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A Hybrid MCDM Approach Using Fuzzy AHP–TOPSIS to Evaluate Digital Logistics Market Performance in Selected Asian Economies

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Abstract: National logistics benchmarks such as the Logistics Performance Index (LPI) still focus mainly on operational performance and say little about the digital capacity of logistics systems. To address this gap, this paper combines two complementary sources: the Agility Emerging Markets Logistics Index (AEMLI) and the IMD World Digital Competitiveness Ranking (DCI). Using these sources, the study evaluates digital logistics market performance in 11 selected Asian economies. The analysis applies a fuzzy multi-criteria decision-making framework. Fuzzy AHP is first used to derive criterion weights from expert pairwise comparisons, allowing subjective judgments to be expressed as triangular fuzzy numbers. Fuzzy TOPSIS is then used to rank the countries according to their closeness to the fuzzy positive ideal solution and distance from the fuzzy negative ideal solution. The assessment uses seven criteria: domestic logistics opportunities, international logistics opportunities, business fundamentals, digital readiness, knowledge, technology, and future readiness. The results place the UAE and China in the two leading positions, followed by Qatar. Malaysia and Saudi Arabia form the next group, while Jordan and the Philippines appear at the lower end of the ranking. Cross-checks using Fuzzy AHP–ARAS and Fuzzy AHP–COPRAS produce broadly consistent rankings. The originality of this paper lies in linking these two indicator sets with fuzzy weighting and ranking procedures, offering a novel and practical way to compare digital logistics readiness across the selected economies.

Keywords: MCDM; AEMLI; DCI; Fuzzy AHP; Fuzzy TOPSIS.

JEL classification: L91; O57; D81.

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1. INTRODUCTION

In emerging economies, logistics competition is no longer decided only by ports, roads, customs clearance, warehouse capacity, or freight cost. Those variables still matter, and in many countries they remain binding constraints. The change is that logistics systems are now judged increasingly by their ability to coordinate data, connect firms across platforms, support real-time visibility, and adapt to disruptions in global supply chains. For macroeconomic policy, this shift is not cosmetic. A country with growing trade volumes can still lose competitiveness if its logistics sector cannot absorb digital technologies, integrate information flows, and support faster decision-making across firms, regulators, and service providers.

The established literature has treated logistics as a major channel through which economies improve trade performance, productivity, and participation in global value chains. For cross-country evidence, the usual reference point is the Logistics Performance Index (LPI). It reports six dimensions of national logistics systems: customs, infrastructure, international shipments, logistics competence, tracking and tracing, and timeliness (Arvis *et al.*, 2023). Studies using LPI data generally find that better logistics conditions go together with stronger trade performance, although the estimated relationship changes by sample, period, and empirical design (Martí *et al.*, 2014; Bugarčić *et al.*, 2023; Ejaz and Naz, 2023). Infrastructure alone does not explain these outcomes. Skills, institutional openness, and firms' capacity to operate across different regulatory and market settings also matter These findings are useful, but they do not fully capture the new source of differentiation among national logistics systems: digital capacity (Özmutlu and Arun, 2025).

This limitation becomes clearer when logistics is viewed through the lens of digital transformation. Digital logistics is not merely the installation of software in transport firms. Platform-based logistics can reduce coordination costs among carriers, shippers, intermediaries, and public agencies, but realizing those gains requires digital infrastructure deep enough to support real-time data exchange, and institutions capable of acting on that data operationally — neither of which is uniformly present across the emerging markets examined here (Barykin *et al.*, 2021; Kocaoglu, 2024). Kuhlmann and Klumpp (2017) document a related constraint at the workforce level: where managers and logistics workers lack the skills to operate digital systems, those systems tend to remain either underused or internally fragmented rather than delivering the coordination benefits intended. Research on maritime logistics reaches a consistent conclusion — digital adoption raises performance only where organizational readiness and institutional support are already in place (Yang and Lin, 2024). Firm-level evidence from China indicates that digital transformation raises supply-chain efficiency primarily through improvements in information processing and inter-firm coordination (He *et al.*, 2024), but whether national economies can capture these gains depends on conditions that differ sharply across markets — knowledge infrastructure, technological absorptive capacity, and institutional readiness for digital change (Młynarzewska-Borowiec, 2022). Physical throughput and market size tell only part of the story; the digital layer that determines whether logistics systems can learn, adapt, and coordinate under uncertainty must also enter the assessment.

Standard benchmarks address this incompletely. The Agility Emerging Markets Logistics Index (AEMLI) scores countries across four dimensions — domestic logistics opportunities, international logistics opportunities, business fundamentals, and digital readiness — and sits close to the logistics market itself (Agility, 2023). The IMD World

Digital Competitiveness Ranking (DCI) was developed from a different starting point — national technological capacity — and covers knowledge, technology, and future readiness rather than logistics-market conditions specifically (IMD World Competitiveness Center, 2022). The two rankings therefore speak to different sides of the same issue. AEMLI remains closer to logistics-market conditions, while DCI captures the broader digital environment in which those markets operate. Neither source alone is sufficient for assessing digital logistics performance. Combining the two is therefore analytically useful, provided that the criteria are not treated as mechanically equivalent.

Asia offers a suitable empirical setting for this problem. The region contains several of the world's largest manufacturing, trade, energy, and logistics hubs, while also displaying wide differences in digital readiness, institutional quality, and market maturity. China, India, ASEAN economies, Gulf economies, and selected Central and West Asian markets are exposed to different supply-chain pressures, yet they are all increasingly judged by their ability to support digitally enabled logistics. This diversity is useful for the analysis because the sample includes large logistics markets, energy-based trade hubs, manufacturing exporters, and middle-income economies still building digital capacity. The Asian sample used in this study is also constrained by data availability: only countries with complete and comparable information across the seven selected AEMLI and DCI criteria are retained. This keeps the assessment consistent, although it narrows the country coverage.

Multi-criteria decision-making methods have often been used to compare logistics performance across countries because such evaluation requires several criteria to be considered at the same time. A range of techniques — entropy weighting, WASPAS, MABAC, CoCoSo, SWARA, CRITIC, and Best Worst Method among others — have been brought to bear on logistics performance, logistics productivity, and market evaluation across different country samples and regional contexts (Rezaei *et al.*, 2018; Arikan Kargi, 2022; Kara *et al.*, 2022; Mešić *et al.*, 2022; Özekenci, 2023; Pehlivan *et al.*, 2024; Stević *et al.*, 2024). Taken together, this body of work has established two things: that logistics rankings shift meaningfully depending on how criteria weights are constructed, and that structured decision models offer more analytical leverage than simple index comparison (Bulut and Abacıoğlu, 2025). Many of these approaches, however, still rely on crisp weights and exact performance values. This makes the models easier to implement, but it also narrows the way uncertainty is represented.

