Check for updates

Employees Perception of AI-Enabled HRM Practices: An Exploratory Factor Analysis in Indian IT Companies

Aditi Tiwari, Mahima Rai

IIS (Deemed to be University), Jaipur, Rajasthan, India

aditisharmatiwari07@gmail.com

Abstract. Artificial Intelligence (AI) is increasingly reshaping Human Resource Management (HRM) functions by streamlining processes such as recruitment, performance management, learning and development, and employee engagement. Despite its growing organizational adoption, limited empirical research has examined how employees perceive AI-enabled HRM practices, particularly within Indian IT sector. The study aims to identify the key latent dimensions underlying employees perception of AI-enabled HRM practices and to examine how these dimensions shape the overall acceptance of AI-enabled HRM. Primary data were collected from 119 IT professionals across various Indian cities using a structured questionnaire. Given the exploratory nature of the study and the contextual specificity of Indian IT companies, Exploratory Factor Analysis (EFA) was employed to uncover the underlying factor structure of employees perception. Using the Kaiser Criterion and visual inspection of the scree plot, a robust three factor solution emerged. The extracted dimensions were conceptually interpreted and labeled as 1) Perceived HR system effectiveness, 2) AI-enabled Decision and Performance Support, and 3) Ethical and Governance Concerns. Reliability analysis indicated strong internal consistency across all the three factors; the scale demonstrated acceptable reliability, validity and stability. The findings underscore that while employees acknowledge the efficiency and performance- enhancing potential of AI-enabled HRM practices, ethical considerations related to fairness, transparency, and bias significantly influence acceptance. The study highlights the need for organizations to adopt transparent, ethical, and human- centric AI implementation strategies to ensure sustainable integration of AI technologies within HR functions.

Keywords: AI-enabled HRM, Employees Perception, Exploratory Factor Analysis, Indian IT Sector, Technology Acceptance.

P. Pankaj et al. (eds.), *Proceedings of the 13th International Youth Conference in the series of "Youth for India @2047, AI Disruption and Opportunities: Preparing Youth for Global Challenges (IYC 2026)*, Advances in Intelligent Systems Research 208,
https://doi.org/10.2991/978-94-6239-676-0_21

1 INTRODUCTION

The 21st century business environment is defined by digital disruption, with Artificial Intelligence serving as the foundational technology driving a new wave of organizational change (Tambe, 2019); (Yadav & Sharma, 2019). AI, encompassing technologies like Machine learning (ML), Natural Language processing (NLP), and predictive analytics, has transitioned from automating routine tasks to augmenting strategic decision-making across all corporate functions (Dr. Owais Ahmed, 2018; Meena & Hussain, 2021).

Within the corporate system, HRM is undergoing a transformation from traditional HRM to AI based HRM. AI is no longer a futuristic concept but a present reality, integrated almost at every stage of the employee lifecycle. Key AI application in HRM now includes Recruitment and Selection: Automated resume screening, candidate ranking and AI-driven video interview analysis (Geetha & BhanuSree Reddy D, 2018).

Performance Management: Real time performance monitoring, objective feedback generation, and predictive systems for identifying potential high- performances or flight risks (Santosh K.V & TanviRana, 2019). Learning and Development: Personalized training recommendations and automated careerpathing (Shivani Tiwari, 2020).

Employee Engagement: AI- driven chat bots for instant query resolution, improving HR service quality (Anisha Parveen, 2019).

For organizations, AI adoption promises clear strategic advantages: enhanced operational efficiency, reduced administrative costs, and the implementation of more objective, data-driven decision-making in talent management (Lochan Sharma Tandon et al., 2017; QiongJia et al., 2018). This pursuit of efficiency is particularly aggressive within the highly competitive and technologically advanced Indian IT sector, making it a critical ground for AI implementation.

1.1 Factors that Influence Employees Perception of AI-enabled HRM

Despite the documented technological benefits, the ultimate success and sustained value of AI-enabled HRM depend almost entirely on employees acceptance and perception (Davis, 1989; Venkatesh & Davis, 2000). AI systems are not neutral systems which run in the background; they actively interact with employees and influence how they feel and respond to them. The literature highlights two broad and contrasting of factors that shape employee perceptions.

Positive Perception Factors (Utility and Support).

Employees tend to accept and embrace AI when they perceive it as a reliable, supportive tool that enhances their work environment. These factors include:

System Effectiveness and Utility

The belief that AI systems improve the accuracy, speed, and fairness of HR processes, leading to better outcomes for both the individual and the organization (George & Thomas, 2019).

Performance Support and Augmentation.

