SCIENTIFIC OASIS

Spectrum of Engineering and Management Sciences

Journal homepage: www.sems-journal.org
ISSN: 3009-3309

Evaluating Innovation Levels based on Standard Deviation of Parameters and MCDM Methods

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ARTICLE INFO

Article history:
Received 1 February 2026
Received in revised form 6 March 2026
Accepted 28 March 2026
Available online 7 April 2026

Keywords:
Minimum three keywords; Avoid too general and too specific keywords; Innovation, Weights, Standard deviation, SD method, LOPCOW method, LOPCOW-SD method

ABSTRACT

Innovation is the process of implementing novel ideas into practice to generate solutions, products, or enhanced procedures that deliver value. Comparing innovation efforts across provinces within a nation is essential, as it clarifies the specific strengths and weaknesses of each locality, providing a comprehensive overview of development capacity rooted in science and technology. This study was conducted to evaluate the innovation performance of several Vietnamese provinces, utilizing data sourced from the Vietnam Economy and Forecast Magazine. Seven parameters were employed to characterize innovation efforts: institutions (C1), human capital and research (C2), infrastructure (C3), market sophistication (C4), business sophistication (C5), knowledge, creativity, and technology outputs (C6), and impacts on production, business, and society (C7). The weights of these parameters were determined by analyzing their standard deviations using the LOPCOW weighting method, the SD weighting method, and the LOPCOW-SD method—an integration of the two primary approaches. The results indicated that the institutional parameter (C1) was identified as the most significant factor, whereas the impact on production, business, and society (C7) was the least significant. The ranking of provinces regarding innovation performance was executed using eight distinct MCDM methods, including MOORA, MARCOS, COCOSO, ROV, PIV, RAM, TOPSIS, and CRADIS. The findings demonstrated that, regardless of the methodology applied, the study consistently highlighted the same high-ranking and low-ranking provinces. Finally, Spearman and WSPE coefficients were utilized to compare the weighting methods, revealing that SD and LOPCOW-SD exhibit higher efficiency compared to the LOPCOW method.

1. Introduction

Innovation is the process of generating and implementing novel and valuable ideas, methods, products, or services. It yields immense effects, promoting socio-economic development, enhancing competitiveness, and improving the quality of life [1]. Innovation is a holistic process where

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https://doi.org/10.31181/sems41202666

production functions, technology, and new product research and development converge, driving value creation and fostering competition among sustainable organizations [2]. Innovation activities not only encourage the development of new ideas but also transform them into useful products or services that consumers need [3]. Innovation is a challenging but highly valuable and effective process for achieving desired results [3].

In general, if we ask anyone what innovation is, we will likely receive a simple answer: innovation is something new. This is the core of the innovation concept and central to all definitions [4]. Today, innovation is an inherent part of our daily lives, and all projects contain innovative elements [4]. The fundamental differences between innovation and science and technology include: innovation's objective is to promote innovation activities; innovation creates a unified connection between the units that generate innovative knowledge, the units that use it, and other supporting units; and in the context of innovation, the enterprise plays a central role [5].

Because innovation takes many forms, its scale and impact can also be measured in various ways [6]. Innovation is classified in numerous ways [7]. Some common classifications include: By content, innovation can take forms such as product innovation, service innovation, process innovation, etc. By speed of implementation, classifications include incremental innovation, radical innovation, and "game-changing" innovation [8]. Innovation is also classified based on the degree of novelty and the field of activity [4]. Another approach groups innovation based on the aspects of the phenomenon, including entrepreneurship theory, technological and social aspects, and strategic aspects, leading to categories such as open innovation, agile innovation, and the "spiral model" [9]. Recently, a new concept, "green innovation," has emerged. It is the fusion of green development driven by innovation, considered the best method to overcome environmental issues and optimally implement sustainable approaches in any field [10].

Despite the various approaches to innovation, they all converge on the necessity of requiring and facilitating a unified system between knowledge utilization and knowledge creation [5].