The restriction is more serious in digital logistics evaluation than in conventional logistics benchmarking. Country-level digital logistics performance involves measurable indicators, but it also contains judgmental components: how experts interpret readiness, how they compare the importance of logistics-market conditions and digital capabilities, and how they assess economies whose strengths are uneven across criteria. Kara and Yalçın (2022) evaluated digital logistics market performance in developing countries by drawing on AEMLI and DCI data within an MCDM framework, and Özbek and Özekenci (2023) extended this line of work through a hybrid multi-method design covering seven criteria from the same two sources — demonstrating that logistics-market conditions and digital competitiveness indicators can be evaluated within a single analytical structure. What remains less developed is the handling of uncertainty in the weighting and evaluation process itself. Collapsing expert judgments into point estimates discards information about the range and imprecision of those judgments rather than incorporating it into the analysis.

Fuzzy set theory offers a way to address this directly. Rather than requiring experts to assign exact numerical values, it represents judgment as a membership function that spans a bounded

range (Zimmermann, 2010). This is relevant in the present context because expert assessments in digital logistics are rarely precise: a practitioner may be confident that future readiness matters more than domestic logistics opportunities without being able to specify by exactly how much. Triangular fuzzy numbers formalize this kind of bounded, ordered judgment through lower, modal, and upper values (Zhang *et al.*, 2014; Anand and Bharatraj, 2017), and decision-making frameworks built around such numbers allow imprecision to be retained through the analysis rather than resolved prematurely (Lee-Kwang and Lee, 1999; Natraj *et al.*, 2020).

Fuzzy AHP and Fuzzy TOPSIS serve different roles in this structure. In standard AHP, each pairwise comparison between criteria is entered as a precise numerical ratio, following the structure of the original method proposed by Saaty (1980). Later work has focused on the consistency and reliability of such comparison matrices (Alonso and Lamata, 2006). In practice, however, experts assessing national digital logistics systems rarely hold views precise enough to justify a single number; they can rank criteria and indicate rough magnitudes, but the boundaries are genuinely uncertain. The fuzzy extension handles this by replacing each crisp ratio with a triangular fuzzy value drawn from a linguistic scale, so that the imprecision in expert judgment is carried forward into the weights rather than discarded at the point of data collection (Singh, 2016; Liu *et al.*, 2020). Fuzzy TOPSIS is then used to rank alternatives according to their distance from the fuzzy positive ideal solution and the fuzzy negative ideal solution. In the present setting, Fuzzy AHP captures uncertainty in criterion importance, and Fuzzy TOPSIS converts the weighted fuzzy evaluations into a country ranking.

The gap addressed here is narrower but important. Existing logistics performance studies have produced useful cross-country rankings, but many rely on deterministic MCDM structures that leave limited room for judgmental uncertainty. Studies on digital logistics performance have started to combine logistics and digital indicators, yet the joint use of logistics-market conditions and broader digital competitiveness indicators remains underdeveloped. This study asks the following research question: how can digital logistics market performance in selected Asian economies be compared when logistics-market indicators and digital competitiveness indicators must be assessed together under uncertain expert judgment?

To answer this question, the study evaluates 11 selected Asian economies using seven criteria derived from AEMLI and DCI: domestic logistics opportunities, international logistics opportunities, business fundamentals, digital readiness, knowledge, technology, and future readiness. The selected economies are China, India, Indonesia, Jordan, Kazakhstan, Malaysia, the Philippines, Qatar, Saudi Arabia, the United Arab Emirates, and Thailand. Fuzzy AHP is used to obtain criterion weights from expert pairwise comparisons, and Fuzzy TOPSIS is used to rank the countries. Fuzzy AHP–ARAS and Fuzzy AHP–COPRAS are then used as supporting stability checks, not as separate claims of methodological novelty.

The study makes three main contributions. First, it links AEMLI logistics-market indicators with DCI digital-competitiveness indicators in a single country-level assessment structure, thereby treating digital logistics performance as both a logistics-market and digital-capability problem. Second, it models expert uncertainty explicitly through fuzzy pairwise weighting and fuzzy distance-based ranking, rather than converting expert judgments into crisp values at the outset. Third, it provides comparative evidence for 11 selected Asian economies and examines whether the main ranking pattern remains stable when alternative fuzzy aggregation procedures are applied.

The remainder of the paper is organized as follows. Section 2 presents the methodological framework, including fuzzy sets, Fuzzy AHP, and Fuzzy TOPSIS. Section 3 describes the

criteria, data sources, expert assessments, fuzzy weights, and country rankings. Section 4 reports the supporting stability checks using Fuzzy AHP–ARAS and Fuzzy AHP–COPRAS. Section 5 discusses the main findings and their policy and methodological implications. Section 6 concludes with the main findings, limitations, and directions for future research.

2. MATERIALS AND METHODS

This study adopts a two-stage hybrid MCDM framework grounded in fuzzy set theory, which provides the analytical basis for converting uncertain expert judgments into triangular fuzzy numbers. In the weighting stage, Fuzzy AHP is employed to build fuzzy pairwise comparison matrices and to obtain the relative weights of the criteria. The resulting weights indicate how strongly experts regard each criterion in comparison with the others. In the ranking stage, Fuzzy TOPSIS evaluates the 11 countries by comparing their distances from two reference points: the fuzzy positive ideal solution and the fuzzy negative ideal solution. The role of each method is therefore distinct: Fuzzy AHP handles the elicitation of subjective criterion weights, while Fuzzy TOPSIS translates those weights into a distance-based country ranking.

2.1. Fuzzy sets

Expert judgments in this study are not treated as exact scores. They are expressed with fuzzy sets, in which membership is measured by degree rather than by a binary yes/no rule; the value ranges from 0 to 1 (Zadeh, 1965; Zimmermann, 2010). This notation fits MCDM problems where information is incomplete, imprecise, or stated in linguistic terms (Natraj *et al.*, 2020). A fuzzy number gives that idea a computable form (Lee-Kwang and Lee, 1999). This study adopts triangular fuzzy numbers because three points — lower, modal, and upper — are sufficient to represent the range of an expert assessment without adding unnecessary complexity (Zhang *et al.*, 2014; Anand and Bharatraj, 2017).

A typical TFN is expressed as $\tilde{d} = \left(\underline{d}, d, \overline{d}\right)$, where $\underline{d}$, d, and $\overline{d}$ denote the lower bound, modal value, and upper bound, respectively. The membership function takes a piecewise linear form, as shown in Equation (1):

$$\mu_{\tilde{d}}(\xi) = \begin{cases} 0, & \xi < \underline{d}, \\ \dfrac{\xi - \underline{d}}{d - \underline{d}}, & \underline{d} \le \xi \le d, \\ \dfrac{\overline{d} - \xi}{\overline{d} - d}, & d \le \xi \le \overline{d}, \\ 0, & \xi > \overline{d}. \end{cases} \tag{1}$$

Figure no. 1 illustrates the membership function of a TFN defined by these three parameters.

