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Evaluating Generative AI Initiatives in Human Resources: Multiple Criteria Decision Analysis

Dewi Shinta[1,*] | Khalil Nasir Khan[2] | Muhammad Nadeem[3]

[1] *Independent Researcher, Jakarta, Indonesia*

[2] *Department of Business and Accountancy, Lincoln University College Malaysia, Lahore, Pakistan*

[3] *National College of Business Administration and Economics, Lahore, Pakistan*

*Corresponding author: *dewiishintaa@gmail.com*

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Abstract: The current study introduces a systematic framework to address the critical challenge of prioritizing Generative Artificial Intelligence (GenAI) initiatives within Human Resources (HR) Management. Confronted with multiple high-potential yet resource-intensive options, HR leaders require an objective method for strategic investment. The study employs a Multi-Criteria Decision-Making (MCDM) methodology, integrating the Analytical Ordinal Priority Approach (AOPA) and the Dynamic Grey Relational Analysis (DGRA). Ten distinct GenAI use cases are identified and evaluated against eleven strategic criteria—spanning impact, feasibility, risk, and organizational momentum—based on the judgments of a diverse panel of experts from HR, Information Technology, Finance, Legal, and Operations. The results yield a validated, consolidated ranking of initiatives. The Employee Sentiment & Trend Analyzer emerges as the highest-priority initiative, followed by the Intelligent HR Helpdesk Chatbot and the Automated Recruitment Coordinator, while the Interactive Leadership Training Simulator is consistently ranked lowest. The study provides HR leaders with a transparent, data-driven framework for phased implementation, advocating for initial investments in initiatives that balance strategic value, strong return on investment, and manageable risk to build organizational confidence and momentum in the adoption of transformative AI technologies.

Keywords: Generative Artificial Intelligence; Human Resource Analytics; Analytical Ordinal Priority Approach; Dynamic Grey Relational Analysis; Multiple Criteria Decision Analysis

1. Introduction

Generative Artificial Intelligence (GenAI) is reshaping the operational and strategic role of Human Resources (HR) Management. This technology, capable of generating novel text, insights, and solutions from learned patterns, presents unprecedented opportunities to automate complex tasks (Alla, 2025), personalize employee experiences (van der Merwe & Veldsman, 2025), and derive strategic intelligence from unstructured data. From intelligent chatbots that provide instant policy guidance to sophisticated tools that analyze workforce sentiment or identify skill gaps, GenAI promises to enhance HR's efficiency, effectiveness, and strategic impact (Singh & Chouhan, 2023; Krishnasamy & Lee, 2024). Consequently, HR leaders are under increasing pressure to explore and adopt these innovations to drive organizational agility, talent retention, and competitive advantage.

However, translating GenAI's potential into realized value presents significant challenges. Organizations, particularly HR departments, face a dizzying array of possible applications, each with varying degrees of complexity, cost, and strategic alignment (Levenson & Fink, 2017). The decision of where to begin—or how to prioritize a portfolio of initiatives—is not trivial. Investing in an overly complex, high-risk project with poor data readiness can lead to costly failures, erode stakeholder confidence, and waste finite resources (Kendrick, 2015; Rauscher, 2024). Conversely, prioritizing only low-impact, incremental solutions may yield minimal return and cause the organization to fall behind in the strategic application of AI (Jeon, 2025; Behrendt *et al.*, 2021). This dilemma underscores a critical gap: the lack of a robust, systematic, and transparent framework to guide HR leaders in evaluating, selecting, and sequencing GenAI initiatives based on a holistic view of strategic value, feasibility, risk, and organizational readiness.

In response to this gap, this study proposes a structured Multi-Criteria Decision-Making (MCDM) framework designed to support HR leaders in making data-driven investment decisions regarding GenAI adoption. The framework moves beyond anecdotal justification or supplier-driven hype, introducing a disciplined approach to prioritization. As detailed in the next section, we identify and define ten prominent GenAI use cases within HR (e.g., Intelligent Helpdesk Chatbots, Automated Recruitment Coordinators, Employee Sentiment Analyzers) and evaluate them against eleven critical criteria spanning four key dimensions: Strategic Impact, Feasibility & Resource Requirements, Risk & Compliance, and Organizational Momentum.

This study makes two primary contributions. First, it synthesizes a comprehensive set of evaluation criteria specifically designed for pre-implementation GenAI decision making in HR, where outcomes are uncertain but investment decisions must remain transparent and defensible. Second, it applies a formal MCDM methodology—aggregating expert judgments from a diverse panel of HR, IT, Finance, Legal, and Operations leaders to convert qualitative evaluations into a ranked portfolio of initiatives. The approach enables decision-makers to answer not only which project to start with but also to develop a rational roadmap for sequential implementation based on clear strategic trade-offs between value, effort, and risk.

