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Article

Applying MCDM to evaluate benchmark scores in the logistics sector for the period 2021–2023: Application to universities in Vietnam

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Abstract: Choosing a university is a crucial decision for each field of study, as it significantly influences the quality of graduates. An important factor in this decision is the university's annual benchmark scores. The benchmark score represents the minimum score required for admission. This study evaluates the benchmark scores in the logistics sector for several prominent universities in Vietnam during the period 2021–2023. The research process utilized data on the benchmark scores for the years 2021, 2022, and 2023. The weights of these benchmark scores were calculated using the Rank Order Centroid (ROC) method, and the Probability method was employed to compare the benchmark scores of the universities. The analysis identified C3 as the criterion with the highest importance, while U3 emerged as the top-ranked alternative. The two-stage comprehensive sensitivity analysis revealed that universities consistently ranked high or low regardless of the method used to calculate benchmark score weights or the method employed for ranking. Additionally, the smallest weight change that affected the overall Probability ranking was 4.61%. This study provides significant guidance for students in selecting a university for logistics studies and serves as a foundational reference for universities to assess their capabilities in logistics education, thereby fostering healthy competition among institutions.

Keywords: logistics sector; benchmark scores; probability method; ROC method; sensitivity analysis

1. Introduction

Vietnam's geographical location is highly advantageous for trade and logistics development. Covering an area of 327,500 km^2 and with a coastline extending over 3260 km, Vietnam is situated on the Indochina Peninsula and shares borders with China, Laos, Cambodia, and the East Sea. This strategic positioning not only provides favorable conditions for expanding trade exchanges but also offers significant potential to become an international transshipment hub. Its three sides bordering the sea and its location at key maritime and aviation crossroads further enhance its strategic importance (Tai, 2019).

Vietnam ranks 10th out of 50 emerging logistics markets, with an average annual growth rate of 14% to 16% in the logistics sector. Currently, the logistics sector in Vietnam is ranked 43rd globally (Nguyen, 2023). It is projected that by 2025, the contribution of logistics services to Gross Domestic Product (GDP) will reach approximately 5% to 6% (Hai et al., 2023). Even during the COVID-19 pandemic, Vietnam's logistics services supported various sectors, including agriculture, medical equipment, consumer goods, and e-commerce, thereby helping the economy sustain its annual GDP growth momentum (Nguyen, 2021). Additionally, the Vietnamese government aims for logistics services to contribute around 10% to GDP by 2030 (Ha, 2023).

Several proposals have been made to develop Vietnam's logistics sector, including improving the institutional and policy framework for logistics services, developing logistics infrastructure in a synchronized manner, enhancing connectivity, and improving business capacity and service quality, among other measures (Chau and Dat, 2021; Ha et al., 2023; Hong et al., 2021; Hieu and Huy, 2024). Among these, high-quality human resources and infrastructure are identified as the two most significant limitations in Vietnam's logistics sector (Nguyen, 2020). To address the demand for high-quality human resources, the logistics field is attracting considerable attention from the public and higher education institutions, with over 40 universities offering related programs. The logistics training curriculum has been benchmarked against those in countries with advanced logistics sectors (Cam and Hong, 2022). However, choosing a university for logistics studies presents a challenge for students due to the varying strengths and limitations of each institution. The decision-making process depends on various factors, including annual benchmark scores, tuition fees, university facilities, training quality, and extracurricular activities. Among these factors, most people tend to base their decision primarily on the university's annual benchmark scores. However, relying on a single year's benchmark score can lead to an inaccurate choice, as these scores may fluctuate annually. For example, in 2021, University A's benchmark score was higher than University B's, but in 2022, University B's score surpassed that of University A. This variability complicates the process of making an informed selection. Multi-Criteria Decision-Making (MCDM) methods are considered effective solutions for addressing this challenge (Paul et al., 2021).

This study employs MCDM methods to comprehensively evaluate the logistics benchmark scores of several prominent universities in Vietnam for the period 2021–2023. The Rank Order Centroid (ROC)-Probability model was used to prioritize criteria and obtain alternative scores, respectively. The Probability method was chosen because, since its proposal in 2021, it has not been applied in research (Zheng et al., 2021), which raises curiosity about its effectiveness. The ROC weight method provides approximate values for weights by identifying the centroid of all possible weights, thus minimizing the maximum error for each weight while preserving the ranking of objective significance. This method offers greater accuracy compared to other rank-based formulas, features a straightforward procedure, and includes suitable implementation tools (Erkan and Elsharida, 2020; Barron and Bareet, 1996). To assess the model's stability, a two-stage sensitivity analysis was conducted, which involved comparing results obtained using the Probability method with those derived from different MCDM methods and determining the threshold required to alter the current ranking produced by the Probability model.