Viewing AI as a collaborative partner (aligned with Industry 5.0 principles) that augments human capabilities rather than replacing them, assisting with complex tasks and providing personalized feedback (Alpaslan et al., 2019; Jatobáa et al., 2019).

1.2 Negative Perception Factors (Ethical and Control Concerns)

Conversely, employee resistance and apprehension arise from perceived threats and ethical risks inherent in algorithmic systems (Bogen & Rieke, 2018):

Ethical and Algorithmic Bias Concerns.

Worry that AI algorithms, trained on historical data, may perpetuate or amplify biases, leading to unfair treatment in hiring or promotion decisions (Chapman, 2019; Gaikwad, 2020).

Trust, Transparency, and Accountability

Concerns over the "black box" nature of complex algorithms and the lack of clarity regarding who is accountable when an AI system makes an error (Lee, 2018; Ranjitha & Usha, 2021).

Surveillance and Job Insecurity.

Apprehension about excessive monitoring by AI systems and the inherent threat of job displacement due to automation, leading to anxiety and reduced engagement (Kellogg et al., 2020; Dr. Saju Mathew et al., 2021).

1.3 The Necessity of Exploratory Factor Analysis (EFA)

The existing body of research largely relies on theoretical framework or western culture and organizational contexts. Empirical studies dedicated to uncovering the latent factor structure of perception within the Indian IT sector remain scarce (Verma & Bandi, 2019; Tahira, 2021).

This research specifically employs Exploratory Factor Analysis (EFA) because it is the most appropriate statistical technique for:

Structure Discovery.

EFA is essential when the theoretical framework is nascent or when applying a phenomenon like AI perception in context to HRM practices to a new, unique cultural and industrial context eg. The India IT sector. It is a data-driven approach that helps identifying the underlying dimensions or latent constructs that explain survey items relate to on another without assuming any pre defined model.

Scale Development/Refinement.

It helps in reducing a large number of initial survey items into a smaller, meaningful, reliable and valid sound set of factors. The EFA results will provide a validated, context specific factor structure that clearly captures the key concerns and acceptance dimensions of Indian IT employees.

This study addresses the critical research gap by empirically investigating and defining the fundamental dimensions of employee perceptions regarding AI-enabled HRM practices in the Indian IT sector.

1.4 The Primary Research Objective is:

To identify and define the key dimensions that structure employee perceptions of AI-enabled HRM practices in the Indian IT sector using Exploratory Factor Analysis (EFA). This research's two main contributions are:

Methodological and Academic Contribution: It offers an empirically derived and validated factor structure that can serve as a foundation for future confirmatory studies (CFA/ SEM).

Practical Contribution: The resulting factors offer HR and IT leaders a precise roadmap of the psychological and ethical concerns that must be addressed (e.g., through governance, training, and transparency policies) to drive successful and ethical AI adoption in the Indian IT workforce.

To situate these objectives within the existing academic discourse, the following section reviews the evolution of AI in HRM and theoretical framework previously used to measure employee acceptance.

2 REVIEW OF LITERATURE

Prior studies suggest that AI adoption in HRM enhances routine work and improves data driven decision making (Tambe, 2019). This shift is driven by potential of AI and machine learning (ML) to dynamically transform core HR processes, including recruitment, performance appraisal, and employee engagement (Malathi & Gandhi, 2017; Lochan Sharma Tandon, 2017; Dr. Owais Ahmed, 2018). AI is moving HR from routine tasks to strategic decision- making (Meena & Hussain, 2021).

Research has highlighted perceive usefulness and system effectiveness as major determinants of employee acceptance of AI technologies (Davis, 2000). The focus on effectiveness is evident in conceptual frameworks exploring AI's role in modernizing HRM and its capacity to provide data driven support for managerial decisions (QiongJia, 2018; A. Hemlatha @ Dr. P. Barani Kumari, 2020). Furthermore, the positive impact of AI on the employee experience and HR service quality has been noted, particularly concerning the reaction of the gen Y workforce (Pandey & Khaskel, 2019; Anisha Parveen, 2019). This perceived utility is supported by studies specifically on the use of AI is streamlining recruitment (Geetha & BhanuSree Reddy D, 2018; Chapman, 2019) and the growing role of AI in various HR functions (Yadav & Sharma, 2019; Shivani Tiwari, 2020), which ultimately link AI functions to perceived system utility and effectiveness.