The remainder of this paper is structured as follows. The next section reviews prior work on GenAI in HR and MCDM applications in technology management. The methodology section describes the development of alternatives and criteria, the expert panel selection, and the chosen aggregation and ranking techniques. The results section presents the analysis, yielding a prioritized list of GenAI initiatives followed by a discussion of managerial implications of the findings, and conclude with limitations and avenues for future research. Through this structured approach, this paper aims to equip HR practitioners and organizational leaders with a practical, scalable tool to navigate the GenAI landscape with greater confidence and strategic clarity.

2. Literature review

This literature review establishes the theoretical and empirical foundation for the study by examining three interconnected domains: (1) the transformative potential and challenges of Generative Artificial Intelligence (GenAI) in Human Resource Management (HRM), (2) the principles and applications of Multi-Criteria Decision-Making (MCDM) methodologies in managerial contexts, and (3) the convergence of these fields in prior research on technology evaluation and prioritization within HR.

2.1 Generative Artificial Intelligence in Human Resource Management

The integration of Artificial Intelligence (AI) into HRM, often termed "HR Analytics" or "People Analytics," has evolved from basic reporting to predictive analytics (Belizón & Kieran, 2022; Lee & Lee, 2024). The emergence of GenAI, a subset of AI capable of creating new content and solutions, represents a significant leap forward (Chuma *et al.*, 2024). GenAI applications in HR, such as large language models (LLMs), offer capabilities for hyper-personalization, conversational interaction, and complex content generation (Singh, 2023).

Scholars highlight its potential across the HR value chain. In talent acquisition, GenAI can automate job description writing (Getto *et al.*, 2025), personalize communications with candidates (Kirchherr *et al.*, 2025), and screen for soft skills through conversational interfaces (Nofal *et al.*, 2025). In onboarding and development, it can create customized learning modules and simulate training scenarios (Marinelli *et al.*, 2025). For employee services, intelligent chatbots provide 24/7 support, while sentiment analysis tools offer real-time insights into organizational climate (Krishnasamy, 2024). Furthermore, GenAI can model workforce scenarios and draft compliance documentation, elevating HR's role as a strategic partner (Ioannidis *et al.*, 2023; Rani *et al.*, 2025).

However, the literature also documents substantial barriers. Key challenges include high implementation costs and complexity (Subramanian, 2024), ethical risks related to data privacy (Uddagiri & Isunuri, 2024), algorithmic bias, and transparency (Phillips-Wren & Virvou, 2025), and organizational resistance due to fears of job displacement and change management hurdles (Phillips-Wren & Virvou, 2025). A critical gap identified is the lack of structured frameworks to help HR leaders navigate these trade-offs—weighing an initiative's strategic payoff against its costs, risks, and feasibility before commitment. This study addresses that gap by systematizing these evaluation dimensions.

2.2 Multiple Criteria Decision-Making

Multi-criteria decision-making (MCDM) provides a suite of formal techniques designed to support decision-making when multiple, often conflicting, criteria must be considered simultaneously. Unlike single-criterion optimization, MCDM acknowledges the multifaceted nature of real-world business problems. Common methods include the Analytic Hierarchy Process (AHP) for deriving criterion weights through pairwise comparisons (Munier & Hontoria, 2021), the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and the Grey Relational Analysis (GRA) for ranking alternatives based on their distance from an ideal solution (Yoon & Kim, 2017; Ouali, 2022).

The strength of MCDM lies in its ability to incorporate both quantitative and qualitative data, often sourced from expert judgment or stakeholder surveys, into a transparent and replicable decision model (Voskoglou, 2024). It transforms subjective preferences into objective-looking rankings, providing an audit trail for decisions. These methods have been widely validated in fields such as supply chain management (Mahmoudi *et al.*, 2022), project management (Faisal *et al.*, 2023), mechanical engineering (Abifarin *et al.*, 2021), banking and finance (Beheshtinia & Omidi, 2017; Hallerbach & Spronk, 2002), among others. Despite witnessing a lot of applications in HR management (Costa *et al.*, 2021), their applicability to HR technology selection, however, remains underexplored, particularly for nascent technologies like GenAI where historical data is scarce and expert foresight is paramount.

2.3 MCDM Applications in HR and Technology Evaluation

The application of MCDM in HRM has grown, primarily focusing on discrete problems like candidate selection and performance appraisal (Manoharan *et al.*, 2011; Costa *et al.*, 2021). For instance, AHP and TOPSIS have been used to rank job applicants based on a balanced scorecard of technical and soft skills (Aggarwal *et al.*, 2025). Similarly, MCDM methods have been employed for evaluating barriers to adoption of electric vehicles (Darbinian *et al.*, 2023), study critical factors for ERP in banking sector (Ahmadzadeh *et al.*, 2021), selection of ERP software in manufacturing sector (Kazancoglu & Burmaoglu, 2013), selection of robots (Chodha *et al.*, 2022), and personnel selection in software industry (Ersoy, 2021).

