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Original Research Paper

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MULTI-CRITERIA DECISION MAKING APPROACH FOR AI IN HRM USING ANALYTICAL HIERARCHY PROCESS

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ABSTRACT In this study, the application of Analytical Hierarchy Process (AHP), a multi-criteria decision-making (MCDM) technique, to identify and prioritize the key rationale behind the integration of artificial intelligence (AI) in human resource management (HRM). The primary goal of MCDM is to derive structured and quantifiable representation of expert judgments regarding the significance of various decision considerations that influence AI adoption in HRM. Recognizing the prominence of AI-driven tools in HRM, this study purpose is to replace subjective and intuitive decision-making with transparent and systematic evaluation framework. With implementation of AHP, this research had translated expert insights into a hierarchical model that revealed the underlying logic and priority structure which guide technology adoption in HRM. The research methodology of this study implemented purposive expert-judgment design involving five senior HR professionals. The results of the analysis revealed a clear hierarchical structure of priorities, indicating that immediate operational and user-centered considerations were viewed as more critical than long-term or infrastructural aspects when evaluating AI adoption in HRM. This outcome reflected an expert consensus emphasizing ease of use and time saving as dominant decision drivers, while automation, scalability, and security were accorded progressively lesser importance. The findings underscored the practical relevance of the AHP approach in clarifying decision rationales and providing actionable insights for HR strategists and policymakers. The study concluded that the AHP framework improves the objectivity and consistency of multi-criteria decisions and presents replicable decision-support tool adaptable to other organizational or technological adoption contexts.

KEYWORDS : MCDM, AHP, AI, HRM, multi-criteria decision making, AI-HRM.

INTRODUCTION

The integration of Artificial Intelligence (AI) in Human Resource Management (HRM) has acquired significant attention because organizations seek to improve their efficiency. This study investigates the prioritization of factors which influence the adoption of AI technologies in HRM based on multi-criteria decision-making (MCDM) framework. By implementing the Analytical Hierarchy Process (AHP), the research intends to elucidate the underlying rationale that motivates organizational preferences when integrating AI solutions with HRM. The integration of AI into HRM has revolutionized organizational practices by enhancing decision-making, efficiency, and workforce management, thus reshaping both individual and organizational outcomes (Budhwar et al., 2022). AI in HRM represents an interdisciplinary domain, combining technical advancements in AI development through insights from social sciences to direct implementation and appraise organizational and workforce impacts (Pan and Froese, 2023).

Given the rapid evolution of AI and its potential to transform HR functions, it is essential to recognize and evaluate the criteria that induce successful implementation (Yadav et al., 2025). The AI-assisted HRM is recognized as potential strategy for mounting organizational productivity, yet existing literature lacks comprehensive framework to guide HR managers in its effective adoption and implementation (Malik et al., 2023). This study adopts expert judgment to conduct pairwise comparisons among relevant factors that provides rigorous approach to distill complex decision processes into quantifiable priorities. Hence concentrating on thematic elements rather than specific criteria names, the research gives importance to objective insights into decision-making patterns that ultimately provides insights to both academic discourse and practical applications in HR technology management.

Need and Scope

The need for this study developed due to growing importance of Artificial Intelligence (AI) as a transformative tool in Human Resource Management (HRM). Despite increasing AI implementation, there remains inadequate structured understanding of the specific priorities that influence successful integration of AI in HR functions. This research fills that gap by implementing rigorous MCDM approach to systematically evaluate the relative importance of decision factors thus providing clarity and strategic direction for HR professionals and organizational leaders. The scope of the study involves the identification and ranking of these key factors through expert judgment, offering a replicable framework adaptable to various organizational contexts. Hence, focusing on critical decision aspects without limiting the inquiry to pre-defined criteria names, the study enhances its relevance and flexibility, catering to diverse HR environments. This study intends to inform both scholarly research and practical applications, supporting evidence-based adoption of AI technologies that align with organizational goals and promote operational effectiveness.

Research Questions

- What are the main factors influencing the adoption of advanced technology in human resource management?
- How do organizations prioritize different aspects when deciding to implement AI?

Research Objectives

- To examine the influential factors in the adoption process within human resource management.
- To evaluate the relative importance of these factors using a structured decision-making approach.
- To provide recommendations based on the prioritized factors for better implementation strategies.