Trust in AI systems has been also been identified as a crucial factor in influencing employee attitudes, especially when algorithms are involved in performance evaluation and decision making (Lee, 2018). This trust is often linked to the extent employees perceive AI as a robust support mechanism, improving objectivity and efficiency in HR related decisions and performance facilitation (George & Thomas, 2019; Jatobaa, 2019). This perception aligns with the emerging concept of industry 5.0, which emphasizes human robot co working and the supportive function of AI rather than pure replacement (Alpaslan, 2019; Rani, 2019). The successful amalgamation of HR and automation is seen as key to fostering employee acceptance of AI as a collaborative support tool (Santosh K.V & Tanvi Rana, 2019; Kiran Kumar M & Elangovan, 2021).

At the same time, scholars have raised concerns regarding ethical issues, algorithmic bias, transparency, and loss of human judgment in AI driven HR practices (Bogen & Rieke, 2018). The potential for bias and the need for accountability in systems used for selection and screening processes are critical areas of scholarly concerns (Chapman, 2019; Gaikwad, 2020; Akanksha Saxena, 2020). Studies conducted in organizational settings indicate that employees often express apprehension about excessive monitoring and lack of accountability in AI systems (Kellogg, 2020; Dr. Saju Mathew, 2021). This highlights the necessity for strong governance and ethical safeguards to ensure that AI implementation is both fair and transparent (Tambe, 2019; Ranjitha & Usha, 2021). Sanyaolu & Atsaboghena (2022) provided and overview of benefits and challenges, underscoring the need for a balanced view. Moreover, research focused on the challenges and opportunities for international HRM (Budwara, 2022; Ch Jhansi, 2022) and empirical evidence from the IT sector in Pakistan (Tahira, 2021; Kshetri, 2020) confirms that ethical management and governance are decisive factors for technology acceptance, especially in geographically similar emerging markets (Varsha Bhardwa, 2022).

However, much of the existing literature is either conceptual or based on western contexts. Empirical studies focusing on employee perceptions of AI based HRM practices in the Indian IT sector remain scarce (Verma & Bandi, 2019), hence necessitating exploratory research to uncover context specific perception dimensions and validate the balance between technological utility and human centric concerns.

While the existing literature establishes a global trend toward AI adoption, the specific dimensions of employees perception in the Indian context remain under explored, necessitating the specialized methodological approach detailed below.

3 RESEARCH METHODLOGY

Although AI is growing rapidly in HRM the following research still persists in the current literature.

Lack of Indian Context: Most of the research on AI in HR comes from western countries. There isn't enough data on the Indian IT sector (Verma & Bandi, 2019)

Empirical Gap in the Indian Context: Most current evidence is generic, which makes it necessary to conduct a study to see how AI impacts the human centric nature of management in our specific work culture (Tahira, 2021).

Stakeholder Imbalance: Existing research mainly focuses on improving organizational efficiency and reducing costs, while paying much less attention to how employees feel about these changes and how they affect workplace relationships (Tambe, 2019).

3.1 Objective of the study

To identifying the underlying dimensions of employee perceptions towards AI- enabled HRM practices in the Indian IT industry.

To examine how these dimensions shape overall employee acceptance of AI-enabled HRM system.

3.2 Research Design

The study adopts a descriptive and exploratory research design to examine employee perceptions of AI-enabled HRM practices.

3.3 Sample and Data Collection

Primary data were collected through a structured questionnaire administered to 120 IT professionals, after data cleaning and screening for incompleteness 119 valid responses were used for analysis. Respondents were drawn from large, medium and small Indian IT companies located across major technological corridors. The distribution of respondents was across Tier-1 IT hubs such as- Bangalore, Hyderabad, Pune, and Gurgaon. Tier-2 IT centers such as Ahmadabad, Nagpur and Jaipur, providing a balanced geographical representation of the industry.

The questionnaire consisted of 15 items measuring various aspects of AI-enabled HRM practices, including recruitment systems, decision making, employee engagement, biases and ethical concerns, and system effectiveness. Responses were recorded on 5-point likert scale ranging from (1) Strongly Disagree to (5) Strongly Agree.

The sample (N=119) deemed sufficient for the pilot study, as it exceeds the 5:1 ratio of observations to variables required for Exploratory Factor Analysis (EFA), which comprised professionals from diverse roles within the Indian IT industry, including software development, HR, middle management and senior management, ensuring a broad representation of the sectors workforce.

Data collection was restricted to employees currently working in IT firms located in major Indian IT clusters to maintain relevance.