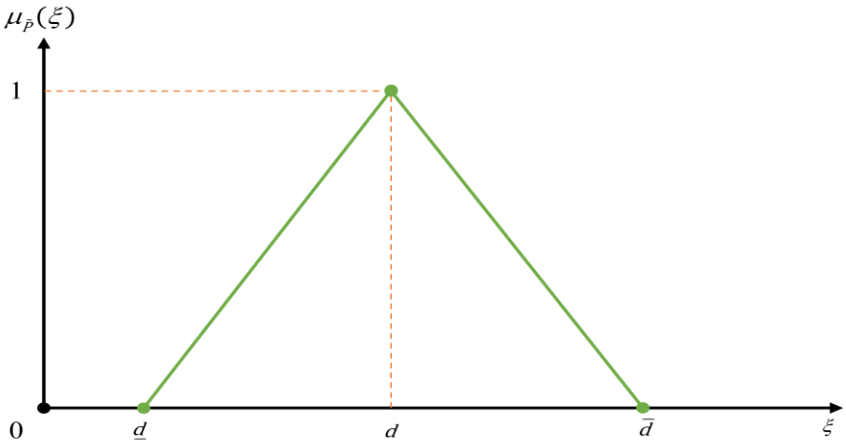

Figure no. 1 – Triangular-shaped fuzzy representation

2.2. Fuzzy AHP

Saaty (1980)'s AHP is a pairwise-comparison method for deriving criterion weights. It has been applied in engineering, management, and environmental assessment, among other fields (Alonso and Lamata, 2006). In its standard form, however, each comparison is entered as a precise ratio; this is difficult when experts work with uncertain or qualitative judgments. This study therefore uses Fuzzy AHP. The method keeps the comparison logic of AHP, but expresses expert preferences through fuzzy linguistic scales grounded in fuzzy set theory (Buckley, 1985; Singh, 2016; Liu *et al.*, 2020). The implementation follows these steps.

Step 1: Establish pairwise comparisons between evaluation criteria.
Decision-makers compare criteria using the fuzzy linguistic scale shown in Table no. 1.

Table no. 1 – Scores for the weight vector's fuzzy evaluation

Linguistic term	Label	Fuzzy value
Equal importance rating	EIR	(1, 1, 1)
Very weak importance rating	VIR	(1, 2, 3)
Weak importance rating	WIR	(2, 3, 4)
Weakly to moderately important rating	WMR	(3, 4, 5)
Moderate importance rating	MIR	(4, 5, 6)
Moderate to strong importance rating	MSR	(5, 6, 7)
Strong importance rating	SIR	(6, 7, 8)
Very strong importance rating	VSR	(7, 8, 9)
Extreme importance rating	EXR	(8, 9, 10)

Step 2: Construct the pairwise comparison matrix.

$$\tilde{P}^k = \begin{bmatrix} \tilde{d}_{11}^k & \tilde{d}_{12}^k & \cdots & \tilde{d}_{1n}^k \\ \tilde{d}_{21}^k & \tilde{d}_{22}^k & \cdots & \tilde{d}_{2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{d}_{n1}^k & \tilde{d}_{n2}^k & \cdots & \tilde{d}_{nn}^k \end{bmatrix} \tag{2}$$

where $\tilde{d}_{ij}^k$ represents the preference of decision-maker k when criterion i is compared with criterion j.

Step 3: Aggregate the pairwise comparison matrices.

$$\tilde{d}_{ij} = \frac{1}{K}\sum_{k=1}^{K}\tilde{d}_{ij}^k \tag{3}$$

The aggregated comparison matrix is:

$$\tilde{P} = \begin{bmatrix} \tilde{d}_{11} & \tilde{d}_{12} & \cdots & \tilde{d}_{1n} \\ \tilde{d}_{21} & \tilde{d}_{22} & \cdots & \tilde{d}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{d}_{n1} & \tilde{d}_{n2} & \cdots & \tilde{d}_{nn} \end{bmatrix} \tag{4}$$

Step 4: Calculate the fuzzy geometric mean of each criterion.

$$\tilde{r}_i = \left(\prod_{j=1}^{n}\tilde{d}_{ij}\right)^{1/n}, \quad i = 1, 2, \ldots, n \tag{5}$$

Step 5: Calculate fuzzy weights.

$$\tilde{w}_i = \tilde{r}_i \otimes \left(\tilde{r}_1 \oplus \tilde{r}_2 \oplus \cdots \oplus \tilde{r}_n\right)^{-1} \tag{6}$$

Step 6: Defuzzify fuzzy weights using the centroid method.

$$M_i = \frac{dw_i^L + dw_i^M + dw_i^U}{3} \tag{7}$$

Step 7: Normalize the defuzzified weights.

$$N_i = \frac{M_i}{\sum_{i=1}^{n} M_i} \tag{8}$$

2.3. Fuzzy TOPSIS

Fuzzy TOPSIS ranks alternatives according to their distance from the fuzzy positive ideal solution and the fuzzy negative ideal solution (Hwang and Yoon, 1981; Chen, 2000). The procedure is as follows.

Step 1: Determine the evaluation criteria and alternatives.

$$\tilde{x}_{ij}^{k} = \left(t_{ij1}^{k}, t_{ij2}^{k}, t_{ij3}^{k}\right) \tag{9}$$

The fuzzy weight of criterion C_j is:

$$\tilde{w}_{j}^{k} = \left(w_{j1}^{k}, w_{j2}^{k}, w_{j3}^{k}\right) \tag{20}$$

Table no. 2 – Fuzzy rating scale for evaluating alternatives

Linguistic term	Label	Fuzzy value
Very poor rating	VPR	(0, 0, 1)
Poor rating	PR	(0, 1, 3)
Medium poor rating	MPR	(1, 3, 5)
Fair rating	FR	(3, 5, 7)
Medium good rating	MGR	(5, 7, 9)
Good rating	GR	(7, 9, 10)
Very good rating	VGR	(9, 10, 10)

Step 2: Aggregate the fuzzy ratings and criterion weights.

$$t_{ij1} = \min_k \{t_{ij1}^{k}\}, \quad t_{ij2} = \frac{1}{K}\sum_{k=1}^{K} t_{ij2}^{k}, \quad t_{ij3} = \max_k \{t_{ij3}^{k}\} \tag{11}$$

$$w_{j1} = \min_k \{w_{j1}^{k}\}, \quad w_{j2} = \frac{1}{K}\sum_{k=1}^{K} w_{j2}^{k}, \quad w_{j3} = \max_k \{w_{j3}^{k}\} \tag{12}$$

Step 3: Normalize the fuzzy decision matrix.

For benefit-type criteria:

$$\tilde{\xi}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*} \right), \quad c_j^* = \max_i \{c_{ij}\} \tag{13}$$

For cost-type criteria:

$$\tilde{\xi}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}} \right), \quad a_j^- = \min_i \{a_{ij}\} \tag{14}$$

Step 4: Compute the weighted normalized fuzzy decision matrix.

$$\tilde{v}_{ij} = \tilde{\xi}_{ij} \otimes \tilde{w}_j \tag{15}$$

Step 5: Identify FPIS and FNIS.

$$A^+ = \{\tilde{v}_1^+, \tilde{v}_2^+, \ldots, \tilde{v}_n^+\}, \quad \tilde{v}_j^+ = \max_i \{\tilde{v}_{ij}\} \tag{16}$$

$$A^- = \{\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^-\}, \quad \tilde{v}_j^- = \min_i \{\tilde{v}_{ij}\} \tag{17}$$

Step 6: Calculate distances from FPIS and FNIS.

$$\hat{D}_i^+ = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^+), \quad \hat{D}_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-) \tag{18}$$

Step 7: Calculate the closeness coefficient.

$$KT_i = \frac{\hat{D}_i^-}{\hat{D}_i^+ + \hat{D}_i^-} \tag{19}$$

The best alternative is the one with the highest closeness coefficient.