The contributions and motivations of this study can be summarized as follows: i) The primary motivation for this research is the absence of studies combining the ROC-Probability model in the literature. ii) This study is the first to evaluate the logistics admission scores of multiple universities in Vietnam. iii) The results of this study are expected to provide a foundation for universities to assess their capabilities in logistics education and to foster healthy competition among institutions. iv) The two-stage sensitivity analysis facilitates not only the comparison of the Probability method with various MCDM methods but also determines the threshold required to alter the current ranking obtained through the Probability model and the ranking of the best alternative.

The remainder of the study is organized as follows: Section 2 introduces several studies that have applied MCDM methods to logistics-related activities. Section 3 outlines the steps for employing the ROC and Probability methods. Section 4 presents a comparison of the logistics benchmark scores for several Vietnamese universities. Section 5 details a comprehensive sensitivity analysis conducted to test the accuracy of the model. Finally, the study concludes with a summary of the findings.

2. Literature review

Logistics is the backbone of the economy, connecting all stages from manufacturing to final consumption. Efficient logistics operations not only ensure that goods reach the right place at the most suitable time but also promote economic growth, create jobs, improve quality of life, and enhance national security (Calık et al., 2022; Nila and Roy, 2023). Logistics plays a crucial role in meeting people's needs, fostering international cooperation, and contributing to the development of a sustainable society (Akhtar, 2023; Chejarla et al., 2021). The significance of logistics has led to substantial research and comparative analysis in related activities. To optimize supply chain efficiency, logistics experts continuously compare and evaluate different options. This comparison not only assists businesses in selecting the most optimal solutions but also encourages healthy competition among service providers, thereby contributing to the overall improvement of logistics service quality (Boakai and Samanlioglu, 2023).

Comparing and evaluating options in logistics is a complex process that requires careful consideration of various criteria such as cost, time, safety, and sustainability. To make optimal decisions, logistics experts often encounter MCDM challenges, where criteria frequently conflict with one another. Choosing one option often involves trade-offs with other criteria. Therefore, the use of MCDM methods is essential to support the decision-making process (Lee and Yang, 2018; Norkaew and Sureeyatanapas, 2019).

MCDM methods have permeated many aspects of logistics activities. In supplier selection, numerous studies have applied single MCDM methods such as the TOPSIS method (Evcioglu and Kabak, 2023; Luyen and Thanh, 2022), the ELECTRE method (Alazzawi and Zak, 2020), and the LMAW method (Pamucar et al., 2021). Some studies have employed multiple methods simultaneously, such as the TOPSIS and VIKOR methods (Servait et al., 2020). There are even studies that have used eleven methods concurrently, including SAW, PROMETHEE, TOPSIS, ARAS, EDAS, MABAC, WASPAS, COPRAS, CODAS, MAIRCA, and MARCOS, to select green logistics services (Osintsev, 2021). In distribution center selection, many studies have applied MCDM methods such as the fuzzy-AHP method (Wang et al., 2010), the FDMM method (Hanzl, 2020), and the TOPSIS method (Stopka et al., 2022; Zhang et al., 2021), among others.

In third-party logistics (3PL) service selection, MCDM methods have been applied, including the ARAS method (Jovcic and Prusa, 2021), the grey SWARA method, and the grey CODAS method (Ulutas, 2021), among others. In warehouse location selection, MCDM methods such as the FMCA method (Bairagi, 2022), the ELECTRE method (Żak, 2019), and the grey PIV method and grey PSI method (Ulutas et al., 2021) have been utilized. For port location selection, methods including EDAS (Gorcun and Kucukonder, 2021), ELECTRE (Zak and Węgliński, 2014), BWM (Çıkmak et al., 2023), and PROMETHEE (Yildirim and Onder, 2014; Komchornrit, 2017), among others, have been employed. MCDM methods have also been applied in various other logistics-related activities, such as evaluating the logistics performance index of companies using the MARCOS method (Mesic et al., 2022), selecting logistics operators using the Fuzzy TOPSIS method (Tubis and Wojciechowska, 2023), and evaluating public and urban transportation systems using the TOPSIS method (Keshavarz-Ghorabaee et al., 2022), among others.

