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

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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		

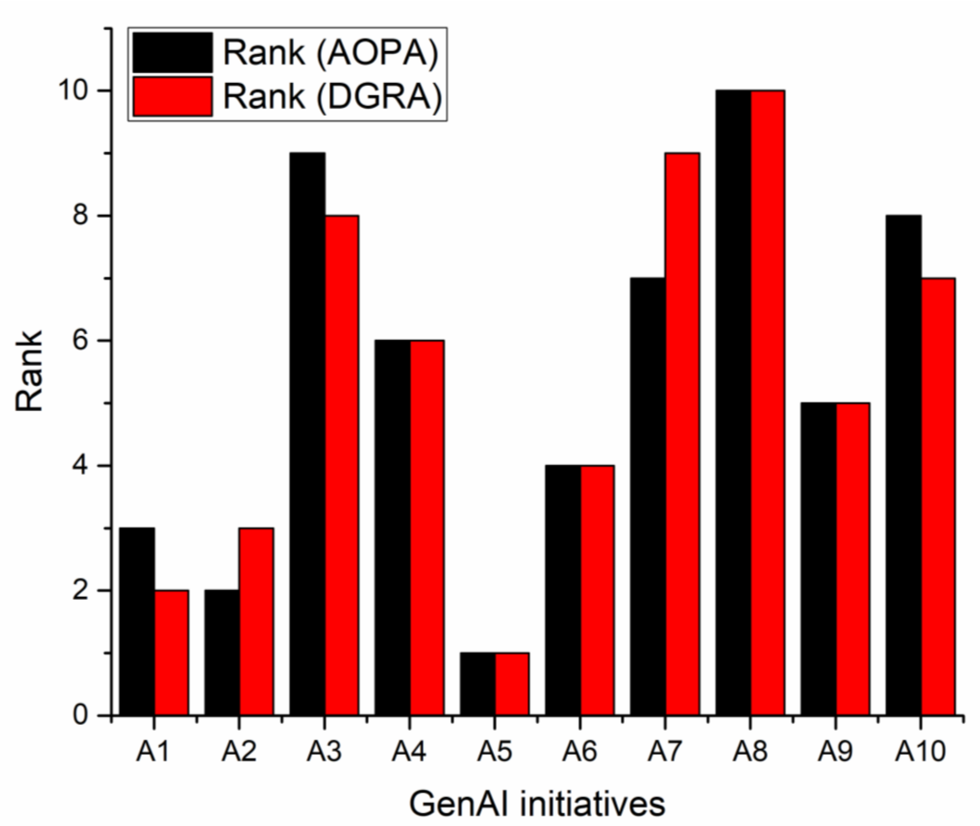

Fig 1. The rankings of the Generative AI Initiatives for Human Resources Management

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

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

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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Factors Influencing the Adoption of AI-Enhanced Enterprise Resource Planning in Logistics

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Abstract: This study aims to evaluate and prioritize the critical factors influencing the adoption of AI-enhanced Enterprise Resource Planning (ERP) systems within China's logistics sector. A hybrid multi-criteria decision-making (MCDM) methodology is employed, integrating the Dynamic Grey Relational Analysis (DGRA) and the Analytical Ordinal Priority Approach (AOPA). Data were collected from 223 logistics professionals via a structured questionnaire, and the factors were ranked based on their distance to an ideal reference and their ordinally derived importance weights. We found Data Security & Privacy to be the most critical factor based on both models. We also found the strong convergence between DGRA and AOPA results confirms the robustness of the ranking. This study provides the first empirically validated, multi-model approach specifically designed to prioritize AI-enhanced ERP factors for the logistics industry.

Keywords: Artificial Intelligence; Enterprise Resource Planning; Logistics; Dynamic Grey Relational Analysis; Analytical Ordinal Priority Approach; Technology Adoption

1. Introduction

The logistics sector of China has reached a new phase in the process of digital modernization, which is conditioned by the active development of e-commerce, global trade, and the nationwide supply-chain integration (Shevchenko *et al.*, 2021). With the growing complexity of logistics networks and their time sensitivity, companies are switching to enterprise resource planning (ERP) solutions with inbuilt AI to enhance forecasting, routing, warehouse management, and cross-platform coordination (Yin *et al.*, 2023). Unlike in the past where these AI-enhanced ERP systems only perform transactional processing, they have become smart decision engines that learn with real-time demand trends and operational uncertainties (Chimpiri, 2025). But their effective assessment and application involve the systematic interpretation of technological, organisational, and human factors to influence the adoption results in the logistics environment.