3.4 Sample Characteristics

Demographic Profile of Respondents

Demographic Variable	**Category**	**Frequency (n)**	**Percentage (%)**
Gender	Male	65	54.6
	Female	47	39.5
	Others	7	5.9
Age Group	Below 25 years	15	12.6
	26–35 years	48	40.3
	36–45 years	34	28.6
	46–55 years	13	10.9
	Above 56 years	9	7.6
Work Experience (Years)	< 1	9	7.6
	1–3	44	37.0
	3–5	34	28.6

Demographic Variable	Category	Frequency (n)	Percentage (%)
	5–10	19	16.0
	Above 10	13	10.9
Job Role	Software Engineer / Senior Engineer	50	42.0
	HR Executive / Manager	50	42.0
	Team Lead	19	16.0
Department	Analytics	32	26.9
	Operations	24	20.2
	Support	23	19.3
	HR	20	16.8
	IT Development	20	16.8
Organization Size	Large	47	39.5
	Medium	30	25.2
	Small	42	35.3

Demographic Variable	Category	Frequency (n)	Percentage (%)
Location	Tier-1 Hubs (Bangalore, Pune, Mumbai, etc.)	61	51.3
	Tier-2 Centers (Nagpur, Jaipur, Ahmedabad)	53	44.5
	Others (Global/Unspecified)	5	4.2
Total		**119**	**100.0**

As shown in the demographic profile of the respondent above, the sample is primarily composed of male respondents (54.6%), with a significant concentration in the 26-35 age brackets (40.3%). Professionally, the participants are evenly distributed between technical and managerial roles, with 42% serving as engineers and 42% in HR capacities. Geographically, the study maintains a balanced representation between established tier-1 IT hubs (51.3%) and emerging tier-2 IT hubs like Nagpur and Jaipur (44.5%), covering small, medium and large-scale Indian IT companies.

3.5 Data Analysis Technique

Exploratory Factor Analysis (EFA) using Principal Component Analysis (PCA) with Varimax rotation was conducted using IBM SPSS Statistics for identifying the underlying dimensions of employee perceptions.

4 ANALYSIS AND FINDINGS

4.1 Construct (Variable) Abbreviation

RS- Recruitment & Selection, TD- Training & Development, EE- Employee Engagement, DM- Decision Making, PF- Perceived Fairness, JS- Job Satisfaction, EU-Ease of Use, EA- Employee Attitude, BC- Biases & Concerns, ES- Employee Satisfaction.

Suitability of Data for Factor Analysis

Kaiser- Meyer-Olkin (KMO) value: 0.847, indicating excellent sampling adequacy presented in Table 1.

Bartlett's Test of Sphericity: Significant ($\chi^2 = 711.544$, $p < 0.001$), confirming that factor analysis was appropriate.

Table 1. KMO and Bartletts' Test Table

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.847
Bartlett's Test of Sphericity	Approx. Chi-Square	711.544
	do	105
	Sig.	.000

The suitability of the data for factor analysis was assessed using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity. The KMO statistic was found to be 0.847, exceeding the commonly recommended threshold of 0.60 and indicating a meritorious level of common variance among the variables. This suggests that the correlations observed are compact enough to yield reliable factors.

Moreover, Bartlett's Test of Sphericity was statistically significant ($\chi2(105)=711.544, p<0.001$). The rejection of the null hypothesis confirms that the correlation matrix is not an identity matrix, meaning that the variables are sufficiently correlated to warrant factoring. Collectively, these results strongly support the appropriateness of applying factor analysis to the dataset.

4.2 Communalities Table

Table 2. Communalities Table

Communalities		
	Initial	Extraction
RS_Q1	1.000	.699
RS_Q2	1.000	.525

RS_Q3	1.000	.590
TD_Q10	1.000	.499
EE_Q15	1.000	.646
DM_Q20	1.000	.505
PF_Q28	1.000	.689
PF_Q29	1.000	.597
JS_Q38	1.000	.579
EU_Q54	1.000	.630
EA_Q56	1.000	.425
BC_Q64	1.000	.592
EC_Q68	1.000	.556
EC_Q69	1.000	.344
ES_Q71	1.000	.622
Extraction Method: Principal Component Analysis.		

In table 2 the Communalities table presents the proportion of the variance in each item that is accounted for by the extracted components. In Principal Component Analysis, a commonly accepted standard for retaining an item is an extraction communality value greater than 0.40 or 0.50, indicating that a sufficient amount of the item's variance is shared with other variables and explained by the factor structure.

The majority of the items demonstrated acceptable communality values, ranging from high 0.699 (RS_Q1) to a low of 0.344 (EC_Q69). EC_Q69 exhibited the lowest communality which is 0.344 suggesting that approximately 65.6% of its is error variance and not captured by the derived components. While this value is slightly below the 0.40 threshold, it can be retained depending on the theoretical relevance and its performance in the factor loading matrix. Also, items such as RS_Q1 (0.699), PF_Q28 (0.689), and EE_Q15 (0.646) are well represented by the current factor structure, indicating strong reliability and shared variance within the model. Table 3 presents Total variance table.