Conversely, while there are no studies in the literature that combine both the ROC and Probability methods, there are examples of studies that employ each method individually. The Probability method, developed based on probability theory, facilitates the comparative ranking of alternatives according to their total suitability probabilities. This method has been utilized for tasks such as selecting suitable dwelling walls, choosing project managers, and evaluating contractors for construction projects (Zheng et al., 2021). In contrast, the ROC method has been applied in various contexts, including the production processes of mechanical products (Trung, 2022), employee performance appraisal (Widjaja et al., 2024), online sales platform selection (Wijaya et al., 2022), airport site selection (Erkan and Elsharida, 2020), and turning process optimization (Hoang, 2023).

It is noted that MCDM methods have been widely used to compare options in specific areas of logistics activities. However, the selection of universities for logistics studies has not received substantial attention from researchers. This study aims to address this under-researched area. Additionally, the ROC and Probability methods have not been extensively applied in logistics-related activities. This gap has motivated the application of the ROC and Probability methods in ranking the logistics benchmark scores of universities. While this study focuses on some Vietnamese universities, the authors believe that the methodology presented is entirely suitable for application in other countries and regions.

3. Materials and methods

To evaluate the logistics benchmark scores for the period 2021–2023 across universities, it is first necessary to identify prominent universities offering logistics programs and to collect their logistics benchmark scores for the years 2021, 2022, and 2023. Suppose there are m universities to be compared and n criteria for evaluating each university. Criteria where higher values are preferable are denoted as BC (Benefit Criteria), while criteria where lower values are preferable are denoted as NC (Cost Criteria). In this context, the data consist of the logistics benchmark scores for the years 2021, 2022, and 2023, making these scores the three criteria, or in other words, n equals 3. A decision matrix is constructed as in Equation (1). In this matrix, x_{ij} is the value of criterion j for option i, with $i = 1 \div m$, and $j = 1 \div n$. Let w_j be the weight of the *j*-th criterion.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \ddots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

After constructing the decision matrix as shown in Equation (1), the sequence for ranking the logistics benchmark scores of universities using each method is as follows:

3.1. Probability method

The ranking of options using the Probability method is performed as follows (Zheng et al., 2021). For BC criteria, the probability of achieving favorable results in the decision-making process is calculated according to Equation (2).

$$P_{ij} \infty X_{ij}, \quad P_{ij} = \alpha_j X_{ij,} i = 1, 2, \ldots, m, \quad j = 1,2, \ldots n \quad (2)$$

where α_j is the normalization coefficient for the *j*-th BC criterion calculated according to Equation (3).

$$\alpha_j = \frac{1}{\sum_{i=1}^{m} x_{ij}} \quad (3)$$

For NC criteria, the probability of achieving favorable results in the decision-making process is calculated according to Equation (4).

$$P_{ij} \infty \left(x_{j\max} + x_{j\min} - x_{ij}\right), \quad P_{ij} = \beta_j \left(x_{j\max} + x_{j\min} - x_{ij}\right)$$
$$i = 1, 2, \ldots, m, \quad j = 1,2, \ldots, n \quad (4)$$

where β_j is the normalization coefficient of the *j*-th NC criterion calculated according to Equation (5).

$$\beta_j = \frac{1}{m\left(x_{j\max} + x_{j\min} - \frac{\sum_{i=1}^{m} x_{ij}}{m}\right)} \quad (5)$$

Considering the weight w_j of the *j*-th criterion, the overall favorable probability of option *i* is calculated according to Equation (6). The best option is the one with the highest overall favorable probability.

$$P_i = \prod_{j=1}^{n} \left(P_{ij}\right)^{w_j} \quad (6)$$

3.2. Weighting method used

The ROC weighting method was employed to determine the criteria weights for this study. This method was chosen because it is considered one of the simplest methods for calculating weights, utilizing only one formula, and it has been widely used in recent studies (Thinh, 2023). The ROC method calculates the weights of the criteria according to Equation (7).

$$w_j = \frac{1}{n}\sum_{k=i}^{n}\frac{1}{k} \quad (7)$$

In Equation (7), k is the priority order of the j-th criterion, where $1 \leq k \leq n$.

