establish trust through addressing transparency, data privacy, and algorithmic justice as necessary prerequisites for successfully retaining staff with AI. Madanchian (2024) synthesised findings into a comprehensive framework for AI-driven HR decision-making, emphasising the importance of transparency, data privacy, and algorithmic justice as fundamental prerequisites for organisations to successfully leverage AI to retain staff. J and Lakshminarayana (2024) analyzed the changes in HRM practices in IT companies due to AI and concluded that AI-driven CPM systems foster a culture of constant engagement, which is directly linked to a lower rate of staff attrition, and that AI poses significant ethical considerations, including data privacy and algorithmic bias.

Bhardwaj and Sharma (2024) found a statistically significant linkage between self-efficacy, organisational efficacy and the tendency of employees to leave the IT industry, showing that a low level of employee self-efficacy and organisational efficacy (in terms of performance orientation) significantly increases the employee turnover, which supported the conceptualization of determinants of employee attrition (DEAW) in this study. Vasudevan et al. (2024) found that in the IT domain, job security and career development are the two HRM dimensions that are most associated with retention, and job satisfaction acts as a key mediator between HRM quality and turnover behaviour (methodological precedent for the mediation model used in this study).

This study's theoretical framework is the Technology Acceptance Model, which offers a framework for understanding user attitudes toward technology. Srivastava (2024) explored employee perceptions of AI in talent acquisition and revealed that employees with knowledge of and positive attitudes toward the "why" of AI's involvement in HR processes were significantly more positive in their attitudes toward AI-mediated interactions, resulting in implications for satisfaction and retention. Tay et al. (2024) explored the growing presence of AI in talent acquisition and showed that AI-based recruitment lowers the time-to-hire and increases the quality of candidate-organization fit, thereby providing the empirical underpinning for the dimension of recruitment and onboarding (RO) of the AIIHRMP construct.

While there have been significant studies addressing HRM practices and employee attrition, and a burgeoning research trend on the use of AI in HRM, there has not yet been a study that models AI integration as a mediator between HRM practice quality and employee attrition in the Indian IT industry empirically. The current work mainly considers AI as a standalone tool for recruitment or efficiency and fails to incorporate the downstream implications of attrition on the remaining workforce, or take AI as an integral part of a holistic HRM system with a focus on retention. This research aims to fill these gaps by resorting to the mediation link of DHRMP -AIIHRMP -DEAW through the framework of Structural Equation Modelling, for the first time quantifying the extent to which the mediation pathway captures the retention effect of HRM practices, when amplified by AI. What is novel about this work is the empirical evidence that AI is not just a technological support tool but truly a mediating force in the talent retention and attrition process and the inclusion of second order effects of attrition on work quality, self-motivation and effectiveness of supervision, giving a more complete mediated model for action in a high attrition industry context.

2. Theoretical Framework and Research Hypotheses

2.1 Social Exchange Theory and AI-Augmented HRM

According to Social Exchange Theory (Blau, 1964), when an organisation is seen as investing in employee welfare (HRM practice quality), it creates a reciprocity of commitment and lessens the likelihood of leaving the organisation. The current research builds on this: AI enhances the accuracy and customisation of organisational investment signals and continuity. AI's ability to provide real-time performance feedback, identify potential attrition risks, offer personalised learning paths, and conduct bias-free appraisals is essentially a qualitatively better type of organisational support for employees. This places AIIHRMP in a role of being a mediating mechanism in the transition of HRM practice quality to improved retention outcomes.

2.2 Technology Acceptance Model

Regarding the treatment of AIIHRMP, the study is based on the Technology Acceptance Model (Davis, 1989), which states that employee acceptance of AI-powered HR solutions is influenced by perceived usefulness and perceived ease of use. Srivastava (2024) and Petre et al. (2024) both found that employees who are knowledgeable about and confident in AI's role in HR processes are much more positive about the changes, and that has an impact on both satisfaction and retention. The transparency of communication on the use of AI decision-making is thus a condition for AIIHRMP's mediating function to become a reality.