3. RESULTS

To evaluate digital logistics performance, this study applies a three-stage empirical procedure. First, the evaluation criteria and country sample are defined. Second, expert judgments are used to derive fuzzy criterion weights through Fuzzy AHP. Third, Fuzzy TOPSIS is applied to rank the countries according to their distance from the ideal solutions.

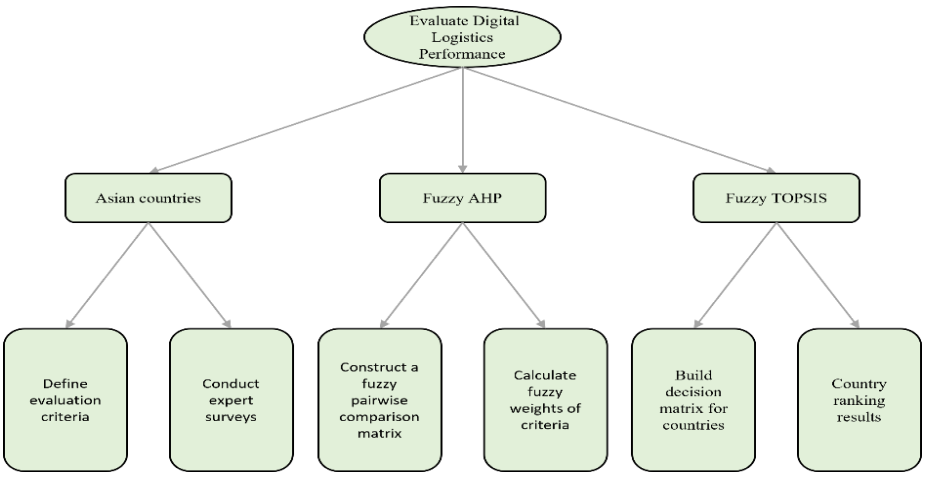

Figure no. 2 - Digital logistics market performance evaluation process

Step 1: Define evaluation criteria

From AEMLI, this study uses four logistics-side criteria: domestic logistics opportunities, international logistics opportunities, business fundamentals, and digital readiness. They cover local logistics demand, cross-border logistics capacity, the business environment, and the digital readiness of the logistics sector. To avoid treating digital logistics as a purely market-based issue, three DCI dimensions are added: knowledge, technology, and future readiness. Together, these criteria reflect an economy's capacity to develop, adopt, and adapt to digital technologies. Table no. 3 lists the seven criteria used in the analysis.

Table no. 3 – List of key criteria used in digital logistics evaluation

Symbol	Criteria	Report	Description	Type
C1	Domestic logistics opportunities	AEMLI	Assesses the ability to sustain and grow local demand through competitive logistics.	Benefit
C2	International logistics opportunities	AEMLI	Measures trade logistics demand and capacity for international operations.	Benefit
C3	Business fundamentals	AEMLI	Evaluates market openness, legal strength, and economic fairness.	Benefit
C4	Digital readiness	AEMLI	Tracks progress toward a digital, skilled, innovative, and sustainable economy.	Benefit
C5	Knowledge	DCI	Measures the ability to discover and understand new technologies.	Benefit
C6	Technology	DCI	Captures the environment supporting digital technology development.	Benefit
C7	Future readiness	DCI	Measures preparedness to leverage digital transformation.	Benefit

Source: IMD World Competitiveness Center (2022); Agility (2023)

All seven criteria are treated as benefit-type measures, so higher values indicate stronger national performance; Equation (13) is therefore used for normalization across the full dataset. The original AEMLI and DCI rankings cover more economies, but this study retains only

countries with complete observations for all seven criteria. The final sample includes 11 Asian economies: China, India, Indonesia, Jordan, Kazakhstan, Malaysia, the Philippines, Qatar, Saudi Arabia, the UAE, and Thailand. The sample is dictated by data availability, especially for indicators linked to logistics-market conditions and digital readiness. The input data come from the 2023 AEMLI report and the 2022 IMD World Digital Competitiveness Ranking, which together provide the most complete compatible source for the criteria used here. Since the analysis uses cross-sectional index data, Section 5 treats the results as time-bound rather than longitudinal evidence.

Table no. 4 – Raw data of country performance based on AEMLI and DCI

Country	C1	C2	C3	C4	C5	C6	C7
China	8.47	9.75	7.11	6.63	79.27	76.69	80.93
India	8.04	7.45	5.94	7.61	53.95	60.25	55.20
Indonesia	6.34	5.89	5.77	6.21	42.20	55.33	50.31
Jordan	4.88	4.75	6.72	5.14	48.63	51.19	45.91
Kazakhstan	4.66	4.66	6.19	5.10	67.64	61.56	67.51
Malaysia	5.29	5.88	7.85	6.72	70.08	71.45	65.33
Philippines	5.02	5.28	4.31	5.99	40.51	51.58	43.95
Qatar	5.91	4.96	7.92	6.38	59.11	78.65	74.98
Saudi Arabia	5.38	5.74	7.86	6.30	61.96	72.92	64.34
UAE	5.60	5.89	9.10	7.37	80.67	93.78	77.40
Thailand	5.11	5.98	5.77	6.04	55.52	74.97	51.70

Source: IMD World Competitiveness Center (2022); Agility (2023)

Step 2: Conduct expert survey

To support the weighting and evaluation process, the study uses the judgments of three experts in logistics and supply chain management. The experts were selected based on academic qualifications and professional experience.

Table no. 5 – List of experts

Expert	Age	Educational background	Experience in the field
Expert 1 (DM1)	55	PhD in Logistics and SCM	>15 years
Expert 2 (DM2)	60	PhD in Logistics and SCM	>20 years
Expert 3 (DM3)	57	PhD in Logistics and SCM	>15 years

Using the linguistic scale in Table no. 1, the experts conducted pairwise comparisons of the seven criteria. The results are reported in Tables no. 6–8.

Table no. 6 – Pairwise comparison matrix provided by Expert 1

Criteria	C1	C2	C3	C4	C5	C6	C7
C1	EIR	-	-	-	-	-	-
C2	WIR	EIR	-	-	-	-	-
C3	MIR	WIR	EIR	-	-	-	-
C4	SIR	MIR	WIR	EIR	-	-	-
C5	VSR	SIR	MSR	MIR	EIR	WMR	-
C6	MSR	MIR	WIR	VIR	-	EIR	-
C7	EXR	VSR	SIR	MSR	VIR	WMR	EIR

Table no. 7 – Pairwise comparison matrix provided by Expert 2

Criteria	C1	C2	C3	C4	C5	C6	C7
C1	EIR	-	-	-	-	-	-
C2	VIR	EIR	-	-	-	-	-
C3	WMR	VIR	EIR	-	-	-	-
C4	MIR	WMR	WIR	EIR	-	-	-
C5	SIR	MSR	MSR	WMR	EIR	WIR	-
C6	MSR	MIR	WMR	VIR	-	EIR	-
C7	VSR	SIR	SIR	MIR	WIR	WMR	EIR

Table no. 8 – Pairwise comparison matrix provided by Expert 3

Criteria	C1	C2	C3	C4	C5	C6	C7
C1	EIR	-	-	-	-	-	-
C2	VIR	EIR	-	-	-	-	-
C3	WMR	WIR	EIR	-	-	-	-
C4	SIR	MIR	WIR	EIR	-	-	-
C5	VSR	SIR	MSR	MIR	EIR	WIR	-
C6	MSR	MIR	WMR	WIR	-	EIR	-
C7	EXR	VSR	SIR	MSR	WIR	WMR	EIR

Step 3: Construct the aggregated fuzzy pairwise comparison matrix

After collecting the expert assessments, linguistic terms were converted into triangular fuzzy numbers. The fuzzy values were aggregated using Equation (3). The resulting average comparison matrix is shown in Table no. 9.