Although AI-enabled ERP solutions have multiple strategic advantages, logistics companies in China are continuing to experience issues concerning the security risk, automation reliability, barriers to integration, and transparency of AI-made decisions (Hao & Demir, 2025; Su *et al.*, 2024). These issues become further exacerbated since logistics processes are heavily reliant on data flows that are not interrupted, cross-border regulatory adherence, and predictable automation response (Trichias *et al.*, 2025). Managerial willingness to invest directly depends on issues of security of data, efficiency in operations and real time visibility of data, legacy integration, and reliability of these systems determine the perceived value and continuity of operations. Meanwhile, more subtle aspects, like user trust, decision transparency, and ease of use can have a significant impact on defining behavioural acceptance especially in the settings where AI remains uncertainty-filled and perceived as risky.

Since this is a multidimensional approach, the assessment of AI-enhanced ERP systems needs an influential analytical design, which reflects not only the adaptive relationships between the factors but also the proximity of each factor to an optimal state of decision. Conventional appraisal strategies are more likely to simplify these dependencies (Tang *et al.*, 2025). Multi- criteria decision-making models (MCDMs), which includes the Dynamic Grey Relational Analysis (DGRA) and Analytical Ordinal Priority Approach (AOPA), are by comparison, suitable to complex logistics scenarios where the information contains uncertainty. The DGRA offers an adaptive relational measure which represents variation and impact of factors to general assessment, whereas the AOPA facilitates organised prioritisation taking into account objective significance and decision adjustments. This study uses DGRA and AOPA to prioritize ten critical factors influencing the adoption of AI-enhanced ERP systems in the Chinese logistics industry. This research will add a holistic approach of evaluating AI-driven ERP adoption plans to logistics managers, system developers, and policy makers by incorporating two different mathematical perspectives.

The paper has taken into account ten crucial variables that affect AI-based ERP assessment, as shown in *Table 1*. This lists ten important considerations to the assessment of AI-enhanced ERP systems in the logistic sector, with each factor being backed by the recent literature. The factors cut across the technological, operational, human as well as the organisational facets of measurement to give a comprehensive assessment framework. AI Decision Transparency and User Trust are designed to solve the socio-, technologically-based acceptance of AI-based recommendations, whereas Operational Efficiency and Real-Time Data Visibility are fundamental logistics performance metrics. Cost-Benefit Perception and Vendor Support are more concerned with economic and sustainability issues, but Data Security, Automation Reliability, and Integration Capability are more concerned with implementation risks and technical robustness. The combination of these aspects offers a systematic platform on which the DGRA and the AOPA can be applied.

2. Research methodology

2.1 Research design and data collection

The proposed research applies a MCDM approach based on quantitative approach to assess the critical factors affecting the adoption of AI-enhanced ERP systems in the logistics industry of

Table 1. Literature based factors and their reference

Code	Factor	Reference
F1	AI Decision Transparency	Madsen and Kim (2024); Rahman *et al.* (2025); Alruwaili and Mgammal (2025)
F2	Cost–Benefit Perception	Matta and Feger (2021); Lokshina *et al.*, (2022); Hossain *et al.* (2024)
F3	Vendor Support & AI Updates	Sarferaz (2025); Vukman *et al.* (2024); Alherimi *et al.* (2025)
F4	Integration with Legacy Systems	Emon and Chowdhury (2025); Khan *et al.* (2025); Rahman *et al.*, (2025)
F5	Automation Reliability	Debbadi and Boateng (2025); Jiang *et al.* (2023)
F6	Data Security & Privacy	Ojha *et al.*, (2024); Gupta and Goyal (2021); Khan *et al.*, (2025)
F7	Operational Efficiency Improvement	Lam *et al.* (2024); Santoso *et al.* (2022); Inmor *et al.* (2025)
F8	Real-Time Data Visibility	Choudhuri (2024); Jamil *et al.*, (2025); Singh *et al.* (2025); Anjaria (2025)
F9	Ease of Use	Li and Wu (2021); Islam *et al.* (2025); Rad *et al.* (2025); Loske and Klumpp (2021)
F10	User Trust & Behavioral Intent	Islam *et al.*, (2025); Anjaria (2025); Dziembek and Turek (2025); Lin and Duan (2024)

China. Since the adoption of ERP is a multidimensional process, including technological, operational, organizational, and human dimensions, a complex framework is required to prioritize the determinants and define areas of critical concern that a logistics manager should focus on. The DGRA and AOPA will be used incorporated in the study to this system.

