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

Beenish Ramzan[1,*]

[1] *College of Economics and Management, Nanjing University of Aeronautics and Astronautics, Nanjing, China*

*Corresponding author: *beenishnawaz033@gmail.com*

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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.

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

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

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

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

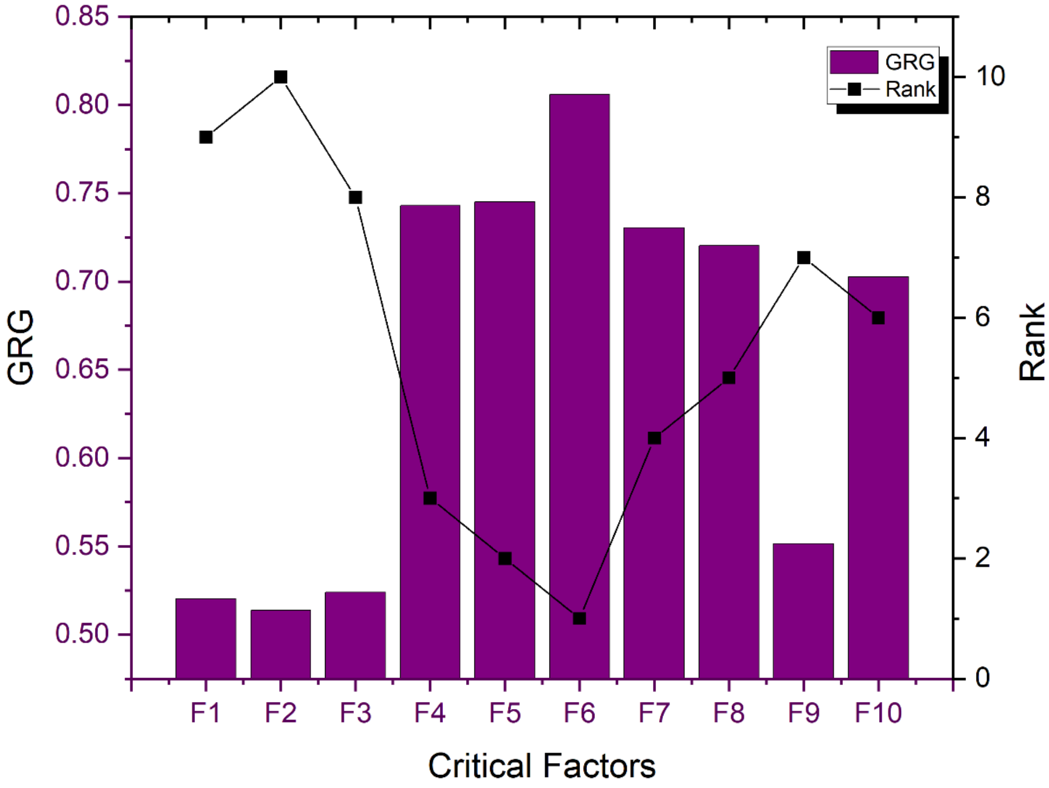