Table no. 9 – Average pairwise comparison matrix of the criteria

Criteria	C1	C2	C3	C4	C5	C6	C7
C1	(1,1,1)	-	-	-	-	-	-
C2	(4/3,7/3,10/3)	(1,1,1)	-	-	-	-	-
C3	(10/3,13/3,16/3)	(5/3,8/3,11/3)	(1,1,1)	-	-	-	-
C4	(16/3,19/3,22/3)	(11/3,14/3,17/3)	(2,3,4)	(1,1,1)	-	-	-
C5	(20/3,23/3,26/3)	(17/3,20/3,23/3)	(5,6,7)	(11/3,14/3,17/3)	(1,1,1)	(7/3,10/3,13/3)	-
C6	(5,6,7)	(4,5,6)	(8/3,11/3,14/3)	(4/3,7/3,10/3)	-	(1,1,1)	-
C7	(23/3,26/3,29/3)	(20/3,23/3,26/3)	(6,7,8)	(14/3,17/3,20/3)	(5/3,8/3,11/3)	(3,4,5)	(1,1,1)

Step 4: Calculate fuzzy weights

Before calculating the fuzzy weights, the pairwise comparison matrix of each expert was checked for consistency. The modal values of the triangular fuzzy numbers were first defuzzified, and the consistency ratio (CR) was then computed following Saaty (1980)'s procedure. The results are acceptable for all three experts: DM1 has $\lambda_{\max} = 7.644$, $CI = 0.107$, and $CR = 0.081$; DM2 has $\lambda_{\max} = 7.495$, $CI = 0.083$, and $CR = 0.063$; and DM3 has $\lambda_{\max} = 7.662$, $CI = 0.110$, and $CR = 0.084$. Since all CR values are below the 0.10 threshold for a seven-criterion matrix, the judgments are consistent enough to be used in the fuzzy weighting stage.

Using the aggregated pairwise comparison matrix in Table no. 9, fuzzy weights were calculated with Equation (6). The results are shown in Table no. 10.

Table no. 10 – Fuzzy weight value of each criterion

Fuzzy weight	Value
$\tilde{w}_1$	(0.015, 0.021, 0.032)
$\tilde{w}_2$	(0.022, 0.032, 0.050)
$\tilde{w}_3$	(0.036, 0.054, 0.083)
$\tilde{w}_4$	(0.064, 0.096, 0.149)
$\tilde{w}_5$	(0.180, 0.265, 0.395)
$\tilde{w}_6$	(0.089, 0.139, 0.214)
$\tilde{w}_7$	(0.268, 0.393, 0.564)

The fuzzy weights are concentrated on the digital-capability criteria. Future readiness (C7) receives the largest weight, followed by knowledge (C5) and technology (C6). Domestic and international logistics opportunities are weighted lower. This result indicates that market scale is not the decisive factor in digital logistics performance; stronger results depend more on knowledge capacity, technological depth, and readiness for future digital change.

Step 5: Construct the fuzzy decision matrix

The experts evaluated each country under the seven criteria using the linguistic scale defined in Table no. 2. The resulting linguistic assessments are reported in Tables no. 11–17. These assessments were then converted into triangular fuzzy numbers and aggregated to construct the fuzzy decision matrix presented in Table no. 18.

Table no. 11 – Experts' assessments of countries according to criterion C1

Criterion	Country	DM1	DM2	DM3
C1	China	VGR	VGR	GR
C1	India	VGR	GR	GR
C1	Indonesia	MGR	MGR	MGR
C1	Jordan	MPR	MPR	PR
C1	Kazakhstan	MPR	MPR	FR
C1	Malaysia	MGR	MGR	FR
C1	Philippines	FR	FR	FR
C1	Qatar	MGR	FR	MGR
C1	Saudi Arabia	FR	FR	FR
C1	UAE	MGR	FR	FR
C1	Thailand	FR	FR	MGR

Table no. 12 – Experts' assessments of countries according to criterion C2

Criterion	Country	DM1	DM2	DM3
C2	China	VGR	VGR	VGR
C2	India	GR	GR	MGR
C2	Indonesia	MGR	GR	GR
C2	Jordan	MPR	MPR	MPR
C2	Kazakhstan	PR	PR	MPR

Criterion	Country	DM1	DM2	DM3
C2	Malaysia	MGR	MGR	MGR
C2	Philippines	FR	FR	FR
C2	Qatar	FR	FR	MPR
C2	Saudi Arabia	MGR	FR	FR
C2	UAE	MGR	MGR	MGR
C2	Thailand	MGR	MGR	FR

Table no. 13 – Experts' assessments of countries according to criterion C3

Criterion	Country	DM1	DM2	DM3
C3	China	MGR	MGR	MGR
C3	India	FR	FR	FR
C3	Indonesia	FR	FR	MPR
C3	Jordan	MGR	FR	FR
C3	Kazakhstan	FR	FR	FR
C3	Malaysia	MGR	MGR	MGR
C3	Philippines	PR	PR	PR
C3	Qatar	GR	GR	GR
C3	Saudi Arabia	GR	GR	MGR
C3	UAE	VGR	VGR	VGR
C3	Thailand	FR	FR	MPR

Table no. 14 – Experts' assessments of countries according to criterion C4

Criterion	Country	DM1	DM2	DM3
C4	China	MPR	FR	FR
C4	India	GR	GR	MGR
C4	Indonesia	PR	PR	PR
C4	Jordan	VPR	VPR	VPR
C4	Kazakhstan	VPR	VPR	VPR
C4	Malaysia	FR	FR	FR
C4	Philippines	PR	PR	VPR
C4	Qatar	MPR	MPR	MPR
C4	Saudi Arabia	MPR	PR	MPR
C4	UAE	MGR	MGR	MGR
C4	Thailand	PR	PR	VPR

Table no. 15 – Experts' assessments of countries according to criterion C5

CRITERION	COUNTRY	DM1	DM2	DM3
C5	China	GR	GR	GR
C5	India	FR	FR	FR
C5	Indonesia	MPR	MPR	MPR
C5	Jordan	FR	MPR	MPR
C5	Kazakhstan	MGR	MGR	MGR
C5	Malaysia	MGR	MGR	MGR
C5	Philippines	MPR	MPR	PR
C5	Qatar	MGR	FR	MGR
C5	Saudi Arabia	MGR	FR	MGR
C5	UAE	VGR	GR	GR
C5	Thailand	FR	FR	FR