Data were collected from logistics and transportation companies operating in Ningbo, China. There were respondents such as IT managers, operations supervisors, decision-makers involved in the direct participation in ERP adoption and management. A structured questionnaire was created, depending on the ten factors found in the literature and reviewed by experts. Considering the unique culture of China, the questionnaire was translated in Chinese language, and were physically distributed to the 510 respondents. The perceptions of the importance of each of the factors were captured using a five-point Likert scale where 1 represented strongly disagree, and 5 represented strongly agree. Stratified random sampling was used to make sure that all sizes of firms, and logistics specializations were represented. 223 respondents filled the questionnaire properly and returned timely, providing sufficient statistical power for both the DGRA and AOPA.

Table 2 shows demographic profile of the sampled population. The age distribution showed that most of the respondents were of age 18 to 47. The youngest group, ≤18 years, constituted only (3.14%), while the oldest group, ≥ 48 years, makes up (13.45%) of the sample. These numbers demonstrate a population that is biased towards younger and middle-adults. When it comes to gender, the sample is mostly male (54.71) of the respondents, and females occupy (44.84). Educational level was diverse, with nearly half of the respondents (48.43%) holding a bachelor's degree, followed by (27.80%) with education up to high school. Advanced degrees are less common, with 15.70% respondents holding a master's degree and 5.38% respondents holding a doctorate, while 2.69% reported other qualifications. Marital status representing (40.36%) were single, (47.53%) were married while (12.11%) divorced. This demographic profile provides valuable context for understanding the sample's diversity and its potential influence on attitudes or behaviours under investigation.

2.2 Data analysis techniques

2.2.1 Dynamic Grey Relational Analysis. The Dynamic Grey Relational Analysis (DGRA) is a sophisticated and intelligent approach to multiple-criteria decision-making (MCDM) and is one of the most prominent recent developments in the field. The DGRA framework was first proposed by Javed (2019) and improved by Javed *et al.* (2022). The structure of this methodology is user-

Table 2. Demographic characteristics

Variable	Category	Sample (N)	Percentage (%)
Gender	Male	122	54.71
	Female	100	44.84
	Do not want to mention	1	0.45
Total		223	100
Age	≤ 18	7	3.14
	18-27	65	29.15
	28-37	63	28.25
	38-47	58	26.01
	≥ 48	30	13.45
Total		223	100
Education	≤ High Schooling	62	27.80
	Bachelor’s Degree	108	48.43
	Master’s Degree	35	15.70
	Doctorate	12	5.38
	Other	6	2.69
Total		223	100
Marital Status	Single	90	40.36
	Married	106	47.53
	Divorced	27	12.11
Total		223	100

friendly and mathematically robust. Several succeeding studies have confirmed the validity of this methodology, such as Ouali (2023), Darbinian *et al.* (2023) and Matambo (2023).

Also, in the DGRA normalization of data is not mandatory but optional, and it can be operated on different types of data, such as ordinal, cardinal, linguistic or fuzzy, etc. This methodological flexibility makes it an extremely powerful tool for investigating consumer perception, where the response is often determined by subjective attitudes and external uncertainties. Unlike the classical Deng's Grey Relational Analysis that involves a parameter, called Distinguishing Coefficient, which is determined subjectively, the DGRA offers a data-driven alternative to that parameter (Angela & Angelina, 2021; Ouali, 2022). Today, it is widely considered as the standard (or canonical) form of the classical Grey Relational Analysis (Nawaz *et al.*, 2025). Consequently, it enables a more objective assessment of systems which may evolve over time or which have variable inter-relations between their constituent variables. The DGRA process encompasses a number of systematic steps to prepare the decision matrix, calculate relationships, and rank factors in terms of influence. Guided by Javed (2019), a step-by-step explanation of the steps of the DGRA has been done as follows.

STEP 1: Identification of Ideal Alternative. An ideal alternative, symbolized as X_0 is established to represent the ideal or optimal performance for each factor. Later, each factor will be compared against this reference sequence to assess their performance. Since the current study employed the 5-point Likert scale, each element of the ideal alternative vector cannot exceed 5.