A nascent stream of research applies MCDM to AI adoption. Some studies have used MCDM methods for the evaluation of GenAI tools for academic research (Radulescu & Radulescu, 2025) or some other areas. However, these studies often treat AI as a monolithic technology or focus on a single application area. The specific context of prioritizing a portfolio of diverse GenAI initiatives within human resources management remains unaddressed. This context is uniquely complex due to the interplay of human-centric criteria (e.g., change management load, employee experience), stringent risk factors (e.g., hallucination risk, data privacy), and strategic HR objectives.

2.4 Research Gap

The ten prominent GenAI use cases within HR and eleven critical criteria spanning four key dimensions identified from the literature are shown in *Tables 1* and *2*, respectively. The literature confirms GenAI's transformative potential in HRM but reveals a strategic dilemma: organizations lack a robust, holistic framework to prioritize investments in a landscape filled with high-potential yet high-uncertainty options. While MCDM offers a proven methodology for structuring such complex multi-criteria decisions, its application has not been tailored to the specific challenges of GenAI initiative prioritization in HR. Previous MCDM studies in HR are either too narrow (e.g., candidate selection) or too broad (e.g., general IT selection), failing to capture the unique criteria blend of strategic HR impact, ethical AI risk, implementation feasibility, and organizational momentum required for GenAI.

Therefore, this study bridges this gap by: (a) Synthesizing from the literature a comprehensive, HR-specific set of criteria for evaluating GenAI initiatives; (b) Proposing and demonstrating an applied MCDM framework that aggregates expert judgment (via survey data) to rank and sequence

Table 1. The Generative AI initiatives for Human Resource Management

Code	Alternative	Description	Reference
A1	Intelligent HR Helpdesk Chatbot	A GenAI interface that provides instant, 24/7 answers to employee policy and benefits questions, drastically reducing routine queries to human HR staff	Tadvi *et al.* (2020); Suhonen (2025)
A2	Automated Recruitment Coordinator	An AI that handles high-volume recruitment scheduling, initial candidate screening based on minimum qualifications, and sends personalized status updates, freeing up recruiters for strategic tasks.	Rathi (2025)
A3	Personalized Onboarding Helper	A GenAI that creates customized onboarding plans for new hires, answers their questions, and proactively guides them through their first 90 days, improving time-to-productivity.	Garcia and Kwok (2025)
A4	Dynamic Content & Policy Summarizer	An AI that automatically digests lengthy HR policy updates, benefit guides, and training materials into concise, actionable summaries and FAQs for employees.	Khan *et al.* (2024); Cano-Marin (2024)
A5	Employee Sentiment & Trend Analyzer	A tool that uses generative AI to analyze internal communications and survey text to provide HR with real-time, thematic insights into morale, burnout risks, and emerging issues.	Majumder and Misra (2025); Lenka and Chanda (2024)
A6	Skills & Competency Gap Analyst	An AI that analyzes job descriptions, performance data, and strategic goals to identify critical skill gaps across the organization and recommend targeted training programs.	Kanagaraj and Thapliyal (2025); Majumdar (2025)
A7	Bias-Conscious Job Description Optimizer	A GenAI tool that scans and suggests edits to job postings to remove biased language, ensuring they are inclusive and appeal to a wider, more diverse talent pool.	Tharayil *et al.* (2025); Masrek *et al.* (2025)
A8	Interactive Leadership Training Simulator	An AI that generates realistic, challenging management scenarios (e.g., conflict resolution, giving feedback) for leaders to practice with in a safe environment.	Khan *et al.* (2024); Jenkins and Khanna (2025)
A9	Personalized Career Advisor	An internal tool that allows employees to explore potential career trajectories within the company, with AI suggesting roles, skills, and mentors based on their profile and goals.	Tan (2024); Mayer *et al.* (2025)
A10	Automated Compliance & Reporting Assistant	An AI that automates the generation of standard HR compliance reports (e.g., EEO-1, turnover analysis) and can answer complex regulatory questions in plain language.	Chandrasekaran (2024)

Table 2. The criteria for evaluating the GenAI initiatives

Area	Criteria	Description	References
Strategic Impact	**C1.** Alignment with Core HR Objectives	How directly the initiative supports a top-tier, measurable HR goal (e.g., reducing time-to-fill, improving employee engagement scores).	Garcia and Kwok (2025); Sánchez *et al.* (2025)
	C2. Scope of Impact	The number of employees (or managers/HR staff) who will directly and regularly interact with or benefit from the initiative.	Gowrishankkar *et al.* (2025)
	C3. Problem Criticality	The level of pain, frequency, and cost (in time or money) associated with the business problem the initiative solves.	De Frutos Pérez (2025)
Feasibility & Resource	**C4.** Implementation Complexity	The estimated difficulty of technical integration with existing systems and the level of custom development required.	Jiang *et al.* (2025)
	C5. Data Readiness	The availability, quality, and accessibility of the clean, structured data needed to train and run the AI model effectively.	Abendroth *et al.* (2025)
	C6. Total Cost of Ownership (TCO)	The total projected cost over 3 years, including licensing, implementation, internal resources and ongoing maintenance.	Anderson *et al.* (2025); Hosanagar and Krishnan (2024)
Risk & Compliance	**C7.** Data Privacy & Security Risk	The sensitivity level of the data the initiative requires to function and the potential impact of a data breach.	Wach *et al.* (2023)
	C8. Hallucination & Accuracy Risk	The business impact of a potential AI error or "hallucination." (e.g., an incorrect policy answer vs. an incorrect offer letter).	Adel and Alani (2025)
	C9. Change Management Workload	The expected level of resistance and the effort required to train users and drive adoption among employees and the HR team.	The current study
Organizational Momentum	**C10.** Time-to-Value	The estimated timeline from project kick-off to the delivery of a Minimum Viable Product (MVP) that demonstrates tangible value.	Sterne (2024)
	C11. Scalability & Strategic Foundation	The potential for the initiative to be expanded to more complex processes or to serve as a foundational component for future AI projects.	Sekli and De La Vega (2025)