4. Results and discussion

Annually, as regulated by the Ministry of Education and Training of Vietnam, the admission scores for the logistics major, as well as other majors at universities, are publicly announced to inform the public of the minimum scores required for admission to these universities. In this article, the admission scores for the logistics major at seven representative universities are considered. These universities are denoted by the symbols U1 through U7. **Table 1** summarizes the admission scores for the logistics major at these universities for the 2021, 2022, and 2023 admission cycles. Each year's admission score is the total score of three subjects graded on a 10-point scale, typically including natural science subjects such as mathematics, physics, and chemistry. The admission scores for these three years serve as the criteria used to evaluate the logistics major at these universities from 2021 to 2023. These criteria are denoted as C1 (2021), C2 (2022), and C3 (2023), respectively, and all are classified as BC.

Table 1. Admission scores for the logistics major at universities.

Universities	2021	2022	2023
	C1	**C2**	**C3**
U1	26.1	25.75	28.6
U2	26.25	26.25	26.25
U3	28.3	28.2	27.4
U4	25	26.75	26.75
U5	25.55	26.25	26.25
U6	27.4	27	27.5
U7	24.75	25	25

Source: (compiled by the authors).

It is observed that in 2021 and 2022, the admission scores for the logistics major at U3 were the highest compared to other universities, at 28.3 and 28.2, respectively. However, in 2023, U1 had the highest admission score for the logistics major, at 28.6. For instance, in both 2021 and 2022, the admission scores for the logistics major at U2 were higher than those at U1, but in 2023, U1's admission score surpassed U2's. Similarly, U4's admission score in 2021 was lower than U5's, but in 2022 and 2023, U4's scores were higher than U5's. These examples illustrate that evaluating the ranking of the logistics major admission scores across universities from 2021 to 2023 by merely observing **Table 1** is insufficient. Therefore, the Probability method must be used to rank the logistics major admission scores at universities. Initially, to rank the options using this method, the weights for the criteria C1, C2, and C3 need to be calculated.

There are two perspectives on the importance of admission scores across different years. The first perspective considers the admission scores of each year as equally important. In contrast, the second perspective asserts that admission scores from years closer to the review time are more significant than those from previous years. This study adopts the second perspective, and the weights of the admission scores for the years have been calculated using the ROC method. The results are summarized in **Table 2**.

Table 2. Criteria weights obtained using the ROC method.

C1	**C2**	**C3**
0.1111	0.2778	0.6111

According to **Table 2**, the criterion with the highest importance was identified as C3 (2023). The overall ranking was C3 (2023) > C2 (2022) > C1 (2021). The Probability method, as described, was used to rank university admission scores based on the weight set calculated using the ROC method. The results are presented below.

Table 3. Results of the Probability method.

	PX1	**PX2**	**PX3**	**Pt**	**Rank**
U1	0.8053	0.5780	0.3167	0.1474	2
U2	0.8058	0.5811	0.3005	0.1407	5
U3	0.8125	0.5928	0.3085	0.1486	1
U4	0.8014	0.5842	0.3040	0.1423	4
U5	0.8034	0.5811	0.3005	0.1403	6
U6	0.8096	0.5857	0.3092	0.1466	3
U7	0.8005	0.5733	0.2917	0.1339	7

According to **Table 3**, the logistics admission scores of U3 are ranked 1st, and U7 is consistently ranked 7th. The overall ranking is U3 > U1 > U6 > U4 > U2 > U5 > U7. This result is very useful for guiding students in choosing a university to study logistics. Furthermore, the results of this study also provide a basis for universities to recognize their strengths in logistics training, fostering healthy competition among universities.

5. Sensitivity analysis

The proposed methodology was validated using a twofold approach: a comparative analysis of the results obtained with alternative MCDM methods, and an assessment of the impact of variations in weights on the results.

5.1. Comparative analysis

Results derived from the Probability method were assessed against those from a range of MCDM techniques, such as PIV, ROV, SAW, and WASPAS. The selection of these methods was influenced by their applicability to real-world problems and their procedural simplicity. The results are presented in **Table 4**.

Table 4. Results of Probability, PIV, ROV, SAW, WASPAS methods.

	Probability		PIV		ROV		SAW		WASPAS	
	Value	**Rank**	**Value**	**Rank**	**Value**	**Rank**	**Value**	**Rank**	**Value**	**Rank**
U1	0.147	2	0.013	2	0.359	2	0.967	2	0.967	2
U2	0.141	5	0.031	5	0.184	5	0.923	5	0.923	5
U3	0.149	1	0.010	1	0.398	1	0.974	1	0.974	1
U4	0.142	4	0.027	4	0.228	4	0.933	4	0.933	4
U5	0.140	6	0.032	6	0.173	6	0.920	6	0.920	6
U6	0.147	3	0.016	3	0.340	3	0.961	3	0.961	3
U7	0.134	7	0.049	7	0.000	7	0.878	7	0.878	7