Table 3. - Total Variance Table

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative%
1	5.793	38.619	38.619	5.793	38.619	38.619	3.040	20.268	20.268
2	1.589	10.593	49.212	1.589	10.593	49.212	2.738	18.251	38.519
3	1.117	7.446	56.658	1.117	7.446	56.658	2.721	18.140	56.658

4	.972	6.477	63.136						
5	.912	6.082	69.217						
6	.782	5.210	74.427						
7	.734	4.892	79.320						
8	.610	4.066	83.386						
9	.530	3.533	86.919						
10	.466	3.109	90.027						
11	.369	2.458	92.485						
12	.331	2.206	94.691						
13	.304	2.029	96.720						
14	.266	1.773	98.493						
15	.226	1.507	100.000						
Extraction Method: Principal Component Analysis.									

The analysis utilized the Kaiser criterion (eigenvalues greater than 1.0) to determine the optimal number of components to retain which is visible in Figure 1. Based on the initial eigenvalues, three components met this threshold.

Component 1- this accounted for the largest proportion of variance, explaining 38.619% of the total variance with an eigenvalue of 5.793. Component 2 and Component 3- these extracted additional variance, with eigenvalues of 1.589 (explaining 10.593%) and 1.117 (explaining 7.446%), respectively.

Altogether, these three Components account for 56.658% of the total variance in the dataset. Following the orthogonal rotation, the cumulative variance explained remains the same (56.658%), but the variance is more evenly distributed across the components. The rotated structure shows that Component 1 now explains 20.268% of the variance, Component 2 explains 18.140%. This redistribution suggests that the rotation successfully achieved a more interpretable factor solution where the components are more balances in their explanatory power.

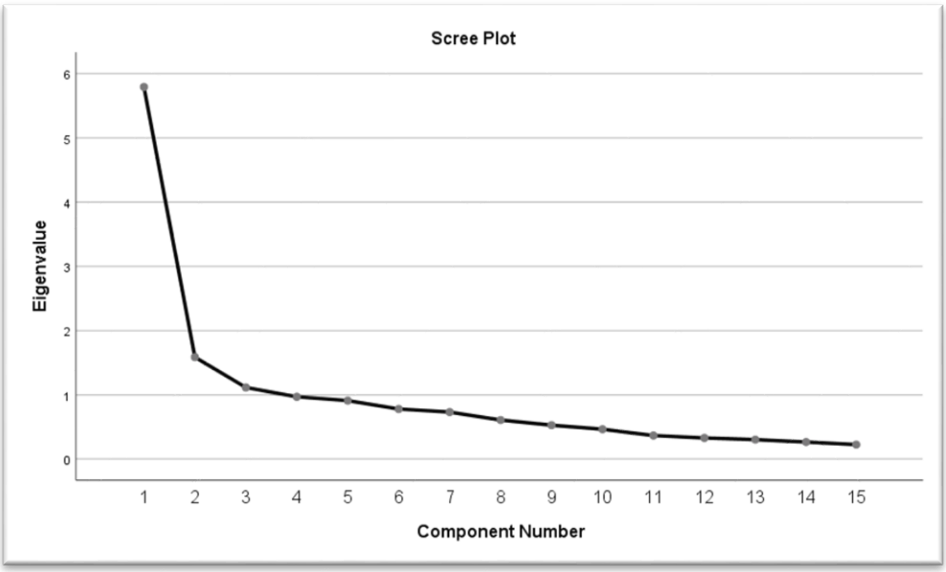

Fig. 1. - Scree Plot

The Scree Plot was analyzed to visually determine the optimal number of components to retain in the factor structure. This plot graphs the eigenvalues (Y- axis) against the corresponding component number (X- axis).

As shown in the Figure 1, the slope of the line drops sharply from Component to Component 2, and the moderately from Component 2 to Component 3. A clear and pronounced “elbow”- the point where the slope significantly levels off, is observed after the third component. Component 4 through 15 exhibit a relatively flat trajectory, indicating that they contribute minimal additional explanatory power and primarily represents random variance. The visual evidence from the scree plot strongly supports the initial statistical decision (Derived from Kaiser eigenvalue>1.0) to extract and retain a three component solution for the dataset. Table 4 presents component matrix

Table 4. - Component Matrix

Component Matrix[a]			
	Component		
	1	2	3
RS_Q1	.630		.418
RS_Q2	.582	-.430	
RS_Q3	.554	-.527	
TD_Q10	.480		-.489
EE_Q15	.682		.415
DM_Q20	.668		
PF_Q28	.778		
PF_Q29	.677		
JS_Q38	.740		
EU_Q54	.610	.498	
EA_Q56	.599		
BC_Q64		.541	.436
EC_Q68	.540	.457	
EC_Q69	.580		
ES_Q71	.727		
Extraction Method: Principal Component Analysis.			
a. 3 components extracted.			