2.3 Research Hypotheses

Table 1: Research Hypotheses for SEM Structural Path Model

H	Structural Relationship	Direction	Test
H1	DHRMP — AIIHRMP: HRM quality drives AI integration in HR functions	Positive	SEM Path
H2	DHRMP — DEAW: HRM quality directly influences employee attrition	Positive	SEM Path
H3	AIIHRMP — DEAW: AI integration mediates the HRM–attrition relationship	Positive	SEM Mediation
H4	DEAW — QQSF: Attrition drives quality, quantity, and stress outcomes	Positive	SEM Path
H5	DEAW — SMSEF: Attrition affects self-motivation and supervision effectiveness	Positive	SEM Path
H6	DEAW — RMNF: Attrition influences perceived monotonous nature of work	Positive	SEM Path

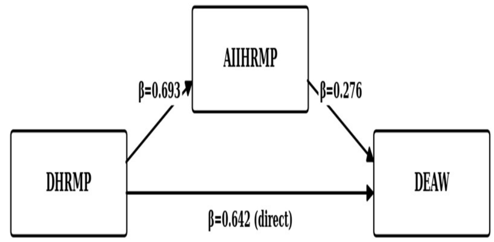

Figure 1: Validated SEM Mediation Model (DHRMP - AIIHRMP - DEAW)

Figure 1 shows the DHRMP — AIIHRMP — DEAW

3. Research Methodology

3.1 Sample and Data Collection

The data for the study were collected from 650 HR professionals in IT organisations located in Chennai city, Tamil Nadu in 2024–2025. Out of the 720 questionnaires sent, 695 were returned and 650 were useable (usable response rate: 90.3%). The sample is 69.7% male, predominantly aged 26–45 (62.5%). IBM SPSS Statistics (Version 22) and IBM AMOS (Version 22) were used in analyzing all the data.

3.2 Constructs and Instrument

AIIHRMP as a newly introduced mediating variable is measured by 21 five-point Likert scale items in four sub-dimensions: HRPDM (7 items), RO (5 items), TD (5 items) and AIPA (4 reported items). An excellent reliability score is found for Cronbach's Alpha for AIIHRMP (α = 0.914). The DEAW construct (27 items, α = 0.908) measures three downstream dimensions: QQSF (α = 0.946), SMSEF (α = 0.924), and RMNF (α = 0.892).

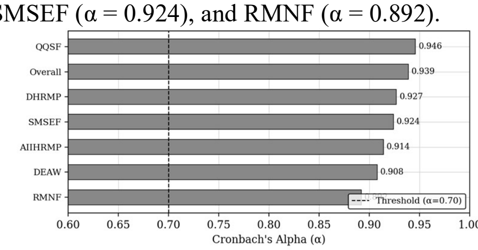

Figure 2 Cronbach's Alpha Reliability Coefficients — All Construct Scales

As Figure 2 demonstrates, all construct scales exceed the 0.70 reliability threshold by a substantial margin, with all values above 0.89, confirming excellent internal consistency across the entire measurement instrument.

4. Exploratory Factor Analysis — DEAW

Prior to EFA, two pre-conditions were verified. Kaiser-Meyer-Olkin (KMO) value for DEAW was 0.875 (above 0.800 acceptable value) and Bartlett's Test of Sphericity was significant (χ^2 = 14,828.237, df = 351, $p < 0.001$), which confirmed the suitability of factor analysis. The 27 variables were reduced to 3 latent factors, accounting for 61.519% of the total variance by Principal Component Analysis (PCA) with Varimax rotation.

Table 2: Total Variance Explained by DEAW — EFA Results

Factor	Factor Name	Acronym	Eigenvalue	Variance %	Cumulative %	Items	α
F1	Quantity, Quality and Stress-Free Factor	QQSF	6.329	23.441	23.441	11	0.946
F2	Self-Motivation and Supervision Effectiveness Factor	SMSEF	5.704	21.125	44.566	10	0.924
F3	Recognised and Monotonous Nature Factor	RMNF	4.577	16.953	61.519	6	0.892

The first factor, QQSF, is the dominant factor (Eigenvalue = 6.329) and the three combined factors explain 61.5 % of the overall variance in determinants of employee attrition, which is a strong cumulative variance explained for a multi-dimensional behavioural construct.

5. Confirmatory Factor Analysis — AIIHRMP Measurement Model

The four-factor measurement model of AIIHRMP was validated by CFA. For all 21 items, all Critical Ratio (CR) values are greater than ±1.96, which means that the differences are statistically significant at the 1 percent level. Items that are highest loading on the factor are: HRPDM — Generate personalised feedback (β = 0.820); RO — Predicting candidate success and cultural fit (β = 0.823); TD — Provide quality training programmes (β = 0.813); and AIPA — Support to measure employee engagement (β = 0.774). Three of four factors (RO, TD, AIPA) have high loadings on all items, while HRPDM has more variation within the factor: two items (anticipating challenges, β = 0.335; allocating resources, β = 0.341) load significantly lower than the other two, suggesting that they are weaker but valid measures of the factor.