Table no. 16 – Experts' assessments of countries according to criterion C6

Criterion	Country	DM1	DM2	DM3
C6	China	GR	GR	GR
C6	India	FR	FR	FR
C6	Indonesia	MPR	FR	FR
C6	Jordan	PR	PR	PR
C6	Kazakhstan	FR	FR	FR
C6	Malaysia	MGR	MGR	MGR
C6	Philippines	PR	PR	PR
C6	Qatar	GR	GR	GR
C6	Saudi Arabia	GR	MGR	GR
C6	UAE	VGR	VGR	VGR
C6	Thailand	GR	MGR	GR

Table no. 17 – Experts' assessments of countries according to criterion C7

Criterion	Country	DM1	DM2	DM3
C7	China	VGR	VGR	VGR
C7	India	FR	FR	FR
C7	Indonesia	FR	MPR	MPR
C7	Jordan	PR	PR	PR
C7	Kazakhstan	MGR	MGR	MGR
C7	Malaysia	MGR	MGR	FR
C7	Philippines	PR	PR	PR
C7	Qatar	MGR	GR	MGR
C7	Saudi Arabia	MGR	FR	FR
C7	UAE	GR	GR	GR
C7	Thailand	FR	MPR	MPR

Based on these linguistic assessments, the aggregated fuzzy decision matrix was constructed using the transformation scale in Table no. 2 and the aggregation procedure described in Equation (11). The resulting matrix is presented in Table no. 18.

Table no. 18 – Fuzzy decision matrix

Country	C1	C2	C3	C4	C5	C6	C7
China	(8.33, 9.67, 10)	(9, 10, 10)	(5, 7, 9)	(2.33, 4.33, 6.33)	(7, 9, 10)	(7, 9, 10)	(9, 10, 10)
India	(7.67, 9.33, 10)	(6.33, 8.33, 9.67)	(3, 5, 7)	(6.33, 8.33, 9.67)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)
Indonesia	(5, 7, 9)	(6.33, 8.33, 9.67)	(2.33, 4.33, 6.33)	(0, 1, 3)	(1, 3, 5)	(2.33, 4.33, 6.33)	(1.67, 3.67, 5.67)
Jordan	(0.67, 2.33, 4.33)	(1, 3, 5)	(3.67, 5.67, 7.67)	(0, 0, 1)	(1.67, 3.67, 5.67)	(0, 1, 3)	(0, 1, 3)
Kazakhstan	(1.67, 3.67, 5.67)	(0.33, 1.67, 3.67)	(3, 5, 7)	(0, 0, 1)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)
Malaysia	(4.33, 6.33, 8.33)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(4.33, 6.33, 8.33)
Philippines	(3, 5, 7)	(3, 5, 7)	(0, 1, 3)	(0, 0.67, 2.33)	(0.67, 2.33, 4.33)	(0, 1, 3)	(0, 1, 3)
Qatar	(4.33, 6.33, 8.33)	(2.33, 4.33, 6.33)	(7, 9, 10)	(1, 3, 5)	(4.33, 6.33, 8.33)	(7, 9, 10)	(5.67, 7.67, 9.33)

Country	C1	C2	C3	C4	C5	C6	C7
Saudi Arabia	(3, 5, 7)	(3.67, 5.67, 7.67)	(6.33, 8.33, 9.67)	(0.67, 2.33, 4.33)	(4.33, 6.33, 8.33)	(6.33, 8.33, 9.67)	(3.67, 5.67, 7.67)
UAE	(3.67, 5.67, 7.67)	(5, 7, 9)	(9, 10, 10)	(5, 7, 9)	(7.67, 9.33, 10)	(9, 10, 10)	(7, 9, 10)
Thailand	(3.67, 5.67, 7.67)	(4.33, 6.33, 8.33)	(2.33, 4.33, 6.33)	(0, 0.67, 2.33)	(3, 5, 7)	(6.33, 8.33, 9.67)	(1.67, 3.67, 5.67)

Step 6: Normalize the fuzzy decision matrix

Since all seven criteria are of the benefit type, normalization is performed exclusively using Equation (13). Equation (14), which applies to cost-type criteria, is not relevant to this study. The resulting normalized fuzzy decision matrix $\tilde{R}$ is presented in Table no. 19.

Table no. 19 – Normalized fuzzy decision matrix $(\tilde{R})$

Country	C1	C2	C3	C4	C5	C6	C7
China	(0.833, 0.967, 1.000)	(0.900, 1.000, 1.000)	(0.500, 0.700, 0.900)	(0.241, 0.448, 0.655)	(0.700, 0.900, 1.000)	(0.700, 0.900, 1.000)	(0.900, 1.000, 1.000)
India	(0.767, 0.933, 1.000)	(0.633, 0.833, 0.967)	(0.300, 0.500, 0.700)	(0.655, 0.862, 1.000)	(0.300, 0.500, 0.700)	(0.300, 0.500, 0.700)	(0.300, 0.500, 0.700)
Indonesia	(0.500, 0.700, 0.900)	(0.633, 0.833, 0.967)	(0.233, 0.433, 0.633)	(0.000, 0.103, 0.310)	(0.100, 0.300, 0.500)	(0.233, 0.433, 0.633)	(0.167, 0.367, 0.567)
Jordan	(0.067, 0.233, 0.433)	(0.100, 0.300, 0.500)	(0.367, 0.567, 0.767)	(0.000, 0.000, 0.103)	(0.167, 0.367, 0.567)	(0.000, 0.100, 0.300)	(0.000, 0.100, 0.300)
Kazakhstan	(0.167, 0.367, 0.567)	(0.033, 0.167, 0.367)	(0.300, 0.500, 0.700)	(0.000, 0.000, 0.103)	(0.500, 0.700, 0.900)	(0.300, 0.500, 0.700)	(0.500, 0.700, 0.900)
Malaysia	(0.433, 0.633, 0.833)	(0.500, 0.700, 0.900)	(0.500, 0.700, 0.900)	(0.310, 0.517, 0.724)	(0.500, 0.700, 0.900)	(0.500, 0.700, 0.900)	(0.433, 0.633, 0.833)
Philippines	(0.300, 0.500, 0.700)	(0.300, 0.500, 0.700)	(0.000, 0.100, 0.300)	(0.000, 0.069, 0.241)	(0.067, 0.233, 0.433)	(0.000, 0.100, 0.300)	(0.000, 0.100, 0.300)
Qatar	(0.433, 0.633, 0.833)	(0.233, 0.433, 0.633)	(0.700, 0.900, 1.000)	(0.103, 0.310, 0.517)	(0.433, 0.633, 0.833)	(0.700, 0.900, 1.000)	(0.567, 0.767, 0.933)
Saudi Arabia	(0.300, 0.500, 0.700)	(0.367, 0.567, 0.767)	(0.633, 0.833, 0.967)	(0.069, 0.241, 0.448)	(0.433, 0.633, 0.833)	(0.633, 0.833, 0.967)	(0.367, 0.567, 0.767)
UAE	(0.367, 0.567, 0.767)	(0.500, 0.700, 0.900)	(0.900, 1.000, 1.000)	(0.517, 0.724, 0.931)	(0.767, 0.933, 1.000)	(0.900, 1.000, 1.000)	(0.700, 0.900, 1.000)
Thailand	(0.367, 0.567, 0.767)	(0.433, 0.633, 0.833)	(0.233, 0.433, 0.633)	(0.000, 0.069, 0.241)	(0.300, 0.500, 0.700)	(0.633, 0.833, 0.967)	(0.167, 0.367, 0.567)

Note: Normalization is performed using $c_j^* = \max_i \left(c_{ij}\right)$. The divisor for C1–C3 and C5–C7 is 10.000. The divisor for C4 is 9.670.