a portfolio of HR GenAI alternatives; (c) Providing a practical, evidence-based decision-support tool for HR leaders navigating the early stages of GenAI adoption.

3. Research methodology

This study employs a quantitative, decision-modeling approach structured in three sequential phases to systematically prioritize Generative AI initiatives for HRM. The methodology is designed to transform expert judgments into a robust, actionable ranking of alternatives.

3.1. Data Collection

A critical step involved constituting a diverse panel of ten (10) experts from Pakistan to ensure a holistic evaluation encompassing all strategic, technical, financial, and operational dimensions of GenAI adoption. As detailed in *Table 3*, the panel was deliberately composed of two senior representatives from each of five critical functional domains: HR Leadership, IT & Data, Finance, Legal & Compliance, and Talent & HR Operations. This structure guarantees that the evaluations reflect balanced cross-functional expertise. Each expert was provided with comprehensive definitions of the ten (10) GenAI initiatives (A1-A10) and the eleven (11) evaluation criteria (C1-C11). They were then asked to relatively rank the criteria, and the data is shown in *Table 4*. They were also asked to evaluate each GenAI initiative against every criterion using a 7-point Likert scale

Table 3. The demographic profile of the experts

ID	Functional Group	Position	Age	Educational Qualification	Work Experience (Years)
H1	HR Leadership	Sr. HR Manager	48	MBA	22
H2	HR Leadership	VP of HR	45	Master's in HRM	18
I1	IT & Data	CTO	50	MS Computer Science	25
I2	IT & Data	Head of Data Governance	42	BSc Computer Science	16
F1	Finance	CFO	52	BS Banking & Finance	28
F2	Finance	Finance Manager	39	Chartered Accountant	14
L1	Legal & Compliance	Company Secretary & Head of Legal	47	LLB (Hons), LLM	20
L2	Legal & Compliance	Head of Internal Audit & Risk	44	Chartered Accountant	17
T1	Talent & Development	Director of Talent Acquisition	41	M.Com	15
T2	Talent & Development	Director of Training & Development	46	MBA	19

Table 4. The ranking of criteria by the experts

ID	H1	H2	I1	I2	F1	F2	L1	L2	T1	T2
C1	1	2	7	8	3	4	6	7	4	5
C2	2	3	9	9	6	7	7	8	1	2
C3	3	4	10	10	7	8	8	9	2	3
C4	8	9	1	2	8	9	9	10	8	9
C5	9	10	2	1	9	10	10	11	9	10
C6	7	8	6	6	1	1	9	6	7	8
C7	10	11	3	3	10	11	1	1	10	11
C8	11	7	4	4	11	6	2	2	11	7
C9	6	6	11	11	5	5	3	3	3	4
C10	4	5	8	7	2	2	11	5	5	6
C11	5	1	5	5	4	3	4	4	6	1

(where 1 = Very Poor and 7 = Excellent), resulting in a complete expert-by-alternative-by-criteria assessment matrix for each expert. Later, median was used for aggregation (Liu *et al.*, 2007) and to prepare a final decision matrix, which is shown in *Table 5*.

3.2. Data Analysis Techniques

The collected data from the expert panel was processed using two complementary MCDM methods to ensure methodological rigor and validate the stability of the results. One method was the Analytical Ordinal Priority Approach (AOPA) and the other was the Dynamic Grey Relational Analysis (DGRA).

3.2.1 Analytical Ordinal Priority Approach. The Ordinal Priority Approach is a breakthrough technique of multiple criteria decision analysis, and represents one of the rarest methods that can simultaneously estimate the weights of the experts, criteria and alternatives (Javed & Du, 2023). The Analytical Ordinal Priority Approach method provides the closed-form solution to the OPA. It was selected as the primary weighting and ranking tool due to its specific suitability for ordinal data (and Likert scales) and its capacity to integrate expert weights based on their predefined ranks of expertise (work experience) without requiring complex pairwise comparisons. The AOPA method was applied following the steps mentioned in Javed and Mahmoudi (2025).