Table 3 CFA Model Fit Indices — AIIHRMP Measurement Model

Fit Index	χ^2/df	GFI	AGFI	CFI	TLI	NFI	RMSEA
AIIHRMP CFA Value	4.472	0.912	0.895	0.969	0.955	0.961	0.072
Threshold	< 5.0	≥ 0.90	≥ 0.90	≥ 0.90	≥ 0.95	≥ 0.90	< 0.080

6. K-Means Cluster Analysis — AIIHRMP Engagement Profiles

K-Means Cluster Analysis revealed three groups of respondents: Cluster 1 (Higher AI Integration, n = 358, 55.1%), Cluster 2 (Highest AI Integration, n = 273, 42.0%), and Cluster 3 (High AI Integration, n = 19, 2.9%). The solution was validated using Discriminant Analysis where 98.6% of the classification accuracy was achieved.

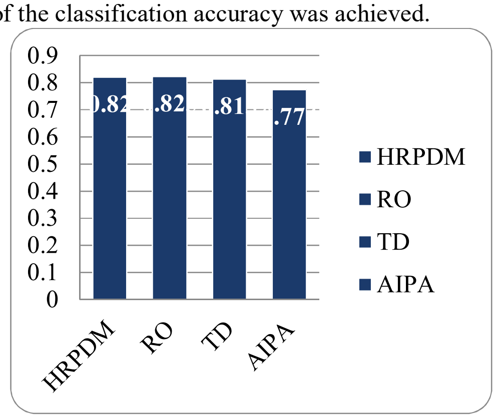

Figure 3 AIIHRMP Final Cluster Means by Factor (K-Means Cluster Analysis)

As noticed in Figure 3, it was found that Cluster 2 is always the one with the highest AI integration on each of the four factors, and Cluster 3, which is the smallest group consisting of 2.9%, records significantly lower scores, indicating the lowest level of AI-HRM adoption; and consequently, the highest attrition vulnerability. The highest absolute cluster means for all groups represent AIPA, which is the most widely-adopted AIIHRMP dimension.

7. Structural Equation Modelling — Full Model Results

The full SEM demonstrated a very good fit on each of the multiple indices (CMIN/DF = 1.669, GFI = 0.996, AGFI = 0.985, CFI = 0.999, TLI = 0.997, NFI = 0.997, RMSEA = 0.032, $p = 0.154$) — the first study in this research domain to confirm a three-construct HRM–AI–attrition structural model with this very comprehensively excellent fit.

Table 4: SEM Structural Path Results — All Hypotheses Supported at $p < 0.001$

H	Path	β (Std.)	C.R.	p	Decision
H1	DHRMP — AIIHRMP	0.693	24.482	< 0.001	Supported
H2	DHRMP — DEAW	0.642	18.119	< 0.001	Supported
H3	AIIHRMP — DEAW (Mediation)	0.276	8.070	< 0.001	Supported
H4	DEAW — QQSF	0.892	11.241	< 0.001	Supported
H5	DEAW — SMSEF	0.710	21.406	< 0.001	Supported
H6	DEAW — RMNF	0.879	30.489	< 0.001	Supported

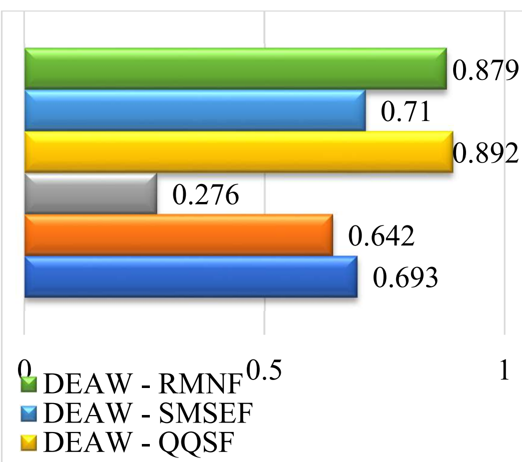

Figure 4: SEM Standardised Path Coefficients — All Six Paths Significant

The relative strength of all six structural paths is visualised in figure 4. The strongest paths from DEAW are both downstream, DEAW — QQSF (β = 0.892) and DEAW — RMNF (β = 0.879), followed by the direct HRM effects, with the AIIHRMP — DEAW mediation path (β = 0.276) being the least but nonetheless highly significant, confirming partial mediation.