The normalized fuzzy decision matrix is then multiplied by the fuzzy criterion weights according to Equation (15), yielding the weighted normalized fuzzy decision matrix. Since all criteria are benefit-type and are therefore maximized, the FPIS for each criterion is determined by the maximum weighted normalized fuzzy value across all countries, whereas the FNIS is determined by the corresponding minimum value, as specified in Equations (16) and (17). The distances of each country from the FPIS and FNIS are computed using Equation (18), and the results are presented in Table no. 20.

Table no. 20 – Distance of countries to FPIS and FNIS

Country	$\hat{D}_i^+$	$\hat{D}_i^-$
China	0.049	0.497
India	0.246	0.300
Indonesia	0.382	0.164
Jordan	0.494	0.046
Kazakhstan	0.241	0.310
Malaysia	0.175	0.377
Philippines	0.520	0.020
Qatar	0.159	0.395
Saudi Arabia	0.216	0.335
UAE	0.043	0.507
Thailand	0.318	0.229

Step 7: Rank countries using Fuzzy TOPSIS

The closeness coefficient KT_i is calculated using Equation (19). A higher value indicates a stronger digital logistics performance.

Table no. 21 – Closeness coefficients of countries in digital logistics performance

Country	KT_i	Rank
UAE	0.923	1
China	0.909	2
Qatar	0.713	3
Malaysia	0.682	4
Saudi Arabia	0.608	5
Kazakhstan	0.563	6
India	0.550	7
Thailand	0.418	8
Indonesia	0.300	9
Jordan	0.085	10
Philippines	0.037	11

The ranking results are illustrated in Figure no. 3.

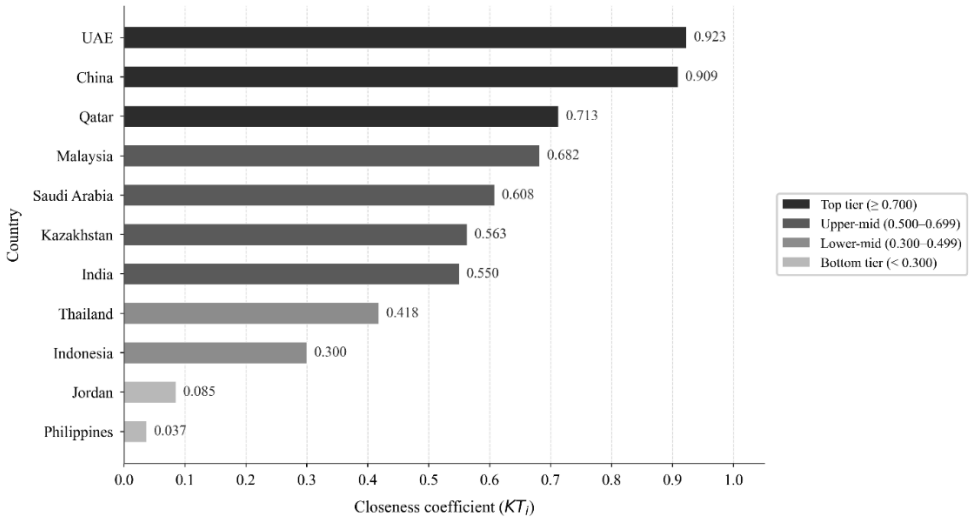

Figure no. 3 – Digital logistics performance ranking by country, sorted in descending order of closeness coefficient (KT_i)

The ranking separates the selected economies into three broad groups. At the top, the UAE ranks first, just ahead of China. Its advantage comes from a high AEMLI score for digital transformation and strong DCI performance in knowledge, technology, and future readiness. China's position is supported by large domestic and international logistics opportunities, together with an advanced digital profile. Qatar ranks third, mainly because of its technology and future-readiness scores. Malaysia and Saudi Arabia form the upper-middle group, while Kazakhstan and India sit near the centre of the distribution. Thailand, Indonesia, Jordan, and the Philippines occupy the lower positions, largely because their scores are weaker on digitally oriented criteria.

4. ROBUSTNESS ANALYSIS USING ALTERNATIVE FUZZY MCDM METHODS

The Fuzzy AHP–ARAS and Fuzzy AHP–COPRAS methods presented in this section were independently implemented by the authors using the same expert assessments, fuzzy criterion weights reported in Table no. 10, and fuzzy decision matrix reported in Table no. 18. They were not adopted or reproduced from prior empirical studies. Their purpose is to serve as cross-validation benchmarks for assessing whether the Fuzzy AHP–TOPSIS rankings remain stable when alternative aggregation logics are applied.

The fuzzy criterion weights applied across all three methods are identical, as are the fuzzy decision matrix and the country sample. This design ensures that any observed ranking differences are attributable to the aggregation procedures rather than to changes in input data. The results of the Fuzzy AHP–ARAS and Fuzzy AHP–COPRAS implementations are presented in Tables no. 22 and no. 23.

Table no. 22 – Ranking of digital logistics performance using Fuzzy AHP–ARAS

Country	S_i^L	S_i^M	S_i^U	S_i	Q_i	Rank
China	0.120	0.148	0.181	0.150	0.969	2
India	0.068	0.099	0.145	0.104	0.675	5
Indonesia	0.026	0.058	0.104	0.063	0.406	9
Jordan	0.011	0.031	0.071	0.037	0.242	10
Kazakhstan	0.062	0.091	0.139	0.097	0.631	7
Malaysia	0.077	0.111	0.163	0.117	0.756	4
Philippines	0.005	0.025	0.066	0.032	0.208	11
Qatar	0.079	0.115	0.163	0.119	0.772	3
Saudi Arabia	0.064	0.098	0.148	0.103	0.670	6
UAE	0.122	0.152	0.188	0.154	1.000	1
Thailand	0.040	0.072	0.119	0.077	0.499	8

The Fuzzy AHP–ARAS results support the main ranking structure identified by the primary method. The UAE and China retain the two leading positions, with utility degrees of 1.000 and 0.969, respectively. Qatar remains in third place. At the lower end, the Philippines and Jordan again record the weakest performance. Some differences appear in the mid-tier group. India rises to fifth place under ARAS, while Kazakhstan falls to seventh. These shifts reflect differences in the way each method aggregates weighted performance across criteria rather than changes in the underlying input data.