Innovation is regarded as a sustainable source of value creation and is crucial to a firm's business performance [11]. It is the most vital factor influencing business operations [12, 13] and an essential solution for companies aiming to survive in a competitive environment. Specifically, only through innovation can an enterprise maintain the competitiveness of its goods and products in the market [14]. All companies need to develop new products and services to adapt, stay relevant, and compete. Innovation is the most suitable solution to achieve this, as it is the process of creating completely new things (products, services) or significantly improving existing ones [3]. Therefore, innovation has become one of the most critical competencies for companies to stay ahead of their competitors [15]. Furthermore, innovation provides the foundation for new businesses, new jobs, and productivity growth, and is a major driver of economic growth and development. Innovation can also help solve pressing social and global challenges, including demographic shifts, epidemic risks, resource scarcity, and climate change [16]. A concept has emerged in the economy emphasizing that "no innovation means death" [17].

Innovation is a crucial catalyst for economic growth and development in the modern economy [18]. For a nation, a high level of innovation is important for the economy [19]. Innovation is not only a driver of growth but also a strategy that helps nations maintain a competitive edge. Moreover, it is one of the main components of a nation's economic and sustainable development, assisting countries in overcoming perennial problems [20]. Measuring innovation capacity plays a significant role in guiding development policies. At the national or regional level, the Global Innovation Index (GII) or similar indices are constructed as comprehensive assessment tools for the readiness and effectiveness of innovation activities in each province or city [21]. Innovation becomes a strategic tool in the essential competition to improve, create, and enhance capability, thereby generating a competitive advantage equal to or better than competitors, oriented towards sustainable development [22].

Many factors are used to measure innovation performance, such as human resources, research systems, the business environment, an innovation culture, the intellectual property system, infrastructure, and government policies [23]. Measuring innovation can guide policymakers and decision-makers in identifying the most innovative countries and clarifying the most important innovation indicators for evaluation. Various parameters serve as the pillars of innovation, such as institutions, human capital and research, infrastructure, market sophistication, business sophistication, etc. [20]. Given that the concept of innovation encompasses various influencing factors, which may even conflict with one another, Multi-Criteria Decision Making (MCDM) methods are effective tools for assessing the level of innovation [20]. MCDM methods have been applied in various innovation-related contexts, one of which will be referenced in Section 2 of this paper. This study was undertaken to evaluate the innovation performance of several provinces in Vietnam. Establishing a ranking of provincial innovation efforts serves as a vital reference for the national government and local authorities, enabling them to devise appropriate strategies to foster sustainable socio-economic growth for both the localities and the country as a whole. This constitutes the first objective of the present research.

A critical issue when using MCDM methods to rank alternatives in all fields is the selection of a method to determine the weights of the criteria [24-27]. This study does not evaluate existing weighting methods but focuses on comparing two specific weighting methods, LOPCOW and SD (Standard Deviation), both of which consider the standard deviation of the criteria [28, 29]. The rationale for employing LOPCOW and SD to determine criteria weights in the context of innovation is based on the observed reality of provincial data in Vietnam; specifically, the values associated with each innovation criterion exhibit substantial disparities across different localities. Consequently, incorporating the standard deviation of these criteria during the weighting process ensures a more accurate reflection of their relative significance. This approach allows for the identification of factors that exert a profound influence on innovation performance, which serves as the second objective of this research. Furthermore, this study integrates these two methodologies to formulate a novel hybrid approach designated as LOPCOW-SD. This integration aims to demonstrate that the current research extends beyond a mere comparison between the LOPCOW and SD weighting methods, seeking instead to explore the efficacy gained by combining these component techniques. Conducting a comparative analysis of the LOPCOW, SD, and LOPCOW-SD weighting methods constitutes the third objective of this study. In summary, this research determined the criteria weights using the three methods: LOPCOW, SD, and LOPCOW-SD, and compared their effectiveness in evaluating the innovation performance of selected provinces in Vietnam.