STEP 2: Calculation of Grey Relational Coefficients. The Grey Relational Coefficient (GRC) is calculated, giving the relationship between the reference sequence and each factor. For the alternatives $k = 1,2, \dots, m$, the formula for calculating GRC is,

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

where, the following model (Javed *et al.*, 2022) can be used to determine the vector of $\xi(j)$,

$$Maximize\ \xi(j) = h\psi(1) + h\psi(2) \dots + h\psi(n)$$

s.t.

$$\psi(j) = \frac{\frac{1}{n}\sum_{k=1}^{n} |x_0(j) - x_k(j)|}{max_k\, max_j |x_0(j) - x_k(j)|}$$

$$h \in [1,2]$$

$$h\psi(j) \leq 1$$

The result of the model (7) is $\{\xi(1), \xi(2), \dots, \xi(n)\}$. This model ensures that Javed's multiplier h stays within 1 to 2, and therefore, $\xi(j)$ will also stay between 0 and 1. In the current study, h was estimated to be 1.333.

STEP 3: Calculation of Relational Grades. The Grey Relational Grade (GRG) is calculated to provide an aggregate measure of the relationship between each factor and the reference sequence over all time points. It is calculated as,

$$\Gamma_{0k} = \sum_{j=1}^{m} \gamma_{0k}(j)\, , j = 1,2, \dots, n$$

where m denotes the number of critical factors, and n denotes the number of respondents.

2.2.2 Analytical Ordinal Priority Approach. The Ordinal Priority Approach (OPA) is a breakthrough multiple criteria decision analysis technique developed by Amin Mahmoudi and colleagues (Javed & Mahmoudi, 2025; Mahmoudi & Javed, 2023). Unlike most of the MCDM techniques, the OPA neither requires pairwise comparison matrices nor normalization of data as it directly works on ordinal data using a linear programming-based nonparametric approach (Khan *et al.*, 2025). The Analytical Ordinal Priority Approach (AOPA) is a closed-form solution of the Ordinal Priority Approach, and does not require linear programming for its execution. Also, it can be applied on the primary data collected through the Likert scale, after reversing the direction of the scale. Generally speaking, in multiple criteria decision-making context involving p experts, n attributes, and m alternatives, then the weight of k^{th} alternative is given by (Javed & Mahmoudi, 2025),

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

The relative weights estimated by the OPA and AOPA can be represented in both absolute and percentage terms (Javed & Du, 2022), and thus they are very easy to interpret by real-world decision-makers, AI/ERP experts and logistics managers.

3. Results

3.1 Grey relational evaluation

Table 3 evaluates various factors influencing decision-making using the Grey Relational Grade (GRG) and the Grey Relational Standard Deviation (GRS). Among the factors, Data Security & Privacy (F6) emerges as the most influential, with the highest GRG 0.806, indicating its critical importance. Automation Reliability (F5) and Integration with Legacy Systems (F4), with a GRG of 0.745 and 0.743, also holds significant weights and ranked second and third respectively. Factors like Operational Efficiency Improvement (F7), Real-Time Data Visibility (F8) and User Trust & Behavioral Intent (F10), with a GRG of 0.730, 0.720, and 0.703 respectively, exhibit consistent performance, underscoring their moderate level importance. In contrast, Vendor Support & AI Updates (F3), AI Decision Transparency (F1), and Cost–Benefit Perception (F2) rank the lowest, with GRG values of 0.534, 0.520 and 0.514, respectively, indicating limited impact as shown in *Figure 1*. The analysis underscores that the factors, Data Security & Privacy and Automation Reliability, are pivotal, while the factors, AI Decision Transparency and Cost–Benefit Perception, require more emphasis to elevate their relative position.

Another analysis of the uncertainty, in terms of the Grey Relational Grade (GRG) is also included in *Table 3*, which illustrates the effect of variability ($\pm\sigma$) on the GRG of each factor. The values of the GRG lie between 0.514 and 0.806, which shows that there is a significant difference in the effects of the factors. Factors that have greater GRG value, i.e. 0.806 and 0.745, have greater contribution. On the other hand, variables with smaller GRG values (0.520 and 0.514) have larger uncertainty ranges indicating a higher level of uncertainty and doubt about their effects, as shown in *Figure 2*. This examination highlights the comparative power of every variable as well as the ambiguity that lies in the ranking of the variables and as such, offers an effective structure in rank-ordering decisions in diverse circumstances.