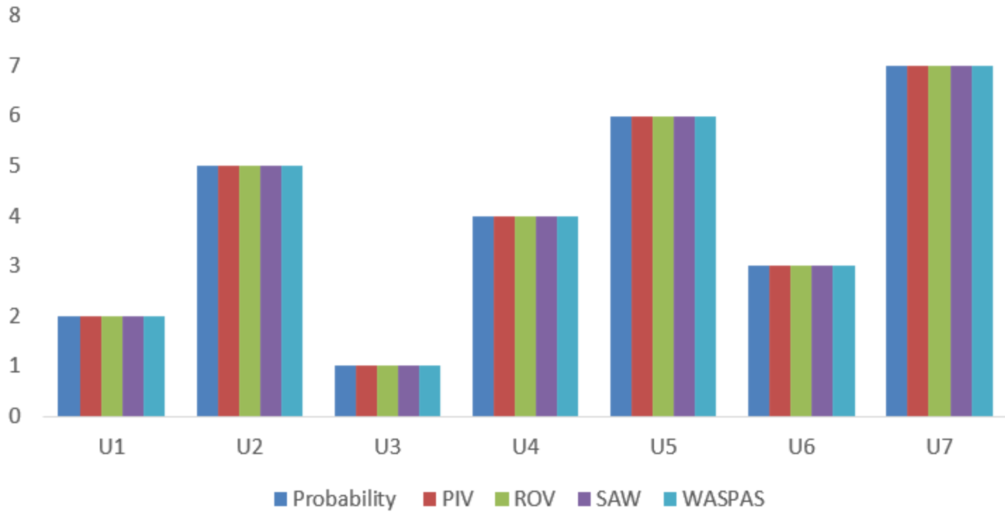

Figure 1. Results of comparative analysis.

Observing **Table 4** and **Figure 1**, it is evident that regardless of the method used to rank the options (Probability, PIV, ROV, SAW, or WASPAS), the rankings obtained from these five different MCDM methods are identical. There is a full correlation between the results obtained using the Probability method and those from other MCDM methods. This indicates that the analysis has been conducted accurately and that the results are corroborated by the outcomes of the other MCDM methods.

5.2. Weight sensitivity analysis

In this section, the impact of 34 different weight variations on the results was examined to test the ranking of alternatives obtained using the Probability method, based on varying criterion weights.

Table 5. Variations in weights.

δ(±0.01, ±0.05, ±0.1, ±0.125, ±0.15, ±0.175, ±0.2, ±0.225, ±0.25, ±0.275, ±0.3, ±0.325, ±0.35, ±0.375, ±0.4, ±0.425, ±0.45)

Source: Kumar and Parimala (2019).

The new weights are calculated using the variations in **Table 5** as follows (Kumar and Parimala, 2019): The new criteria weight (W_i^*) is calculated using Equation (8) and the weight is normalized using Equation (9).

$$W_i^* = |W_i \pm \delta|, \qquad 1 \leq i \leq n \tag{8}$$

$$W_i' = \frac{W_i^*}{\sum W_i^*}, \qquad 1 \leq i \leq n \tag{9}$$

W_i and δ represent the weight obtained by ROC and the weights determined by the scenarios, respectively. n is the number of criteria. By identifying the minimum percentage changes required in the current criterion weights that affect the ranking of alternatives across 34 weighting scenarios, this study also highlighted significant weights and critical decision criteria. The absolute and relative changes in weights, as defined in Equations 10 and 11, respectively, were utilized to determine the weights that influence the ranking of an alternative.

$$\delta_i' = |W_i' - W_i| \tag{10}$$

$$\delta_i'' = (W_i' - W_i) * \frac{100}{W_i}, \text{for } 1 \leq i \leq n \tag{11}$$

where δ_i', δ_i'' represent the absolute and relative change, respectively.

The weights obtained using the ROC method and the results of the ROC-Probability model are presented in the first row of **Table 6**. According to the rankings with 34 different weight variations listed in **Table 6**, the first change in the ranking of alternatives occurred when $\delta = 0.1$, resulting in a swap between the alternatives U6 and U1. However, none of the 34 scenarios with positive weight coefficients altered the position of the top-ranked alternative. The negative weight scenario that changed the position of the top alternative (U3) is $\delta = -0.1$. In summary, the positive and negative weights that alter the ranking results obtained from the ROC-Probability model are $\delta = 0.1$ and $\delta = -0.1$, respectively.