Table no. 23 – Ranking of digital logistics performance using Fuzzy AHP–COPRAS

Country	S_P^L	S_P^M	S_P^U	Q^L	Q^M	Q^U	Q_i	Rank
China	0.495	0.890	1.427	0.495	0.890	1.427	0.987	2
India	0.239	0.555	1.109	0.239	0.555	1.109	0.668	7
Indonesia	0.113	0.359	0.829	0.113	0.359	0.829	0.456	9
Jordan	0.046	0.195	0.575	0.046	0.195	0.575	0.287	10
Kazakhstan	0.265	0.570	1.123	0.265	0.570	1.123	0.687	6
Malaysia	0.306	0.665	1.272	0.306	0.655	1.272	0.784	4
Philippines	0.023	0.154	0.523	0.023	0.154	0.523	0.245	11
Qatar	0.336	0.700	1.288	0.336	0.770	1.288	0.815	3
Saudi Arabia	0.272	0.603	1.176	0.272	0.603	1.176	0.720	5
UAE	0.448	0.898	1.464	0.488	0.898	1.464	1.000	1
Thailand	0.178	0.455	0.958	0.178	0.455	0.958	0.558	8

The Fuzzy AHP–COPRAS results further reinforce this pattern. Under COPRAS, the UAE again ranks first, with the normalized utility score set at 1.000; China and Qatar follow. The Philippines and Jordan remain the two lowest-ranked economies. The middle group also changes little from the TOPSIS ordering. India, for example, stays in seventh place in both calculations. The main ranking, then, is not an artefact of a single fuzzy aggregation procedure.

Table no. 24 – Comparative ranking of digital logistics performance across MCDM methods

Country	Fuzzy AHP–TOPSIS	Fuzzy AHP–ARAS	Fuzzy AHP–COPRAS
China	2	2	2
India	7	5	7
Indonesia	9	9	9
Jordan	10	10	10
Kazakhstan	6	7	6
Malaysia	4	4	4
Philippines	11	11	11
Qatar	3	3	3
Saudi Arabia	5	6	5
UAE	1	1	1
Thailand	8	8	8

As shown in Table no. 24, the ranking results from the three approaches exhibit a high degree of consistency, especially for countries at both ends of the performance spectrum. The UAE, China, and Qatar consistently occupy the top three positions, while Jordan and the Philippines consistently rank near the bottom. This stability supports the reliability of the fuzzy weight structure and decision matrix used in the assessment.

5. DISCUSSION

The ranking results suggest that digital logistics performance is not determined by logistics-market size alone. The UAE, China, and Qatar lead the sample because their logistics conditions are supported by stronger digital-capability indicators, particularly knowledge, technology, and future readiness. Scale matters. But it is not enough. China benefits from large domestic and international logistics opportunities, while the UAE and Qatar perform strongly in digitally oriented criteria that reflect institutional readiness, technological capacity, and the ability to absorb new systems. This pattern is important because conventional logistics indicators may capture throughput and market access, but they do not fully reflect whether a logistics system can coordinate data, platforms, and actors under digital conditions.

For the middle and lower-ranked economies, the results point to a different policy issue. Malaysia and Saudi Arabia show relatively strong positions, yet their rankings remain below the leading group because performance is less even across criteria. Kazakhstan and India occupy intermediate positions, indicating that selected advantages in market size or digital capacity do not automatically translate into balanced digital logistics readiness. The lower-ranked economies face a sharper constraint. Thailand, Indonesia, Jordan, and the Philippines are not simply disadvantaged by logistics-market conditions; their weaker positions are closely associated with digitally oriented criteria. Policy attention should therefore move beyond physical infrastructure expansion. Investment in data systems, digital skills, interoperable platforms, regulatory coordination, and technology adoption capacity is likely to matter more for improving digital logistics performance than isolated improvements in transport assets.

The methodological results also carry a useful implication. Although AEMLI provides a logistics-market view and DCI captures broader digital competitiveness, neither index alone is sufficient for evaluating digital logistics performance. Their joint use is more informative, but it also raises a weighting problem: the relative importance of market opportunities, institutional conditions, digital readiness, knowledge, technology, and future readiness cannot be assumed to

be fixed across contexts. Fuzzy AHP was used to retain uncertainty in expert judgments rather than forcing them into exact values at the start of the analysis. Fuzzy TOPSIS then converted those weighted fuzzy assessments into a ranking. The stability checks using Fuzzy AHP–ARAS and Fuzzy AHP–COPRAS support the main ordering, especially at the top and bottom of the distribution. Still, the small shifts in the middle group are informative. They show that ranking outcomes can vary when aggregation rules change, even when the input data remain the same. Digital logistics rankings should therefore be read as structured comparative evidence, not as absolute measures of national performance.

6. CONCLUSION

Digital logistics market performance across selected Asian economies is evaluated here through a combined Fuzzy AHP–TOPSIS approach. Fuzzy AHP is used to obtain the criterion weights, while Fuzzy TOPSIS ranks the countries by measuring how close each alternative is to the fuzzy positive ideal solution. The use of fuzzy logic allows expert uncertainty and judgmental imprecision to be reflected in the evaluation process. Seven criteria are considered, taken from the AEMLI and DCI datasets, representing two main aspects of performance: logistics-market conditions and digital transformation capacity. To our knowledge, this is among the first studies to integrate these two index families within a unified fuzzy MCDM framework for evaluating digital logistics performance in Asian economies.

The findings indicate that the UAE, China, and Qatar achieve the strongest overall performance among the 11 economies. Their high rankings are mainly linked to better scores in knowledge, technology, and future readiness, together with stronger logistics-market conditions — a pattern broadly consistent with Özbek and Özekenci (2023), though the country ordering differs somewhat given the distinct weighting structure applied here. Malaysia and Saudi Arabia also show relatively favorable results. Kazakhstan and India occupy intermediate positions. Thailand, Indonesia, Jordan, and the Philippines fall into the lower group, largely because of weaker performance in several dimensions of digital readiness. For these economies, the results suggest that targeted investment in digital infrastructure and knowledge-intensive capacity — rather than conventional logistics expansion alone — is the more pressing policy priority.

The robustness checks based on Fuzzy AHP–ARAS and Fuzzy AHP–COPRAS confirm the general stability of the ranking results. The leading and lowest-performing countries remain mostly consistent across the three methods, suggesting that the main findings are not dependent on one specific aggregation procedure. The proposed framework can therefore provide practical decision support for policymakers, logistics enterprises, and investors when comparing digital logistics readiness across national markets.

Several limitations deserve acknowledgment. Expert input came from three specialists — well-credentialed, but inevitably a narrow base for capturing the full range of institutional and country-specific nuances across 11 diverse economies. Data constraints are equally worth noting: the analysis draws on the 2023 AEMLI and 2022 DCI editions, so what emerges is a fixed cross-sectional snapshot rather than any account of directional change. Country inclusion was itself dictated by where complete seven-criterion data existed, not by theoretical sampling logic. Future work might widen this scope by drawing on updated index releases, extending coverage to additional economies, running the framework across multiple time points, or folding in LPI dimensions to allow a side-by-side comparison of conventional and digitally oriented logistics performance.

AI use statement

This study did not use any AI tool or Large Language Model for autonomous content creation. Standard tools for grammar and spelling correction were used in the preparation of this manuscript.

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