3.2 AOPA-based evaluation

Table 4 presents the ranking of factors based on the AOPA where we found the factor: Data Security & Privacy (F6) emerges as the most critical, receiving the highest weight 0.293, indicating

Table 3. The grey relational evaluation of the AI-enhanced ERP adoption

	GRG	Rank (GRG)	GRSD	GRG (L)	GRG (U)
F1	0.520	9	0.179	0.341	0.700
F2	0.514	10	0.180	0.334	0.694
F3	0.524	8	0.185	0.339	0.709
F4	0.743	3	0.211	0.532	0.954
F5	0.745	2	0.214	0.531	0.959
F6	0.806	1	0.194	0.612	1.000
F7	0.730	4	0.206	0.525	0.936
F8	0.720	5	0.207	0.513	0.928
F9	0.551	7	0.199	0.352	0.751
F10	0.703	6	0.223	0.479	0.926

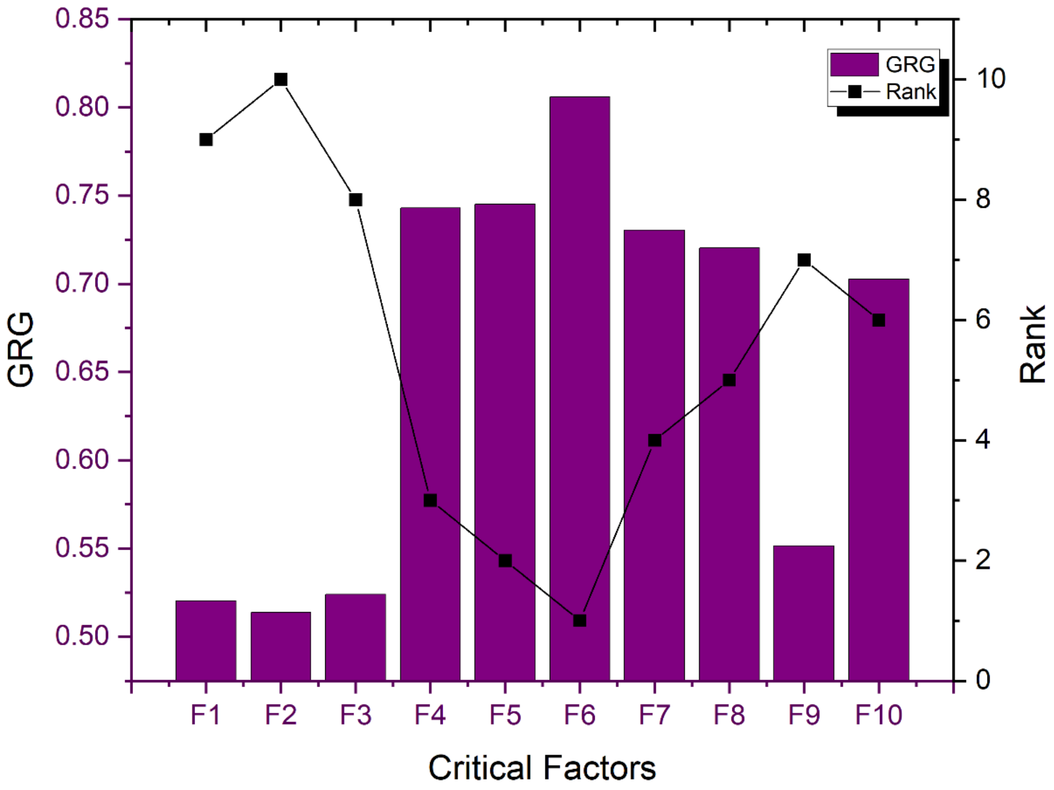

Fig 1. The grey relational evaluation of the critical factors

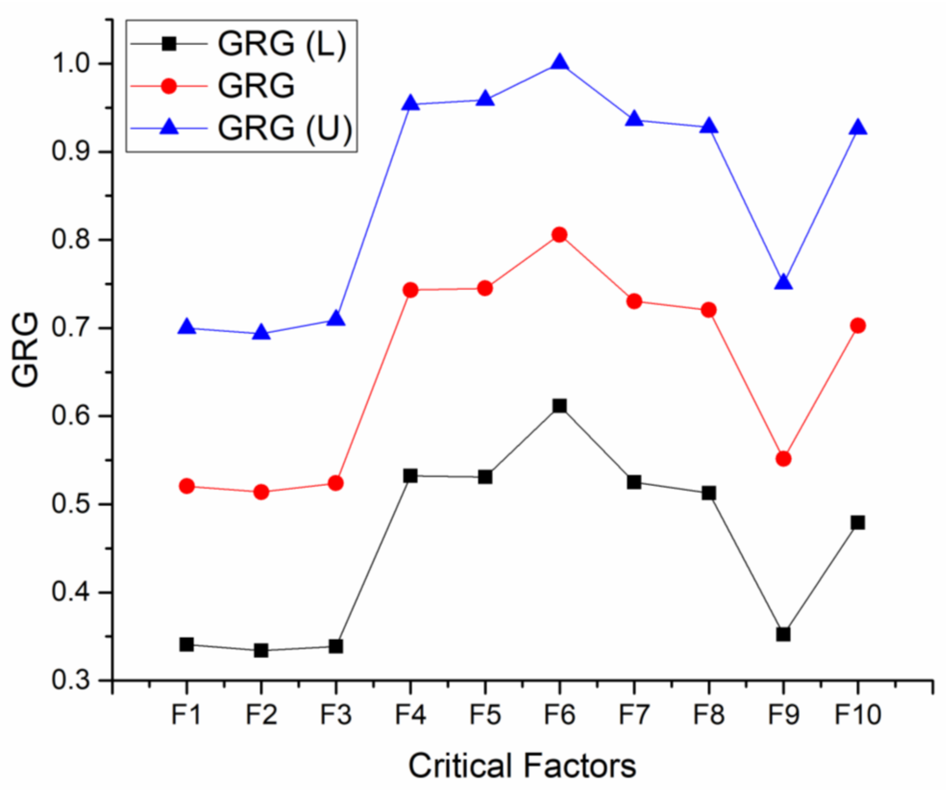

Fig 2. The dynamic grey relational grades and their lower and upper bounds

Table 4. AOPA-based evaluation

Factors	AOPA weights	Importance (%)	Rank (AOPA)
F1	0.021	2.1%	9
F2	0.010	1.0%	10
F3	0.034	3.4%	8
F4	0.193	19.3%	2
F5	0.143	14.3%	3
F6	0.293	29.3%	1
F7	0.110	11.0%	4
F8	0.085	8.5%	5
F9	0.048	4.8%	7
F10	0.065	6.5%	6

it is perceived as the most significant factor. This is followed by Integration with Legacy Systems (F4) with weight 0.193 and Automation Reliability (F5) with weight 0.143, which are moderate in significance but also demand considerable focus. Conversely, factors: AI Decision Transparency (F1) and Cost–Benefit Perception (F2) with weights (0.021) and (0.010) respectively are found with the lowest weights, suggesting they are considered the least severe or impactful. The results provide a quantified, consensus-driven ranking that can effectively guide resource allocation and strategic decision-making, ensuring efforts are concentrated on addressing the most consequential factors first.

The visualization of the AOPA results presented in *Figure 3* provides an intuitive synthesis of factor importance and priority ranking. The AOPA weight is shown on the y-axis and the rank order is shown on the x-axis. The chart shows that the Data Security and Privacy (F6) as the highest bar in the foreground fulfils the status of the most important factor (29.3% weight) and the highest priority. A powerful second level, consisting of Integration with Legacy Systems (F4, 19.3%), Automation Reliability (F5, 14.3%), is conspicuously vivid, creating a cluster of large bars, which are located on the front. Conversely, the shrinking size and backward location of such elements as AI Decision Transparency (F1, 2.1%) and Cost-Benefit Perception (F2, 1.0%) intuitively highlight their comparatively low perceived influence in the logistics dimension. This illustrative figure