Theoretical Background

This study is grounded on the theoretical framework of multi-criteria decision-making (MCDM), particularly the Analytical Hierarchy Process (AHP). Such framework offers robust method for structuring complex decision problems involving multiple conflicting criteria. AHP enables the decomposition of decision factors into hierarchical model which facilitates systematic pairwise comparisons and prioritization based on expert judgments. The application of AHP in the context of technology adoption in Human Resource Management (HRM) aligns with theories of technology acceptance and innovation diffusion, which emphasizes the evaluation of various, attributes influencing organizational adoption behaviors. Therefore integrating these theoretical perspectives supports to develop comprehensive framework to understanding how different factors are weighted in the decision-making process. It further makes contribution to both decision science and HR technology research.

Literature Review

Kapoor (2024) had employed the Analytical Hierarchy Process (AHP) to identify and prioritize the key barriers hindering AI adoption in the recruitment practices of MSMEs and found that environmental and organizational barriers are most influential. Bhatt (2023) had identified that information security and return on investment are perceived by human resource managers as two critical determinants that influence their decision to adopt artificial intelligence in the hiring process through AHP. The fuzzy AHP analysis had proved that trust, regulatory environment, security and privacy are vital factor in banking sector (Do, 2025). AI based HRM practices improves the organizational productivity (Yadav et al., 2025). The adoption of AI could transform existing human resource management structures which mandate the reconfiguration of roles to align with technological advancements. AHP had identified adaptive organizational structures, specialized AI teams, ethical oversight and governance, and innovation infrastructure as critical enablers of effective AI integration (Agarwal, 2025).

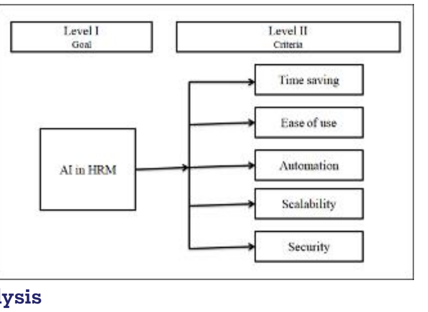
MCDM through AHP conducted by by Di Caprio et al., (2025) proved that work environment has significant association with employee retention. AHP outcomes support for better hiring decision based on criteria such as knowledge, education and experience (Sarangi et al., 2025). The hiring process in line with MCDM fuzzy AHP supports for selection of competent applicants (Taylan et al., 2024). The talent retention is influenced by factors compensation, work-life balance, growth opportunity and competency mapping based on the MCDM-fuzzy AHP conducted by Lin and Wang (2025). The promotion of employee is significantly influenced by performance as per the AHP conducted by Haddad and Sanders (2024). The AI in HRM had been perceived as best solution for informed decision making (Baabdullah, 2024) recruitment and selection (Herold and Roedenback, 2025). Artificial intelligence (AI) refers to a branch of computer science devoted to developing systems capable of performing tasks that conventionally require human intelligence. The concept was first introduced by John McCarthy in 1955 to explore the possibility of enabling machines to use language and solve problems that are inherently human in nature (Nilsson, 2010). AI is an intelligent agent that receives precepts from the environment and performs actions (Rossell and Norvig, 2021).

Research Methodology

The study had adopted purposive expert-judgment design and recruited five senior human resource practitioners, each with more than fifteen years of managerial experience, to provide informed pairwise comparison matrix (PCM). The purposive sampling approach was selected to ensure high content validity through reliance on domain expertise rather than statistical representativeness. Prior to elicitation, each expert received a written explanation of the pairwise comparison procedure and the rationale for the exercise. The experts were give sufficient time to complete and revise their judgments wherever necessary. The informed consent was obtained that explicitly permitted re-contact for clarification or reconciliation of any ambiguities in responses. The instrument was prepared as a Word document and disseminated by e-mail, and follow-up reminders were issued to maximize response completeness (Appendix A). Given the cognitive demands of pairwise comparison, thorough care was taken to confirm that each returned matrix reflected a considered judgment. Such procedural attention was intended to reduce random error and to improve the substantive quality of the elicited data prior to aggregation. The guidelines as per Satty (2001) have been followed for AHP during data analysis. Analytic Hierarchy Process (AHP) is a theory of measurement through pairwise comparisons and relies on the judgments of experts to derive priority scales (Satty, 2008).