Fig 1. The grey relational evaluation of the critical factors

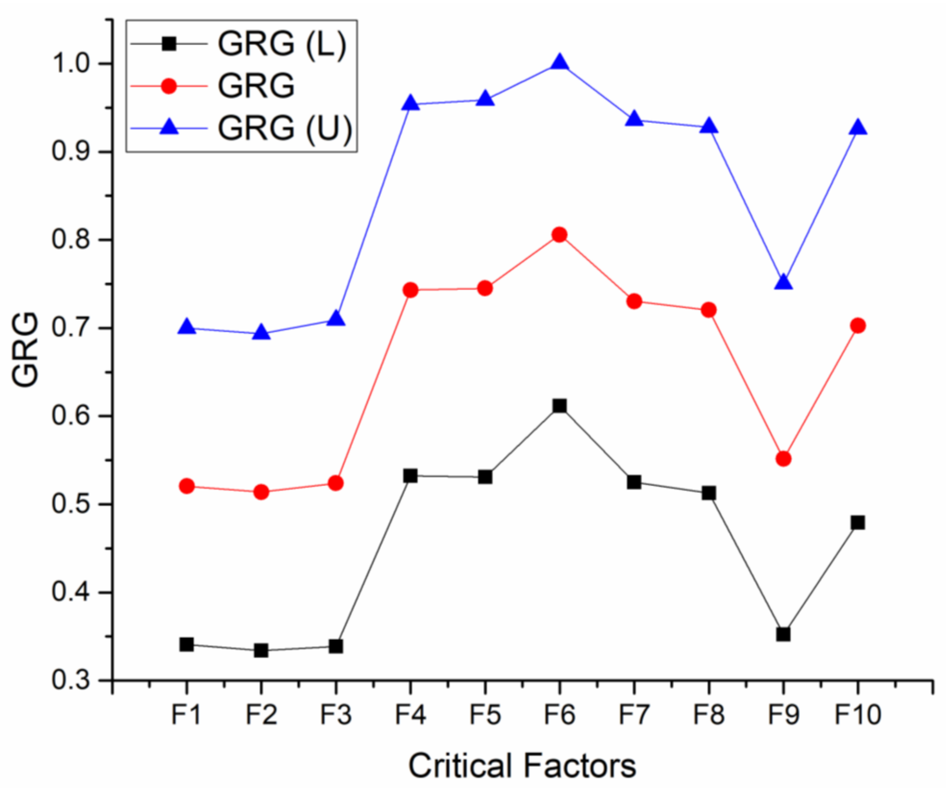

Fig 2. The dynamic grey relational grades and their lower and upper bounds

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

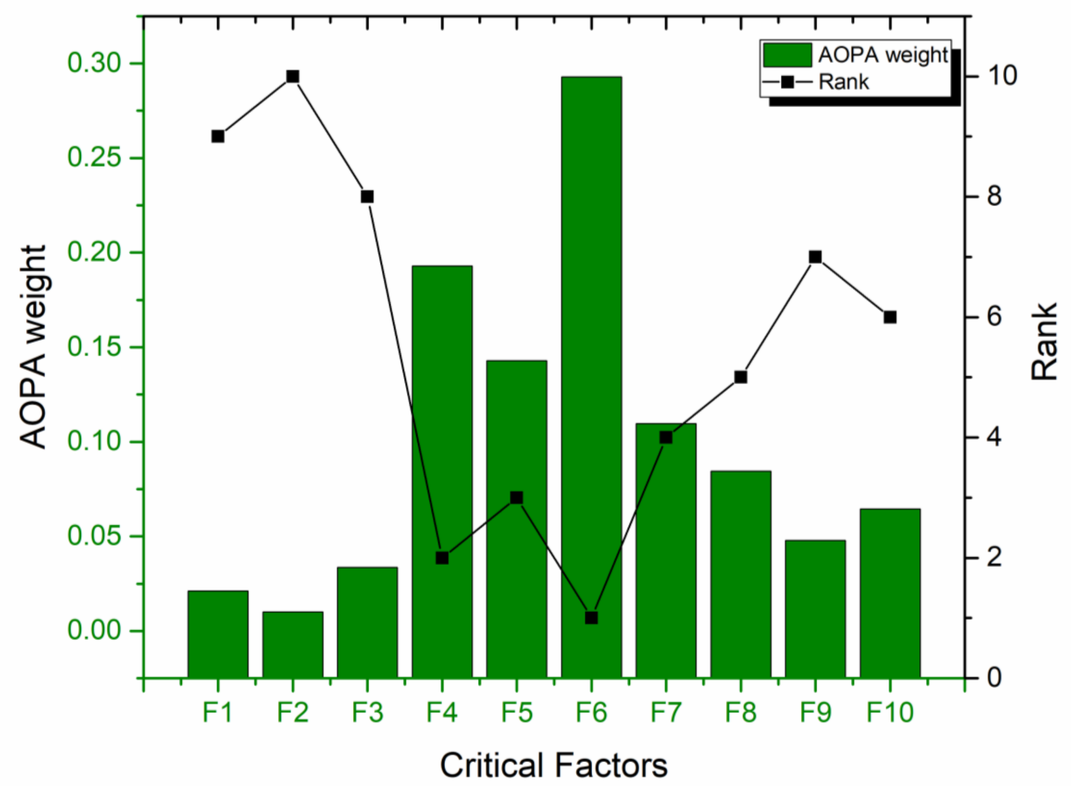

Fig 3. The weights and ranks of the critical factors using the AOPA

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.

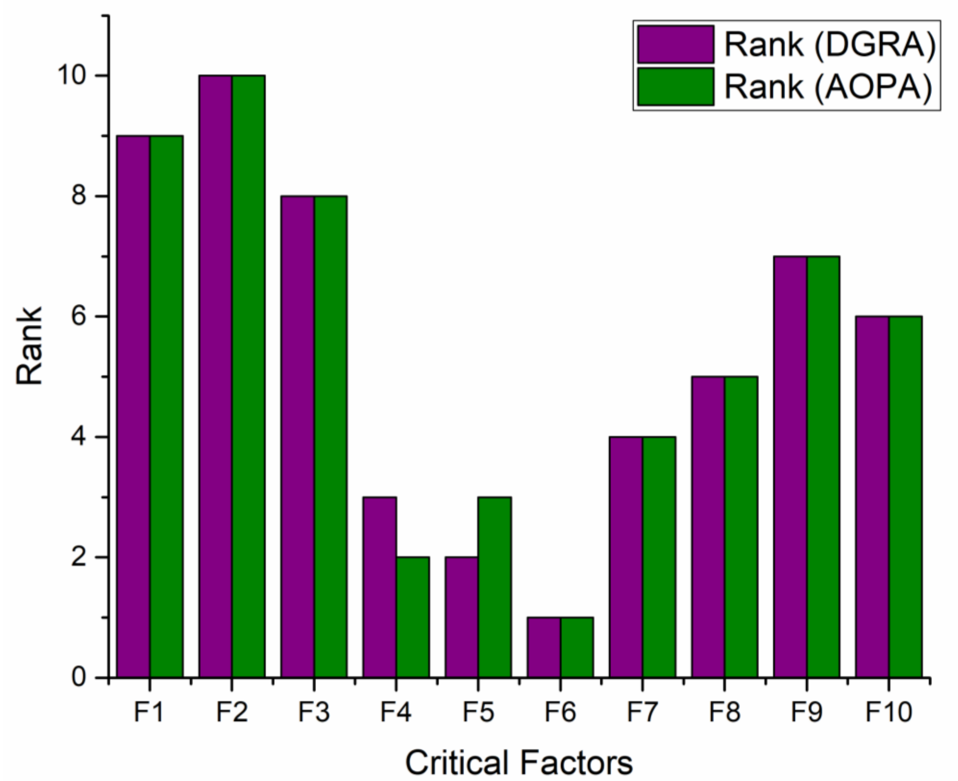

Fig 4. The comparative analyses between the DGRA and AOPA results

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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