If r_i is the rank of i^{th} expert, and r_{ij} is the rank of j^{th} criterion and r_{ijk} is the rank of k^{th} GenAI initiative, and the number of experts are p, the number of criteria are n, and the number of alternatives are m, then the weights of k^{th} GenAI initiative, j^{th} criterion and i^{th} expert are respectively given by (Javed & Mahmoudi, 2025)

Table 5. The decision matrix prepared through the aggregated responses of the experts

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
A1	6	7	5	4	5	6	3	4	5	6	6
A2	5	5	6	6	6	7	2	3	4	5	5
A3	5	4	4	5	4	5	4	5	6	4	5
A4	4	5	3	3	6	4	5	6	3	7	4
A5	6	6	5	7	3	5	2	6	7	5	7
A6	7	4	4	6	2	4	6	5	5	6	6
A7	4	3	3	2	5	3	7	7	2	7	3
A8	5	3	4	7	3	4	5	4	6	3	4
A9	6	5	5	5	4	5	4	4	5	5	7
A10	5	4	6	4	5	6	1	2	4	4	5

$$W_k|\text{GenAI initiative} = \frac{\sum_{i=1}^{p}\left(\sum_{j=1}^{n}\left(\frac{1}{r_i r_{ij}} \times \sum_{r_{ijk}=k}^{p}\frac{1}{r_{ijk}}\right)\right)}{\sum_{k=1}^{m}\left(\sum_{i=1}^{p}\left(\sum_{j=1}^{n}\left(\frac{1}{r_i r_{ij}} \times \sum_{r_{ijk}=k}^{p}\frac{1}{r_{ijk}}\right)\right)\right)}$$

$$W_j|\text{criterion} = \frac{\sum_{i=1}^{p}\left(\frac{1}{r_i r_{ij}}\right)}{\sum_{j=1}^{n}\left(\sum_{i=1}^{p}\left(\frac{1}{r_i r_{ij}}\right)\right)}$$

$$W_i|\text{expert} = \frac{\frac{1}{r_i}}{\sum_{i=1}^{p}\frac{1}{r_i}}$$

3.2.2 Dynamic Grey Relational Analysis. The Dynamic Grey Relational Analysis (DGRA) is an adaptive and objective method of distance-based multiple criteria decision analysis that can operate on both ordinal and cardinal data (Javed, 2019). It measures the distance of an alternative from an ideal reference sequence. The DGRA method was applied following the steps mentioned in Javed *et al.* (2022). The core metric of the DGRA method is called the Grey Relational Grade (GRG), which is the weighted mean of the Grey Relational Coefficients (GRC). If $X_0 = [x_0(1), x_0(2), \dots, x_0(n)]$ is the ideal sequence, and $X_0 = [x_0(1), x_0(2), \dots, x_0(n)]$ represents the GenAI initiative in human resource management, then the GRC between them is given by

$$\gamma_{0k}(j) = \frac{min_k\, min_j|x_0(j) - x_k(j)| + \xi(j) \cdot max_k\, max_j|x_0(j) - x_k(j)|}{|x_0(j) - x_k(j)| + \xi(j) \cdot max_k\, max_j|x_0(j) - x_k(j)|}$$

where, $\xi(j)$ is the Dynamic Distinguishing Coefficient, which was estimated using the linear programming-based technique proposed by Javed *et al.* (2022).

4. Results and discussion

This section presents the findings from the application of the Analytical Ordinal Priority Approach (AOPA) and Dynamic Grey Relational Analysis (DGRA) to prioritize ten Generative AI initiatives for Human Resources Management. The results are derived from the expert evaluations provided by the ten-member panel (*Table 3*) and are presented in three parts: (1) the weights derived from the AOPA model, (2) the rankings from the DGRA model, and (3) a synthesized discussion of the implications and convergences between the two methods.

4.1 Analytical Ordinal Priority Approach-based results

The AOPA model processed the ordinal rankings of experts and criteria to generate objective weights at three levels: expert importance, criterion significance, and final alternative priority. The results are summarized in *Table 6*.

Table 6. The analyses using the AOPA

Experts		Criteria		GenAI Initiatives		
ID	**AOPA w**	**ID**	**AOPA w**	**ID**	**AOPA w**	**Rank**
H1	0.114	C1	0.112	A1	0.111	3
H2	0.057	C2	0.084	A2	0.113	2
I1	0.171	C3	0.061	A3	0.087	9
I2	0.043	C4	0.095	A4	0.093	6
F1	0.341	C5	0.070	A5	0.12	1
F2	0.034	C6	0.155	A6	0.106	4
L1	0.085	C7	0.089	A7	0.092	7
L2	0.049	C8	0.063	A8	0.087	10
T1	0.038	C9	0.066	A9	0.103	5
T2	0.068	C10	0.097	A10	0.088	8
		C11	0.109			

First the experts were ranked based on their experience, and the AOPA model was applied. The AOPA model assigned the highest weight to the Chief Financial Officer (F1, w=0.341), followed by the Chief Technical Officer (I1, w=0.171). This outcome directly reflects the pre-defined ranking of experts, where the CFO and CTO were ranked first and second based on their ultimate authority over budget and technical infrastructure, respectively. This weighting signifies that, within the model, financial viability and technical feasibility judgments are accorded the greatest importance in the final aggregation of preferences.