Individual pairwise comparison matrices from the five experts were first inspected for reciprocal structure and then aggregated into single group matrix using the geometric mean, a method chosen because it preserved reciprocity and provided a robust central tendency measure for multiplicative comparison scales. The aggregated matrix was normalized by column sums to convert raw comparison entries into proportional shares, and the priority (weight) vector was derived by averaging normalized row entries to yield each element's relative importance. To evaluate internal consistency, the principal eigenvalue (max) was estimated via the weighted-sum method and the Consistency Index (C.I.) was computed based on formula ([max – n]/[n – 1]). The Consistency Ratio (C.R.) was then obtained by dividing the C.I. by the Random Index (R.I) appropriate for the matrix order and was compared to the conventional 0.10 threshold to assess acceptability. All intermediate worksheets, formulas, and calculation steps were retained as an audit trail to support verification and potential replication. The reserch methodology of this study encompass combined purposive expert sampling, careful elicitation protocols, geometric-mean aggregation, standard AHP normalization and weighting, and formal consistency testing to produce defendable, transparent set of priority factors for interpretive and managerial application.

Figure 1: Goal and Criteria



Data Analysis

The respondents (experts) were contacted through email for collecting demographic profile. The demographic profile of the respondents reflects expert cohort representing senior-level human resource professionals with extensive industry experience. All five participants occupied managerial or senior managerial positions in reputed organizations and possessed a minimum of fifteen years of professional experience in HR functions. Such experience of experts ensures both practical expertise and strategic insight into technology-driven transformations in the field. In terms of gender distribution, three respondents were male and two were female which depicts balanced representation conducive to diverse professional perspectives. The educational qualifications of the experts were uniformly high, with all of them holding postgraduate degrees in management, and two possessing additional certifications related to information systems which demonstrate strong academic and technical foundations. The respondents' belonged to varied sectors in the corporate landscape, including information technology, manufacturing, financial services and consulting, which contributed to the heterogeneity and richness of the judgments elicited. The average age of the experts ranged between 40 and 55 years, situating them in career phase characterized by both managerial maturity and active engagement with digital innovation initiatives in HRM.

Table 1 : PCM

Criteria	1	2	3	4	5
1. Time saving	1.00	2.22	3.00	5.19	6.00
2. Ease of use	0.45	1.00	3.00	5.19	5.53
3. Automation	0.33	0.33	1.00	4.00	5.35
4. Scalability	0.19	0.19	0.25	1.00	3.00
5. Security	0.17	0.18	0.19	0.33	1.00
Sum	2.14	3.93	7.44	15.70	20.88

The aggregated pairwise comparison matrix (PCM) was produced by geometric-mean aggregation of the five experts' judgments and preserved the reciprocal structure required for AHP is presented in Table 1 (for example, the time-saving vs ease-of-use entry of 2.22 corresponded closely to the reciprocal ease-of-use vs time-saving entry of 0.45). The matrix showed a clear hierarchical pattern in which the first two criteria were repeatedly judged superior to the remaining three, while the third criterion occupied an intermediate position and the fourth and fifth criteria were consistently less favored. Specific aggregated ratios illustrated these relations: time-saving was judged moderately to strongly more important than automation (3.00), scalability (5.19), and security (6.00), and ease-of-use likewise dominated the lower-ranked criteria (ease-of-use = 3.00 versus automation; ≈5.19 versus scalability; ≈5.53 versus security). The column sums (2.14, 3.93, 7.44, 15.70, 20.88) reflected that scalability and security accrued the largest column totals because they were most often the objects of higher preference scores by other criteria; consequently, those two criteria were positioned to receive relatively smaller normalized weights after column normalization. The geometric-mean PWCM represented coherent group-level judgments that were directly suitable for normalization, priority-vector derivation, and subsequent consistency testing within the AHP procedure.