Table 6. The impact of weight variations on the results.

	C1	**C2**	**C3**	**Ranking**
wi	0.1111	0.2778	0.6111	U3 > U1 > U6 > U4 > U2 > U5 > U7
δ	C1	C2	C3	
0.01	0.1176	0.2794	0.6030	U3 > U1 > U6 > U4 > U2 > U5 > U7
−0.01	0.1042	0.2761	0.6197	U3 > U1 > U6 > U4 > U2 > U5 > U7
0.05	0.0719	0.2680	0.6601	U3 > U1 > U6 > U4 > U2 > U5 > U7
−0.05	0.0719	0.2680	0.6601	U3 > U1 > U6 > U4 > U2 > U5 > U7
0.1	**0.1624**	**0.2906**	**0.5470**	**U3 > U6 > U1 > U4 > U2 > U5 > U7**
−0.1	**0.0159**	**0.2540**	**0.7301**	**U1 > U3 > U6 > U4 > U2 > U5 > U7**
0.125	0.1717	0.2929	0.5353	U3 > U6 > U1 > U4 > U2 > U5 > U7
−0.125	0.0213	0.2341	0.7446	U1 > U3 > U6 > U4 > U2 > U5 > U7
0.15	0.1801	0.2950	0.5249	U3 > U6 > U1 > U4 > U2 > U5 > U7
−0.15	0.0620	0.2036	0.7345	U1 > U3 > U6 > U4 > U2 > U5 > U7
0.175	0.1876	0.2969	0.5155	U3 > U6 > U1 > U4 > U2 > U5 > U7
−0.175	0.1060	0.1705	0.7235	U1 > U3 > U6 > U4 > U2 > U5 > U7

Table 6. (*Continued*).

	C1	C2	C3	Ranking
0.2	0.1944	0.2986	0.5069	U3 > U6 > U1 > U4 > U2 > U5 > U7
−0.2	0.1539	0.1346	0.7115	U1 > U3 > U6 > U4 > U2 > U5 > U7
0.225	0.2007	0.3002	0.4992	U3 > U6 > U1 > U4 > U2 > U5 > U7
−0.225	0.2060	0.0955	0.6984	U1 > U3 > U6 > U4 > U2 > U5 > U7
0.25	0.2063	0.3016	0.4921	U3 > U6 > U1 > U4 > U2 > U5 > U7
−0.25	0.2632	0.0527	0.6842	U1 > U3 > U6 > U4 > U2 > U5 > U7
0.275	0.2116	0.3029	0.4855	U3 > U6 > U1 > U4 > U2 > U5 > U7
−0.275	0.3260	0.0056	0.6685	U1 > U3 > U6 > U2 > U4 > U5 > U7
0.3	0.2164	0.3041	0.4795	U3 > U6 > U1 > U4 > U2 > U5 > U7
−0.3	0.3617	0.0425	0.5957	U3 > U1 > U6 > U2 > U4 > U5 > U7
0.325	0.2208	0.3052	0.4740	U3 > U6 > U1 > U4 > U2 > U5 > U7
−0.325	0.3909	0.0863	0.5228	U3 > U6 > U1 > U2 > U4 > U5 > U7
0.35	0.2249	0.3062	0.4688	U3 > U6 > U1 > U4 > U2 > U5 > U7
−0.35	0.4175	0.1262	0.4563	U3 > U6 > U1 > U2 > U4 > U5 > U7
0.375	0.2288	0.3072	0.4640	U3 > U6 > U1 > U4 > U2 > U5 > U7
−0.375	0.4419	0.1628	0.3953	U3 > U6 > U1 > U2 > U4 > U5 > U7
0.4	0.2323	0.3081	0.4596	U3 > U6 > U1 > U4 > U2 > U5 > U7
−0.4	0.4643	0.1964	0.3393	U3 > U6 > U1 > U2 > U4 > U5 > U7
0.425	0.2356	0.3089	0.4554	U3 > U6 > U1 > U4 > U2 > U5 > U7
−0.425	0.4850	0.2274	0.2875	U3 > U6 > U1 > U2 > U5 > U4 > U7
0.45	0.2388	0.3097	0.4515	U3 > U6 > U1 > U4 > U2 > U5 > U7
−0.45	0.5042	0,2562	0.2397	U3 > U6 > U1 > U2 > U5 > U4 > U7