The analysis of criterion weights reveals the collective priorities of the expert panel. Total Cost of Ownership (C6) emerged as the most critical factor (w=0.155), underscoring the panel's strong focus on financial discipline and long-term fiscal sustainability. This was closely followed by Strategic Alignment (C1, w=0.112) and Scalability & Strategic Foundation (C11, w=0.109), indicating that initiatives must not only be affordable but also directly support core HR objectives and have potential for future growth. Notably, Time-to-Value (C10, w=0.097) and Implementation Complexity (C4, w=0.095) also received considerable weight, highlighting the desire for initiatives that can demonstrate quick wins without overwhelming technical hurdles.

Based on the aggregated expert preferences and the derived criterion weights, the AOPA model produced a priority ranking of the ten GenAI initiatives. A5 (Employee Sentiment & Trend Analyzer) achieved the highest priority weight (0.120). It was followed closely by A2 (Automated Recruitment Coordinator, w=0.113) and A1 (Intelligent HR Helpdesk Chatbot, w=0.111). This top tier represents initiatives perceived to offer a strong balance of strategic impact, broad scope, and manageable risk. Initiatives like A8 (Interactive Leadership Training Simulator) and A3 (Personalized Onboarding Helper) received the lowest weights (0.087), suggesting they are viewed as either more niche, complex, or offering a less immediate return relative to others.

4.2 Dynamic Grey Relational Analysis-based results

The DGRA evaluated each GenAI initiative's similarity to an ideal GenAI initiative across all criteria. The AOPA weights were used for the criteria. The GRC and corresponding $\xi(j)$ values are shown in *Table 7*, along with the GRG values and their corresponding ranks. It should be noted that $\xi(j)$ is the function of Javed's multiplier h, whose value in the current study was 1.936. The DGRA show a high degree of convergence with the AOPA. A5, A1, and A2 maintain their positions as the top three GenAI initiatives, confirming their robustness as high-priority investments. The strong performance of A5 (GRG=0.736) suggests its profile—offering deep strategic insights into workforce morale with moderate data and implementation requirements—aligns closely with the ideal solution as defined by the weighted criteria.

4.3 Discussion and Implications

The convergent results from two distinct MCDM methodologies provide a strong, validated foundation for strategic decision-making. *Figure 1* synthesizes the final ranking, placing A5 (Employee Sentiment & Trend Analyzer) as the highest-priority initiative.

Table 7. The analyses using the DGRA model

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	GRG	Rank
A1	0.698	1.000	0.750	0.587	0.775	0.734	0.540	0.538	0.633	0.770	0.770	0.713	2
A2	0.536	0.607	1.000	0.810	1.000	1.000	0.485	0.466	0.535	0.626	0.626	0.710	3
A3	0.536	0.507	0.600	0.681	0.633	0.580	0.610	0.636	0.775	0.527	0.626	0.602	8
A4	0.435	0.607	0.500	0.516	1.000	0.480	0.701	0.778	0.463	1.000	0.527	0.619	6
A5	0.698	0.755	0.750	1.000	0.535	0.580	0.485	0.778	1.000	0.626	1.000	0.736	1
A6	1.000	0.507	0.600	0.810	0.463	0.480	0.825	0.636	0.633	0.770	0.770	0.688	4
A7	0.435	0.435	0.500	0.461	0.775	0.409	1.000	1.000	0.408	1.000	0.455	0.602	9
A8	0.536	0.435	0.600	1.000	0.535	0.480	0.701	0.538	0.775	0.455	0.527	0.589	10
A9	0.698	0.607	0.750	0.681	0.633	0.580	0.610	0.538	0.633	0.626	1.000	0.673	5
A10	0.536	0.507	1.000	0.587	0.775	0.734	0.439	0.412	0.535	0.527	0.626	0.607	7
$\xi(j)$	0.548	0.774	0.484	0.677	0.548	0.677	1.000	0.774	0.742	0.581	0.581		