The component matrix presents the correlation coefficients (factor loadings) between each item and three extracted components. Loadings 0.40 or above were considered significant for identifying the underlying structure. The non rotated solution demonstrates a significant presence of a general factor, as indicated by the high loadings of most items on Component 1.Items such as PF_Q28 (0.778), JS_Q38 (0.740), and ES_Q71 (0.727) show the strongest relationships with this primary component.

A notable observation in the non-rotated solution is the presence of cross loadings, where several items load significantly on more than one component (RS_Q1 loads on Component 1 (0.630) and Component 3 (0.418); RS_Q2 loads on Component 1 (0.582) and Component 2 (-0.430)). This ambiguity confirms the necessity of rotating the component structure to achieve a simple structure, where each item loads highly on only one factor and near zero on the others, thereby facilitating clear interpretation and naming of the derived constructs.

The three factors are named and interpreted using the Rotated Component Matrix presented in Table 5.

Table 5. - Rotated Component Matrix

Rotated Component Matrix[a]			
	Component		
	1	2	3
RS_Q1	.816		
RS_Q2	.635		
RS_Q3	.691		
TD_Q10		.692	
EE_Q15	.690		.405
DM_Q20	.404	.558	
PF_Q28		.548	.570
PF_Q29		.699	
JS_Q38	.501	.519	
EU_Q54			.749
EA_Q56	.534		
BC_Q64			.733
EC_Q68		.463	.581
EC_Q69			
ES_Q71		.434	.612
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.[a]			
a. Rotation converged in 6 iterations.			

Varimax rotation produced a clear three factor structure, with items grouping neatly into meaningful dimensions. Items with loadings of 0.40 or higher were treated as significant and assigned to the factor where they showed the strongest association. This rotated solution reduced overlap between factors and made the results easier to interpret.

Component 1: Perceived HR System Effectiveness.

Component 1 is defined by high loadings on items related to recruitment processes, employee engagement, job attitudes, and emotional responses towards AI- enabled HR systems. The items loading strongly on this component include:

RS_Q1 (0.816)
RS_Q (0.691)
EE_Q15 (0.690)
RS_Q2 (0.635)
EA_Q56 (0.534)

Moreover, moderate loadings were observed for JS_Q38 (0.501) and DM_Q20 (0.404), further reinforcing the functional and experimental nature of this component.

Interpretation: This component reflects employees perceptions of the overall effectiveness and usefulness of AI enabled HR systems. High loadings on recruitment and engagement related items indicate that employees perceive AI as enhancing efficiency, consistency, and fairness in HR operations. The inclusion of emotional attitude and engagement variables suggests that effective AI systems positively influence employees feelings toward HR practices and their overall job experience. Thus, component 1 represents a holistic evaluation of AI based HRM in terms of operational efficiency and positive employee experience.

Component 2: AI enabled Decisions and Performance Support.

Component 2 comprises items associated with task requirements, performance facilitation, professional growth, and AI supported decision making. The key defining items include:

PF_Q29 (0.699)
TD_Q10 (0.692)
DM_Q20 (0.558)
PF_Q28 (0.548)
JS_Q38 (0.519)
EC_Q68 (0.463)
ES_Q71 (0.434)

Interpretation: This component captures employees perceptions of AI as a support system for decision making, performance management, and professional development. Strong loadings on task demand and performance related items suggest that employees view AI as facilitating in workload management, improving performance evaluation, and enabling more objective managerial decisions. The presence of job satisfaction and employee satisfaction items indicates that AI enabled decision support is perceives to contribute positively to career growth and work outcomes. Overall, this factor represents AI's role as a performance enhancing and career supporting mechanism within HRM.

Component 3: Ethical and Governance Concerns.

Component 3 is defined by items related to system usability, bias control, ethical safeguards, and contextual support for AI implementation. The defining items include:

EU_Q54 (0.749)
BC_Q64 (0.733)
ES_Q71 (0.612)
EC_Q68 (0.581)
PF_Q28 (0.570)

Interpretation: This component represents ethical, governance, and contextual considerations associated with AI-enabled HRM practices. High loadings on ease of use and bias related items indicate that employees acceptance of AI systems is strongly influenced by transparency, usability and fairness. The presence of ethical concern and satisfaction items highlights apprehensions regarding accountability, discrimination, and responsible AI governance. This factor underscores that ethical safeguards, bias mitigation, and supportive organizational policies are critical for building trust and ensuring sustainable adoption of AI in HR functions.