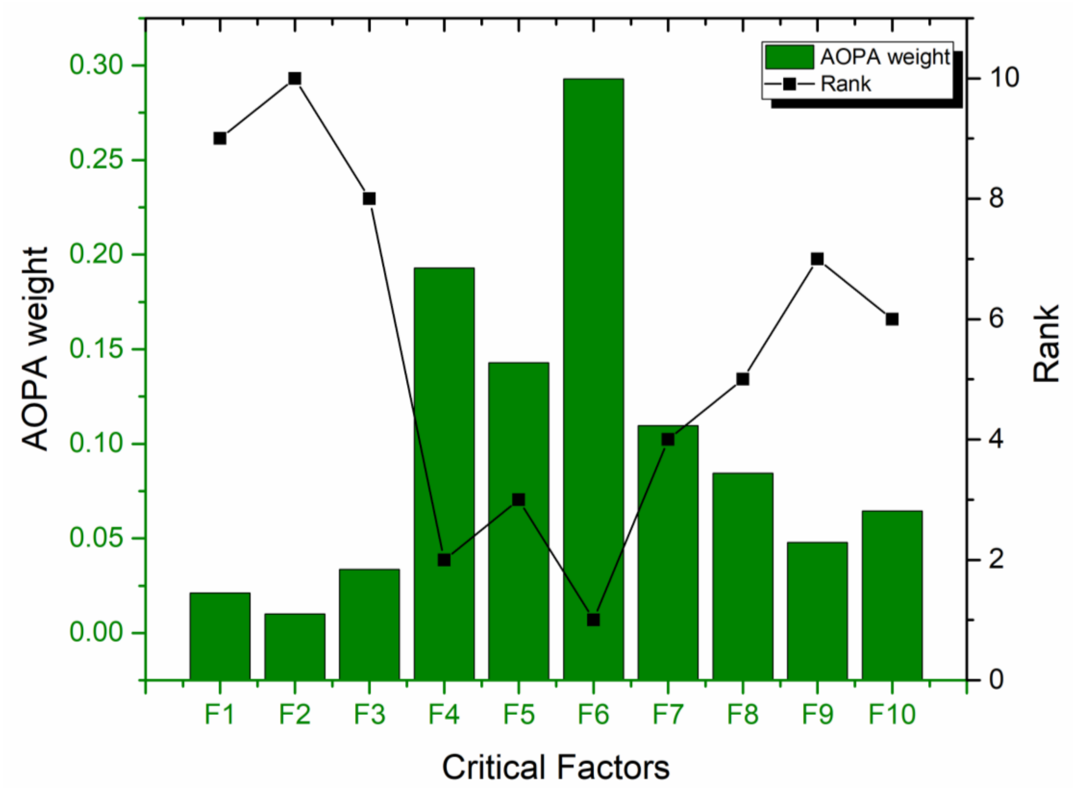

Fig 3. The weights and ranks of the critical factors using the AOPA

supports the analytical results: the logistics professionals are more concerned with the security of the operations, the interoperability of the systems, and their reliability rather than with the financial factors and the transparency of the algorithms when assessing AI-enhanced ERP systems.

4. Discussion

Risk mitigation and operational certainty were the key considerations of the logistics experts in terms of prioritising AI-enhanced ERP systems. The non-negotiable foundation comes out as Data Security & Privacy (F6) which has about 30% of the overall weight. This is indicative of the extreme vulnerability of the sector to breaches and regulatory fines in the cross-border operations, which are data-intensive. It is interesting to note that Integration with Legacy Systems (F4) comes in second, even above core efficiency measures, which highlights importance of realistic deploy of diverse IT environments. The good performance of Automation Reliability (F5) and Operational Efficiency (F7) proves that the fundamental promise of AI-ERP is reliable. On the other hand, the low position of Cost-Benefit Perception (F2) and AI Decision Transparency (F1) is an indicator of a sectoral maturity level of strategic need taking priority over cost justification, and reliability of outcome over explainability of the algorithm in high-stress situations. This priority structure is robust as we found the DGRA and the AOPA rankings are strongly converging.

Figure 4 presents a comparative visualization of the rankings derived from the DGRA and the AOPA. This demonstrates that there is a high overlap between the two methodologies especially the highest and the lowest-ranking factors. Data Security & Privacy (F6) is the most important variable, as it is ranked on the first position in both the DGRA (GRG = 0.76) and the AOPA (weight = 0.293). On the same note, the least significant aspects – AI Decision Transparency (F1) and Cost-Benefit Perception (F2) – are placed at the bottom in both approaches. It also has significant similarity in the middle ranks, where such factors as Operational Efficiency (F7) and Real-Time Data Visibility (F8) hold nearly equal positions. Nonetheless, a slight deviation can be observed on the case of Integration with Legacy Systems (F4), ranked third by the DGRA, and second by AOPA, which has a greater significance upon expert judgments aggregation, as ordinal.