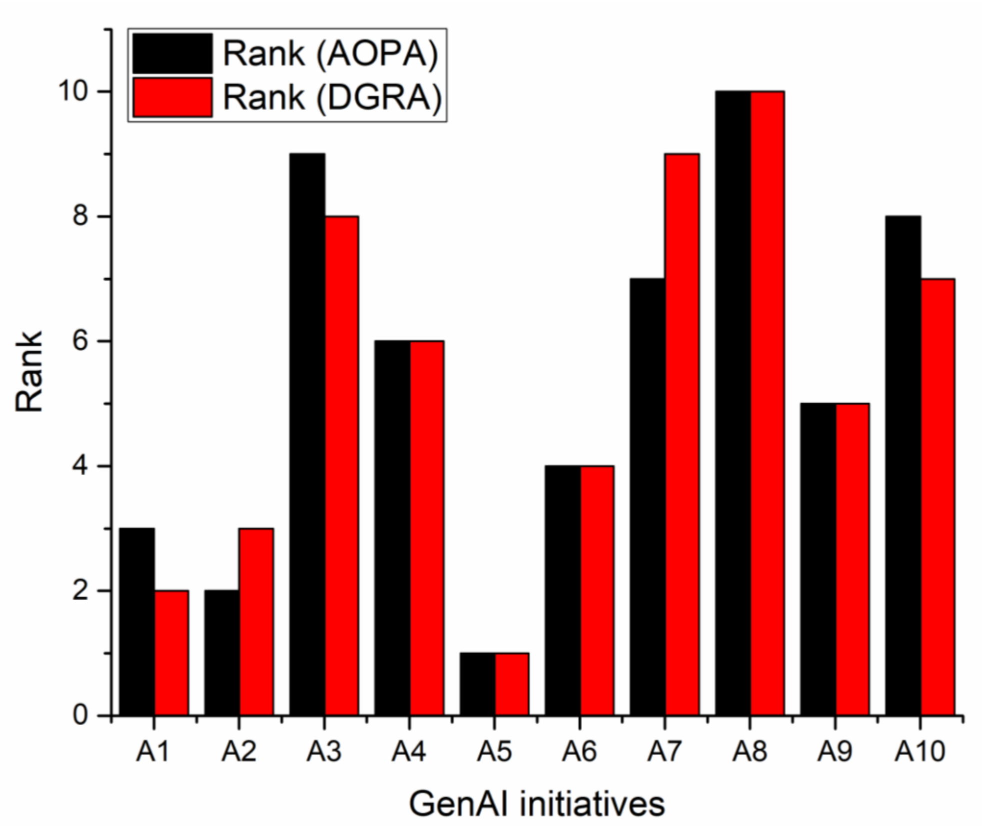

Fig 1. The rankings of the Generative AI Initiatives for Human Resources Management

4.3.1 Analysis of High-Priority Initiatives. The top-ranked initiative, A5, is prioritized because it addresses the high-criticality problem of employee burnout and disengagement (C3) with a wide scope of impact (C2) on the entire organization. It provides actionable strategic intelligence (C1) while leveraging data (internal communications) that, while sensitive, is often more readily available and structured than other types (C5). Its ranking affirms that initiatives providing proactive, organization-wide insights are valued over those automating transactional tasks alone. A1 and A2 follow as they target high-frequency, high-pain operational bottlenecks—recruitment coordination and policy queries. They promise a strong, quick return on investment (high C10, positive impact on C6) by freeing HR staff for strategic work, aligning perfectly with the criterion weights for Time-to-Value and Strategic Alignment.

4.3.2 Interpretation of Mid- and Lower-Tier Initiatives. Initiatives like A6 (Skills Gap Analyst) and A9 (Career Pathing Advisor) rank in the middle, likely due to their high strategic long-term value (C11) being balanced against significant challenges in data readiness (C5) and implementation complexity (C4). The lower ranking of A10 (Compliance Assistant) is particularly noteworthy. While it scores low on risk (C7, C8), experts may perceive its impact as limited to a specialist group within HR (lower C2) and its benefits as primarily "avoiding penalties" rather than driving proactive strategic value (C1). A8 (Leadership Simulator) ranks lowest despite its innovative appeal, potentially due to expert concerns about high change management workload (C9), difficulty in measuring direct ROI, and complexity in creating truly effective simulations.

4.3.3 Consolidated Ranking. The consolidated ranking provides a clear, evidence-based roadmap for HR leadership, as shown in *Table 8*. The top tier (A5, A1, A2) consists of initiatives that offer a powerful combination: addressing organization-wide or high-volume pain points, delivering measurable value quickly, and aligning with core HR and business objectives. Investing in this cluster first maximizes the probability of early success and builds organizational confidence in GenAI. The unanimous last-place ranking of A8 (Interactive Leadership Training Simulator) is particularly instructive. Despite its innovative appeal, experts consistently rated it lower due to anticipated high costs, complexity, and a potentially lower perceived strategic urgency compared to tools that automate repetitive tasks or provide strategic intelligence. This finding suggests that, in the early stages of GenAI implementation, organizations prioritize efficiency gains and actionable insights simulation-based tools.

This study demonstrates that a dual-method MCDM framework effectively synthesizes diverse expert perspectives, transforming them into a clear strategic sequence. It moves investment decisions from intuition to a transparent, criteria-driven process, allowing leaders to confidently allocate resources to initiatives that best meet the organization's blended needs for impact, feasibility, and risk management.

4.3.4 Managerial Implications. For HR leaders, these results advocate for a phased investment roadmap. The first phase should focus on the top-tier initiatives (A5, A2, A1) that deliver quick, visible value and build organizational confidence in GenAI. The successful implementation of, for example, the Sentiment Analyzer (A5) would create a data foundation and positive momentum that could ease the subsequent adoption of more complex, data-dependent initiatives like the Skills Gap Analyst (A6) in a second phase.