Table 2: Normalized PCM

Criteria	1	2	3	4	5	Criteria Weights
1. Time saving	0.467	0.565	0.403	0.330	0.287	0.411
2. Ease of use	0.210	0.255	0.403	0.330	0.265	0.293
3. Automation	0.156	0.085	0.134	0.255	0.256	0.177
4. Scalability	0.090	0.049	0.034	0.064	0.144	0.076
5. Security	0.078	0.046	0.025	0.021	0.048	0.044

The normalized pairwise comparison matrix was presented as column-wise proportions and was interpreted to show each criterion's relative contribution within each comparison and, by row averaging, the emergent priority weights. (Table 2). Each cell represented the proportion of a column's total allocated to the row criterion, and the criterion weights were computed as the arithmetic mean of the row's normalized values. The derived weights indicated that time saving carried the largest relative importance (w = .411), followed by ease of use (w = .293), while automation assumed a moderate role (w = .177) and scalability and security received comparatively small weights (w = .076 and w = .044, respectively). Numerically, the first two criteria together accounted for approximately 70.4% of the total decision weight, revealing a concentrated preference for those considerations over the remaining three; the normalized cell values further showed that the dominant criteria consistently captured larger proportions across most columns (for example, time saving values ranged from .287 to .565 across columns), whereas the lower-weighted criteria contributed only marginal proportions in each comparison. The weights summed to unity in rounding error, confirming that the normalization and row-averaging procedures were correctly executed and produced a coherent priority vector suitable for subsequent consistency assessment and interpretive analysis.

Table 3: Consistency Check

Criteria	1	2	3	4	5	WS	CW	A = WS/CW
1.Time saving	0.411	0.650	0.531	0.394	0.262	2.248	0.411	5.474
2. Ease of use	0.185	0.293	0.531	0.394	0.241	1.644	0.293	5.619
3. Automation	0.137	0.098	0.177	0.304	0.233	0.949	0.177	5.356
4. Scalability	0.079	0.056	0.044	0.076	0.131	0.387	0.076	5.088
5. Security	0.068	0.053	0.033	0.025	0.044	0.223	0.044	5.123

Notes: WS = Weighted Sum, CW = Criteria Weight, n = 5
Source: Output from MS-Excel

$$\lambda(\max) = Average\ of\ Column\ A = 5.332$$

$$\text{Consistency Index (C.I)} = \frac{\lambda\,(max)-n}{n-1} = \frac{5.332-5}{5-1} = 0.083$$

$$\text{Consistency Ratio (C.R)} = \frac{C.I}{R.I} = \frac{0.083}{1.12} = 0.074$$

Table 4: Random Index

n	1	2	3	4	5	6	7	8	9	10
Random Index (R.I)	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

*A CR ≤ 0.1 (i.e., ≤ 10%) indicates that the matrix is consistent and the results are statistically reliable.

*A CR > 0.1 suggests inconsistencies in judgments, warranting revision.

The consistency of the aggregated judgments was evaluated using the weighted-sum method and standard AHP indices (Table 3). The weighted-sum divided by the criterion weights produced the consistency vector values (5.474, 5.619, 5.356, 5.088, 5.123), the average of which yielded the principal eigenvalue (max = 5.332). From this eigenvalue the Consistency Index CI was computed [CI = (max − n)/ (n − 1) = 0.083], The Consistency Ratio (CR) was obtained by dividing the CI by the Random Index (R.I) for a 5×5 matrix (R.I. = 1.12 when n = 5), giving CR = 0.074. Because the CR was below the conventional acceptability threshold of 0.10, the aggregated pairwise comparison matrix was judged acceptably consistent and the derived priority weights were considered reliable for interpretation. The individual entries of the consistency vector clustered closely around the computed max, indicating average of weighted-sum/criteria weights across criteria and thus supporting the internal coherence of the group judgments; consequently, no substantive revision of the aggregated judgments was required prior to reporting and using the priority vector in subsequent analysis.

DISCUSSION AND CONCLUSION

The data analysis using AHP provided clear insights into the prioritization of factors influencing the integration of advanced technology in human resource management. The consistencies of expert judgments ensured the reliability of the results, with time saving and ease of use emerging as the most critical considerations. These findings imply that organizations give importance for scalability and security to ensure that technological solutions can expand effectively with growing needs. Also, automation played moderate roles, indicating that while efficiency and user-friendliness matter, they are secondary to more strategic concerns.