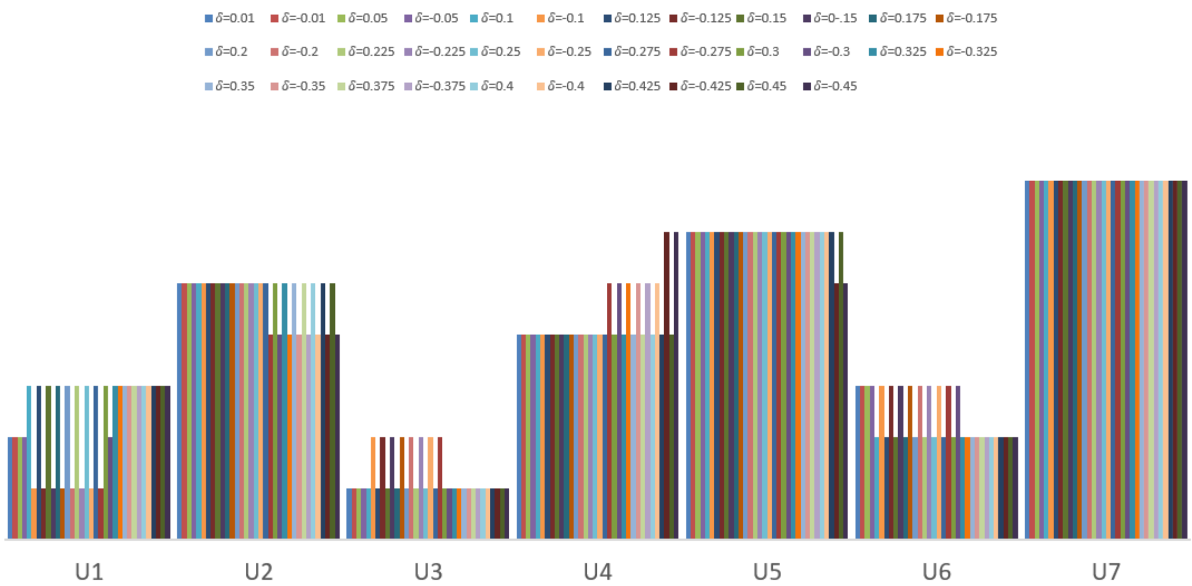

Figure 2. Results across 34 weight scenarios.

According to **Figure 2**, the ranking of alternative U7 remained unchanged across all scenarios, consistently positioned last. The rankings obtained using the ROC-

Probability model remained stable up to Scenario 5 (δ= 0.1), after which the overall ranking of the alternatives changed. In Scenario 6 (δ=−0.1), the top-ranked alternative (U3) shifted to second place, with alternative U1 moving to first position. It was observed that changes in the weights of the criteria particularly affected the rankings of alternatives U1 and U6. In contrast, alternatives U2, U3, U4, and U5 were among the least sensitive to changes in ranking during the sensitivity analysis. As mentioned, alternative U7 showed no sensitivity.

The minimum weight variation that affects the overall ranking and the ranking of the best alternative

After defining the minimum changes, the minimum change (Relative Top) that alters the ranking of the best alternative was first identified, followed by the minimum change (Relative Any) in the criterion weight that affects the ranking of any alternative. The results are shown in **Tables 7** and **8**.

The changes in the overall ranking of alternatives caused by positive and negative weight variations, as well as the relative change percentages, were examined using Equations (3) and (4). Accordingly, the minimum positive and negative changes that alter the ranking of alternatives were determined to be δ = 0.1 and δ = −0.1, respectively. Under the δ = 0.1 condition, the rankings of alternatives U1 and U6 changed, while under the δ = −0.1 condition, the rankings of alternatives U1 and U3 changed.

Table 7. The most critical criterion affecting the overall ranking.

		C1	**C2**	**C3**
wi		0.1111	0.2778	0.6111
		C1	**C2**	**C3**
The minimum change in weight	$\delta = 0.1$	0.1624	0.2906	0.5470
	$\delta = -0.1$	0.0159	0.2540	0.7301
Relative Change (%)		46.17	4.61	10.49
		85.69	8.57	19.47

According to **Table 7**, increasing the criterion weights by 0.10 results in criterion C2 corresponding to the smallest relative weight change of 4.61%, making C2 the most critical factor for altering the ranking of any alternative. Conversely, decreasing the criterion weights by 0.10 results in criterion C2 corresponding to the smallest relative weight change of 8.57%, thus making C2 the most critical factor for altering the ranking of any alternative.

Table 8. The most critical criterion affecting the ranking of the best alternative.