8. Mediation Effect Quantification

The simultaneous confirmation of H1 (β = 0.693), H2 (β = 0.642), and H3 (β = 0.276) establishes partial mediation. The indirect effect of DHRMP on DEAW via AIIHRMP is: $0.693 \times 0.276 = 0.191$. The total effect is therefore $0.642 + 0.191 = 0.833$. This validates the added value of AI integration on the retention effect of HRM practice quality is an additional 29.7 per cent over the direct effect of HRM practice quality alone.

Table 5: Mediation Effect Decomposition — DHRMP — AIIHRMP — DEAW

Effect Component	Calculation	Value	Interpretation
Direct: DHRMP — DEAW	β = 0.642	0.642	HRM directly drives attrition reduction
Indirect: via AIIHRMP	0.693 × 0.276	0.191	AI integration amplifies HRM's effect
Total effect	0.642 + 0.191	0.833	Combined direct and mediated effect
Amplification ratio	0.191 / 0.642 × 100	29.7 %	AI adds 29.7% above HRM's direct effect

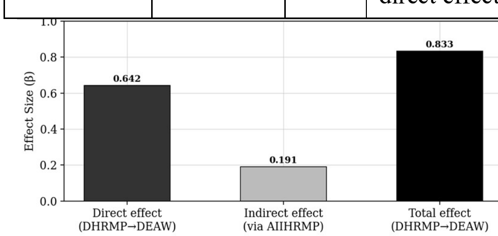

Figure 5 Mediation Effect Decomposition — Direct, Indirect, and Total Effects

9. Discussion

9.1 AI Integration as a Mediating Mechanism

The most theoretically significant finding of this research programme is: The confirmation of H3 — AIIHRMP — DEAW (β = 0.276, CR = 8.070, $p < 0.001$). It is the first study in the Indian IT literature to demonstrate that AI's integration in HRM is an active causal path by which high HRM practice quality is translated into lower propensity to leave the job. The quantified mediation effect (indirect β = 0.191; amplification = 29.7%) proves that the implementation of AI complements HRM's direct effect on retention. The magnitude of H3 is moderate whereas direct effect (H2: β = 0.642) is stronger, which confirms partial mediation that AI tools are enhancing and extending HRM practice, rather than replacing the foundational quality of human-centred HRM systems.

9.2 Downstream Consequences — The Hidden Cost Multiplier

The strong H4 path (DEAW - QQSF: β = 0.892) and H6 path (DEAW - RMNF: β = 0.879) show an underappreciated aspect of the impact of attrition. The almost complete pathway between high attrition and near unity to QQSF suggests a strong degradation effect of the perceived work quality and stress management capability of the remaining employees in high attrition settings. In fact, nearly nine-tenths of the variance of attrition is passed on to the work experience of the remaining staff, meaning that the real cost of attrition to the organisation is around twice the replacement cost.

9.3 Practical Implications for IT Organisations

- Investment in HRM quality as a precondition for the effectiveness of AI (H1: β = 0.693). HRM system is as powerful as AI in HR.
- Use AI to manage attrition proactively, with HRPDM's real-time analytics, personalised feedback and proactive intervention.
- Leverage the mediation amplification, which is a 29.7% retention improvement with every 10% increase in HRM quality when AI is integrated.
- Target the lowest AI-HRM adoption cohort (Cluster 3, 2.9% of sample) and highest attrition-risk group as a cohort for targeted investment in AI integration.
- Monitor remaining employees for downstream attrition consequences as real-time early-warning indicators (QQSF, SMSEF, RMNF).

In addition, employee turnover has significant downstream effects on the quality of work, employee self-motivation, supervisor effectiveness and meaningfulness of work of those who stay, which suggests the real cost of turnover is not just the cost of replacement.

10. Conclusion

This study is the first attempt of empirical validation of AI integration in HRM (AIIHRMP) as a mediating mechanism in the HRM–attrition structural relationship in the Indian IT sector. Comprehensively excellent SEM fit supports all 6 hypotheses at $p < 0.001$, which provides a definitive and empirically strong framework. It is noteworthy that the mediation decomposition showed that the direct effect of HRM on retention is increased by 29.7 percent with the inclusion of AI. This has significant practical and financial implications. The downstream effects validate that the real cost of attrition is not just the replacement cost, it also negatively impacts the quality of work, motivational climate and perceived meaningfulness of the remaining employees, which further perpetuates the attrition cycle.

Combined with the results findings of this study indicate that IT organisations in India can secure significantly lower employee attrition rate, higher workforce stability, and increased organisational competitiveness by investing both in HRM practice quality and in the integration of AI. AI in HRM is not a technological tool for good HRM, at the extent verified in this research, it's its most potent amplifier nowadays.

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