5. Conclusion

This study developed and demonstrated a systematic, multi-criteria framework to address a critical strategic challenge in contemporary HRM: the prioritization of Generative AI initiatives. Faced with an array of promising yet resource-intensive technological options, HR leaders require an objective mechanism to guide investment decisions. By using dual-model framework comprising the Analytical Ordinal Priority Approach (AOPA) and Dynamic Grey Relational Analysis (DGRA), this research provided a robust, transparent methodology for transforming expert judgment into a clear, actionable roadmap.

The core finding of this analysis is a consolidated, validated ranking of ten GenAI initiatives. The Employee Sentiment & Trend Analyzer (A5) emerged as the unequivocal top priority, justified by its unique capacity to deliver proactive, strategic intelligence on workforce morale across the

Table 8. The consolidated ranks of ten GenAI initiatives

GenAI initiatives	AOPA	DGRA	Consolidated Ranks
A5: Employee Sentiment & Trend Analyzer	1	1	1
A2: Automated Recruitment Coordinator	2	3	2
A1: Intelligent HR Helpdesk Chatbot	3	2	
A6: Skills & Competency Gap Analyst	3	3	3
A9: Personalized Career Pathing Advisor	4	4	4
A4: Dynamic Content & Policy Summarizer	5	5	5
A7: Bias-Conscious Job Description Optimizer	7	9	6
A3: Personalized Onboarding Concierge	9	8	
A10: Automated Compliance & Reporting Assistant	8	7	
A8: Interactive Leadership Training Simulator	10	10	7

entire organization. It was followed closely by two high-impact operational tools: the Intelligent HR Helpdesk Chatbot (A1) and the Automated Recruitment Coordinator (A2). These top-tier initiatives represent the optimal blend of strategic alignment, broad scope, strong return on investment potential, and relatively manageable implementation complexity. Conversely, the Interactive Leadership Training Simulator (A8) was unanimously ranked last by both methods, indicating a consensus that its high development cost, complexity, and niche application render it a lower strategic priority in the initial phases of GenAI adoption.

Based on the consolidated ranking, the following actionable recommendations (phased implementation) are proposed for HR leaders and organizational decision-makers. Phase 1: allocate resources to pilot and implement the top-tier initiatives: A5 (Sentiment Analyzer), A1 (Helpdesk Chatbot), and A2 (Recruitment Coordinator). These projects promise quick, visible wins that build organizational confidence, generate tangible ROI, and address widespread pain points. Phase 2: Once foundational systems are in place and data maturity improves, invest in the middle-tier initiatives like A6 (Skills Gap Analyst) and A9 (Career Pathing Advisor). The success of the first phase will create the necessary data infrastructure and stakeholder buy-in for these more complex, strategically transformative tools. Phase 3: Consider the lower-priority initiatives (A4, A7, A3, A10) as targeted solutions for specific process improvements or compliance needs, to be pursued once core strategic systems are operational.

The expert weightings underscore that successful AI adoption is not an HR-only project. A governance committee including senior leaders from Finance (for ROI oversight), IT (for technical feasibility), and Legal/Compliance (for risk mitigation) should be established from the outset to guide selection, implementation, and ethical oversight of all AI initiatives. Also, the top-ranked Employee Sentiment & Trend Analyzer should be viewed not merely as a tool, but as a strategic asset. Its implementation will force critical improvements in data collection and analysis capabilities. The insights it generates will provide evidence-based guidance for other HR interventions, potentially increasing the success rate of subsequent initiatives in the second and third phases.

While this study provides a rigorous framework, its findings are subject to certain limitations that also delineate avenues for future research. For instance, the demographic and functional composition of the expert panel, while deliberately diverse, reflects a specific organizational context (e.g., industry, size, geographic location in Pakistan). The criterion weights and resulting rankings may shift in organizations with different strategic priorities, risk appetites, or technological maturity. Future research can apply this framework in different industrial (e.g., manufacturing, healthcare) and cultural contexts to develop comparative insights. While the criteria were designed for pre-implementation assessment, the actual ROI, user adoption, and unforeseen challenges of each initiative can only be validated through longitudinal study after deployment. Also, the findings are constrained by the composition of the expert panel and the specific contextual judgments they provided. The results may vary in organizations with different strategic priorities, technological maturity, risk appetite and environments (legal, cultural, technical, etc.) in which they operate. Future work could involve retrospective case studies comparing predicted vs. actual performance of implemented GenAI tools.

In conclusion, this research contributes a practical, decision-support framework that equips HR leaders to navigate the complex GenAI landscape with greater confidence and strategic acumen. By moving beyond hype and intuition to a structured, multi-stakeholder evaluation process, organizations can ensure their investments in HR technology are deliberate, defensible, and aligned with long-term strategic value creation.

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