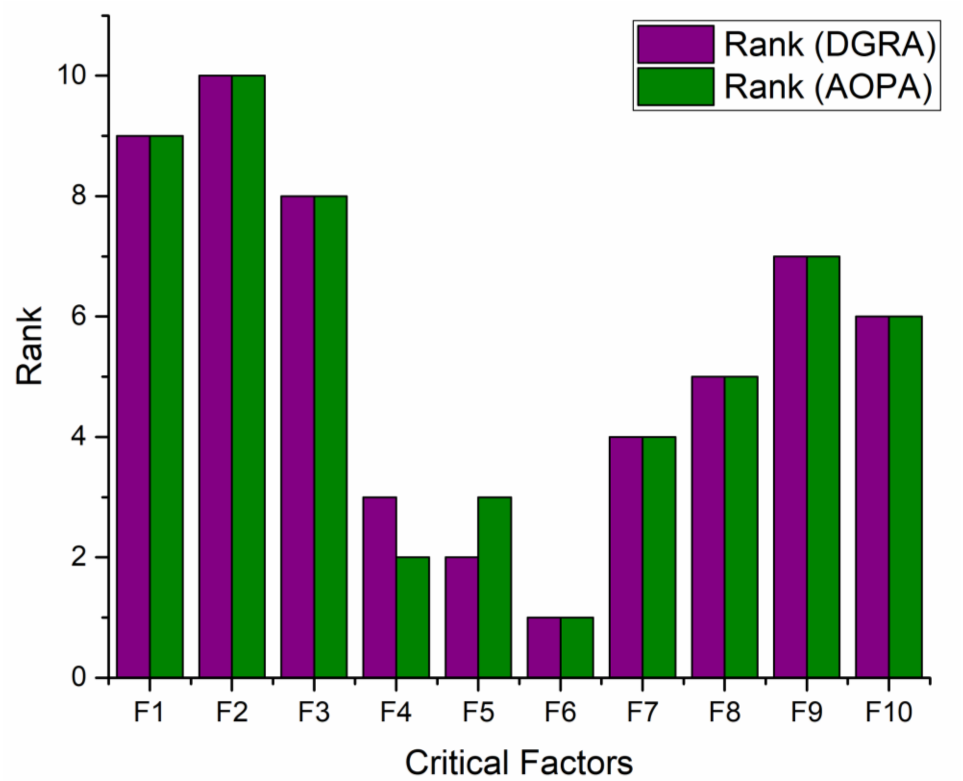

Fig 4. The comparative analyses between the DGRA and AOPA results

The existence of the overall agreement in the ranking of the DGRA and the AOPA confirms the strength of the results and supports the strength of the identified priority arrangement to assess the AI-enhanced ERP systems within the logistics sector.

Practical implications are manifest that the logistics managers need to use security as the first investment strategy and perform strict pre-implementation integration audits. The vendors of the ERP solution must resell their products with a focus on security certifications and interoperability as the key selling points. Such concerns are well-supported by literature (see e.g, Link *et al*., 2018). Policymakers are able to accelerate the digital transformation by creating industry-specific data security requirements and by sponsoring such projects. Limitations encompass geographic scope of the study on China and cross-sectional nature of the study that represents a snapshot that can change with any changes in technology and regulations. To build on these findings, the established factor hierarchy can serve as a validated checklist for organizations conducting internal readiness assessments prior to AI-enchanced ERP adoption. Furthermore, the proposed framework itself presents a transferable model for evaluating complex technology adoption in other industrial contexts.

5. Conclusion

This study concludes that the adoption of AI-enhanced ERP systems in China's logistics industry is primarily driven by the critical need for Data Security & Privacy, followed by Integration with Legacy Systems and Automation Reliability, while factors like AI Decision Transparency and Cost–Benefit Perception are deemed less significant, with the strong convergence between the DGRA and AOPA results validating this robust, hierarchical framework that prioritizes operational certainty and risk mitigation over cost and algorithmic explainability in high-stakes logistics environments.

From methodological perspective, it is the first time that multi-model approach has been used to study the critical factors affecting the adoption of AI-enhanced ERP systems. In future, by incorporating multiple criteria into the current framework the scope of the study can be expanded, and thus, the weights of the experts and criteria can also be estimated using the AOPA. Future studies must work towards longitudinal studies to find causal relationship between these factors and implementation success, cross-cultural comparisons to determine regional differences and whether these priorities vary in different sub-sectors of logistics like cold chain or last-mile delivery. Kruskal-Wallis's test can also be deployed in future studies to examine the variation of the perception of demographics on the top ranked factor.

Disclosure of Conflict of Interest

The author of this article is a partner of the editor-in-chief. To ensure impartiality, the editorial and peer review process was handled independently by Dr. Hafeez Ullah (Shanghai University of Science and Technology), acting as Guest Handling Editor. The editor-in-chief had no involvement in the review, selection of reviewers, or editorial decision-making for this manuscript.

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