This study makes a significant contribution by applying the Analytical Hierarchy Process to systematically identify and prioritize the key factors influencing the adoption of AI in HRM. By aggregating expert judgments through rigorous MCDM framework gives transparent and replicable methodology for understanding the relative importance of diverse decision criteria. This approach improves the theoretical knowledge of technology adoption by integrating decision science with HRM practices. Also, the study provides practical insights for managers to make informed, evidence-based decisions when implementing AI solutions, thus bridging the gap between academic research and real-world applications in organizational technology integration.

This study highlights the importance of focusing on security and scalability when planning technology adoption in HRM. Decision-makers are advised to prioritize these dimensions to achieve successful integration and long-term benefits. The structured multi-criteria approach demonstrated here supports informed and balanced decision-making, providing a replicable framework for organizations considering related technological implementations. Future research could expand this framework by incorporating additional criteria or exploring sector-specific priorities.

Managerial Implications

The findings from this study present valuable managerial implications for organizations seeking to incorporate advanced technologies into human resource management. Managers need to give priority to improve security measures and scalability capabilities when selecting and implementing technological solutions. The priority factors in this study have been identified as most critical by expert consensus. Investing in robust security frameworks will uphold sensitive employee data and build trust, while scalability ensures that systems can grow with organizational needs without compromising performance. As well, automation and ease of use ranked lower, their roles remain important for improving operational efficiency and user acceptance; thus, managers should balance strategic requirements with practical usability considerations. Hence with structured decision-making approach like the Analytical Hierarchy Process, managers can systematically evaluate and align technology adoption decisions with organizational goals, resulting in more informed, effective, and sustainable HR technology strategies.

Limitations and Future Research

This study has certain limitations which have been acknowledged. The sample size consisted of only five experts, which could restrict the generalizability of the findings. Their judgments, while consistent, reflect a relatively small group's perspective and may not capture the full diversity of opinions in different organizational contexts or industries. Additionally, the criteria selected for this study were predefined, potentially overlooking other relevant factors that could influence technology integration decisions in human resource management.

For future research, expanding the expert panel to include broader range of stakeholders from various sectors and geographic regions could enhance the robustness and applicability of the results. Further research in this domain can consider alternatives or additional criteria that capture emerging trends and challenges in technology adoption, such as employee acceptance, cost implications, or ethical considerations. Besides, applying other multi-criteria decision-making methods or hybrid approaches may provide deeper insights and validation of the findings presented here.

Appendix

Expert Evaluation Questionnaire for AHP Pairwise Comparisons

Guidelines for Experts

Dear Expert,

Thank you for participating in this study aimed at understanding the priorities for integrating advanced technology in Human Resource Management. Your expert judgments are crucial for the accuracy and reliability of the results.

Please follow these instructions carefully:

1. Purpose: You will be asked to compare pairs of criteria based on their relative importance in influencing technology adoption decisions in HRM.
2. Pairwise Comparison: For each pair of criteria, indicate which criterion you consider more important and the degree of its importance using the Saaty scale:

Importance Level	Numerical Value
Equal importance	1
Moderate importance	3
Strong importance	5
Very strong importance	7
Extreme importance	9
Intermediate values	2, 4, 6, 8

4. Reciprocal Values: If criterion A is more important than criterion B, enter the corresponding numerical value (e.g., 3). If criterion B is more important than criterion A, enter the reciprocal value (e.g., 1/3).
5. Consistency: Please review your comparisons for consistency; inconsistent judgments may affect the final analysis. If uncertain, try to maintain logical consistency across all pairings.
6. Confidentiality: Your responses will be kept confidential and used only for research purposes.

Pairwise Comparison Matrix

Please complete the comparisons below by filling in the appropriate values in each cell. For each pair, enter how many times the row criterion is more important than the column criterion.

Criterion	Time Saving	Ease of Use	Automation	Scalability	Security
Time Saving	1				
Ease of Use		1			
Automation			1		
Scalability				1	
Security					1

Example:

If you believe that Time Saving is moderately more important than Ease of Use, please enter 3 in the cell where row = Time Saving and column = Ease of Use. Then enter 1/3 in the reciprocal cell (row = Ease of Use, column = Time Saving).

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