		C1	**C2**	**C3**
wi		0.1111	0.2778	0.6111
		C1	**C2**	**C3**
The minimum change in weight	$\delta = -0.1$	0.0159	0.2540	0.7301
Relative Change (%)		85.69	8.57	19.47

To determine the minimum positive and negative changes required to alter the ranking of the best alternative and to identify the most critical criterion, Equations. (3) and (4) were used (see **Table 8**). In this context, the minimum negative change that affects the ranking of the best alternative is $\delta = -0.1$. This indicates that a decrease of 0.1% in the criterion weights results in a change in the ranking of the top alternative (U3). In addition to the 34 scenarios, 22 more scenarios within the [0.45–1] range were analyzed, but no positive change in the weights altered the ranking of the best alternative. Criterion C2 corresponds to the smallest relative weight change of 8.57%. Therefore, when the current weight is reduced, criterion C2 emerges as the most critical factor for changing the ranking of the top alternative.

6. Conclusion

This study evaluates the benchmark scores in the logistics sector for several leading universities in Vietnam from 2021 to 2023. While there are currently more than 40 universities in Vietnam offering logistics programs, a significant portion of them are relatively new institutions that have only recently introduced logistics as a major. In contrast, the seven universities selected for this study have a long-established track record in logistics education and consistently rank among the top institutions in terms of admission scores. Specifically, all seven universities have annual admission scores above 24 points, indicating an average subject score of 8 or higher on a scale of 10. Given their outstanding academic reputation and high admission standards, these seven universities were chosen as the focus of this research. Utilizing a MCDM approach, the study applies the ROC method to determine criterion weights and the Probability method to obtain alternative scores. The robustness of the model is assessed through a two-stage sensitivity analysis.

According to the ROC technique, C3 has been identified as the most significant criterion. Based on the Probability method, the logistics admission scores for U3 are ranked 1st, while U7 consistently ranks 7th. The overall ranking is U3 > U1 > U6 > U4 > U2 > U5 > U7. The robustness of these results has been validated through a two-stage sensitivity analysis. In the first stage, ROC-Probability model results were compared with those obtained using PIV, ROV, SAW, and WASPAS methods, with identical rankings found across different MCDM approaches. This indicates the reliability of the ROC-Probability model results and the accuracy of the analyses. In the second stage of the sensitivity analysis, criterion weights were varied within the range of δ [±0.01, ±0.45], resulting in 34 scenarios. The following results were obtained based on the Probability model: i) The minimum positive and negative changes in weights required to alter the current ranking are $\delta = 0.1$ and $\delta = -0.1$, respectively. The smallest weight change needed to alter the current ranking is 4.61% (with an increase of 0.10) and 8.57% (with a decrease of 0.10). ii) The minimum negative change that affects the order of the best alternative in the current ranking is $\delta = -0.1$, with the smallest weight change needed to alter the ranking being 8.57%. iii) The most critical decision criterion is C2. iv) Additionally, the analysis conducted within the [0.10–1] range revealed that the ranking of the best alternative remained unchanged when the weights were decreased.

Among the seven universities analyzed—U1, U2, U3, U4, U5, U6, and U7—U3 has the highest logistics admission score, while U7 has the lowest. This information is valuable for students selecting a university for logistics studies in the 2024 admission cycle.

Based on the findings of this study, the selection of universities for logistics programs becomes more comprehensive. Specifically, the study considered the admission scores of the program over three consecutive years: 2021, 2022, and 2023. For instance, when considering the top three best universities, the study ranked U3 as number 1, U1 as number 2, and U6 as number 3. This ranking differs from the results obtained by solely considering the admission score in 2023. If we were to rely only on the most recent data from 2023, U1 would rank first, U6 would rank second, and U3 would rank third. This demonstrates the necessity and usefulness of this study for students in selecting universities for logistics programs, as well as providing a foundation for promoting sustainable and stable development among universities rather than short-term improvements.

The results of this study are expected to provide a foundation for universities to assess their capabilities in logistics education and to foster healthy competition among institutions. In this regard, it is anticipated that the study will also serve as an encouragement for future research. On the other hand, the focus on only three years as criteria and on just seven universities constitutes the limitations of the study. Future research should consider expanding the number of universities surveyed to include evaluations of training programs, graduate quality, facilities, faculty, tuition fees, and other relevant factors in logistics education. This would enhance comparisons of the quality of logistics training across institutions. Additionally, the sensitivity analysis approach used in this study is applicable to various MCDM methods.

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