4.3 Cross Loadings and Item Performance

The analysis revealed that item EC_Q69 demonstrated the lowest extraction communality of 0.344 and failed to achieve a significant factor loading of 0.40 or above on any of the three extracted components, suggesting that much of its variance is unique or error related than being captured by the primary factor structure. Some of the items (PF_28, EC_Q68, ES_Q71 and JS_Q38) exhibit moderate cross loadings across Components 2 and 3, indicating conceptual overlap between performance support and ethical or contextual considerations. Such overlap is theoretically justifiable, as perceptions of fairness, satisfaction and performance which are often interconnected in AI driven HR systems. Items EC_Q69 failed to load significantly because it did not reach the 0.40 threshold on any of the extracted component and may be considered for removal or refinement in future research to enhance scale robustness or reliability.

4.4 Summary of Extracted Factors

The rotated component matrix confirms three factor structure underlying employee perceptions of AI-enabled HRM practices:

Perceived HR System Effectiveness: Reflecting functional efficiency and positive employee experience.

AI- Enabled Decision and Performance Support: Representing Artificial intelligence's role in task facilitation, decision making, and professional development.

Ethical and Governance Concerns: Capturing issues related to fairness, transparency, bias control, and responsible use of Artificial Intelligence.

This structure provides a robust and relevant understanding of employee perceptions of AI based HRM practices in the Indian IT sector.

Table 6. - Component Transformation Matrix

Component Transformation Matrix			
Component	1	2	3
1	.613	.588	.528
2	-.594	-.098	.799
3	.521	-.803	.289
Extraction Method: Principal Component Analysis. Rotation Method: Varian with Kaiser Normalization.			

The Component Transformation Matrix presented in Table 6 explains how the factors were mathematically rotated to make the results easier to understand. In this study, varimax rotation was used to clearly separate the components. The Component Transformation Matrix shows that the original three components were successfully rotated into new positions that are easier to interpret. Because varimax is an orthogonal rotation, the resulting factors remain independent of one another, supporting the clarity of the three factors identified in the rotated component matrix.

Based on eigenvalues greater than 1 and scree plot, three factors were extracted, altogether 56.66% of the total variance which is acceptable for social science research.

4.5 Factor Interpretation.

Factor 1: Perceived HR System Effectiveness.

This factor includes items related to recruitment systems, employee engagement, job satisfaction, and overall HR effectiveness. High loadings indicate that employees perceive AI based HR systems as useful tools that enhance the HR services and overall employee experience.

Factor 2: AI based Decision and Performance Support.

Items loading on this factor reflect Artificial Intelligence roles in task delegation, performance facilitation, and managerial decision making. This dimension suggests that employees recognize AI as a support mechanism that improves accuracy and speed in HR related decisions.

Factor 3: Ethical and Governance Concerns.

This factor captures employee concerns related to ethical use, bias control, system consequences, and safeguards. The findings highlight that while employees acknowledge AI's benefits, ethical transparency and governance remains crucial for acceptance.

4.6 Reliability

The reliability analysis indicated acceptable internal consistency for all the extracted factors confirming the stability and reliability of the measurement scale.

5 CONCLUSION

The study reveals that employee perceptions of AI-enabled HRM practices in Indian IT industry are multidimensional. Three key dimensions 1) Perceived HR Systems Effectiveness, 2) AI enabled Decision and 3) Ethical and Governance Concerns significantly shape how employees evaluate AI-enabled HRM. The findings suggest that while employees largely acknowledge the functional benefits of AI-enabled HRM ethical considerations and transparency play an equally important role in building trust and acceptance. Organizations aiming to successfully integrate AI into HR functions must balance technological efficiency with ethical responsibility and human centric implementation.

5.1 PRACTICAL IMPLICATION

BUILDING TRUST THROUGH TRANSPARENCY: HR managers should prioritize transparency when implementing AI- enabled HRM systems. To reduce employee anxiety, organizations must clearly communicate how the algorithms influence decisions in HR functions ensuring that the trust factor is maintained.

UPSKILLING FOR THE AI- HUMAN HYBRID WORKFORCE: The findings suggests that HR practitioners should shift from traditional administrative roles to strategic ‘AI- human’ coordination. Managers should invest in continuous training programs to support employees transition from fearing AI to collaborating with it as a decision support tool.

5.2 SCOPE FOR FUTURE RESEARCH

The study is exploratory in nature and limited to only IT professionals from Indian cities. Future research may:

Extend the study to other sectors such as manufacturing, healthcare, education; etc.

Employ Confirmatory Factor Analysis (CFA) or Structural Equation Modeling (SEM) to validate the identified dimensions.

Examine the moderating role of demographic variables such as age, experience and job role on AI perception.

Conduct longitudinal studies to understand how employee perceptions evolve with increased AI exposure.

REFERENCES

1. Ahmed, O. (2018). Artificial intelligence in human resource management: A conceptual study. *International Journal of Research in Management & Business Studies*, *5*(4), 1–6.
2. Alpaslan, H. I., Green, S. E., & Mitroff, I. I. (2019). Corporate governance in the context of Industry 5.0. *Journal of Business Ethics*, *160*(2), 391–406.
3. Bogen, M., & Rieke, A. (2018). *Help wanted: An examination of hiring algorithms, equity, and bias*. Upturn.
4. Budhwar, P., Malik, A., De Silva, M. T., & Thevisuthan, P. (2022). Artificial intelligence—Challenges and opportunities for international HRM. *The International Journal of Human Resource Management*, *33*(6), 1065–1097.
5. Chapman, D. S. (2019). AI and fairness in employee selection. *Journal of Applied Psychology*, *104*(9), 1114–1122.
6. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340.
7. Gaikwad, V. (2020). Ethical implications of AI in recruitment and selection. *Asian Journal of Management*, *11*(2), 85–92.
8. Geetha, R., & Bhanu Sree Reddy, D. (2018). Recruitment through artificial intelligence: A conceptual study. *International Journal of Mechanical Engineering and Technology*, *9*(7), 63–70.
9. George, G., & Thomas, M. R. (2019). Trust, transparency, and AI-based decision systems. *Academy of Management Perspectives*, *33*(2), 153–169.
10. Hemlatha, A., & Kumari, P. B. (2020). Artificial intelligence and HRM effectiveness: A conceptual framework. *International Journal of Management Studies*, *7*(2), 45–52.
11. Jatobá, A., Bellas, F., Carvalho, P., & Lemos, G. (2019). Human–AI interaction in decision-making systems. *Information Systems Frontiers*, *21*(5), 1113–1128.
12. Jia, Q., Guo, Y., & Barnes, S. J. (2018). Enterprise AI and HR decision support. *Information Systems Management*, *35*(4), 314–329.
13. Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals*, *14*(1), 366–410.
14. Kiran Kumar, M., & Elangovan, N. (2021). Automation and HR integration: Employee perspectives. *International Journal of Human Resource Studies*, *11*(3), 92–107.
15. Lee, J. D. (2018). Trust in automation: Designing for appropriate reliance. *Human Factors*, *60*(5), 721–738.
16. Malathi, S., & Gandhi, R. (2017). Transforming HR through artificial intelligence. *International Journal of Trend in Scientific Research and Development*, *1*(6), 1380–1385.
17. Mathew, S., Joseph, A., & Varghese, J. (2021). Surveillance, automation, and employee anxiety. *Journal of Organizational Change Management*, *34*(4), 901–917.
18. Meena, K., & Hussain, S. (2021). Artificial intelligence in strategic HRM. *Journal of Management Research*, *13*(1), 22–34.
19. Pandey, S., & Khaskel, A. (2019). AI adoption and employee experience in Gen Y workforce. *Journal of Human Resource Development*, *12*(2), 65–78.
20. Parveen, S. A., Srinivasan, P., & Ramasubramanian, K. (2019). Artificial intelligence in employee engagement and HR service delivery. *International Journal of Innovative Technology and Exploring Engineering*, *8*(11), 3272–3276.
21. Ranjitha, R., & Usha, P. (2021). Governance and ethical challenges of AI in HRM. *International Journal of Ethics and Systems*, *37*(3), 405–421.
22. Santosh, K. V., & Rana, T. (2019). Performance management through AI: Emerging practices. *Journal of Business and Management*, *21*(5), 45–52.

23. Tahira, S. (2021). Artificial intelligence and employee perception: Evidence from IT sector. *Pakistan Journal of Commerce and Social Sciences*, *15*(3), 489–506.
24. Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. *California Management Review*, *61*(4), 15–42.
25. Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model. *Management Science*, *46*(2), 186–204.
26. Verma, S., & Bandi, K. (2019). Digital HRM and employee perception in Indian IT firms. *Indian Journal of Industrial Relations*, *55*(1), 73–89.
27. Yadav, S., & Sharma, V. (2019). Artificial intelligence in HRM: A review. *International Journal of Advanced Research*, *7*(5), 874–879.