The remainder of this paper is organized as follows. Section 2 presents a brief overview of relevant studies that have applied MCDM methods to solve innovation-related problems. A summary of the steps for using the weighting methods is presented in Section 3. Section 4 presents the innovation ranking results for the selected provinces in Vietnam. The formulation of diverse scenarios for sensitivity analysis is detailed in Section 5. The conclusion and suggestions for future work conclude this research.

2. Literature Review

MCDM methodologies have been extensively applied across a wide array of disciplines, including the stock market sector [30], healthcare [31], material science for various applications [32-34], and numerous other fields. In relation to the use of MCDM methods for comparing innovation alternatives, several recent studies have been identified and can be summarized as follows.

In assessing the innovation performance of G7 countries, the MEREC method was used to determine the criteria weights, while the CODAS, MABAC, MARCOS, COCOSO, WASPAS, and MAIRCA methods were employed to rank the countries. In this research, the parameters used to characterize the innovation of each country included: institutions, human capital and research, infrastructure, market sophistication, business sophistication, knowledge and technology outputs, and creative outputs [20]. The CRADIS method was utilized to evaluate the innovation capability of five Western Balkan countries, while the weights of the parameters—infrastructure, market sophistication, business sophistication, human capital and research, knowledge and technologies, institutions, and creativity—were calculated using the CRITIC method [35]. To compare the innovation performance of G20 countries, the MAIRCA method was used for ranking, while the LOPCOW method was applied to determine the criteria weights. Seven criteria were used in this study: human capital and research, institutions, market sophistication, infrastructure, business sophistication, knowledge and technology outputs, and creative outputs [36]. The comparison of innovation performance between European Union countries and Turkey was conducted by applying the VIKOR and MAIRCA methods, with criteria weights determined by the CRITIC and Entropy methods [37]. Here, the innovation performance of each country was considered based on nine criteria: R&D personnel, air emission intensity from industry, high-speed internet coverage, share of rail and inland waterways in inland freight transport, gross domestic expenditure on research and development, gross value added in environmental goods and services sector, tertiary educational attainment, patent applications to the European patent office, and share of buses and trains in inland passenger transport [37]. In another study, the CRADIS method was used to rank 30 countries, including EU member states and candidate countries, based on digital innovation performance. The criteria used to characterize each country included: high-tech exports, mobile application creation, GitHub commits/million population, ICT service exports, software expenditure, e-participation, ICT use, and R&D collaboration between universities and enterprises. The weights for these criteria were calculated using the IDOCRIW method, which is an integrated approach combining the Entropy and CILOS methods [38].

MCDM methods are not only used to compare the performance of countries regarding innovation but are also applied to other innovation-related problems. The ranking of 38 innovation ideas submitted by entrepreneurs was carried out using the WSM, TOPSIS, and VIKOR methods, with criteria weights assigned by the decision-maker. Six criteria were used to characterize each idea: the level of innovation of the idea, the efficiency, benefits, and urgency of the idea, the implementation time of the idea, the feasibility of the idea, the competency of the teams, the commercial potential of the idea, and scalability [39]. In another dimension, the EDAS method was used to rank 10 innovation training programs, with Entropy used to calculate the criteria weights. Nine criteria were employed: support for startup resources, curriculum design, collaboration with businesses, technology integration, funding and financial support, student innovation capability, faculty competency, practical training opportunities, and post-graduation employment and startup rate [40].

It can be observed that MCDM methods have been utilized to evaluate innovation performance across various levels, from the enterprise to the national level. The current study is applied to assess innovation performance at the provincial level, a context not commonly found in the published literature, and specifically applied to a selection of provinces in Vietnam, a developing country with a highly stable political environment. Evaluating innovation efforts at the provincial level is an essential and strategic necessity for the nation's sustainable economic advancement. Provinces serve as the primary engines of local economic growth, and the innovation efficiency of each locality exerts a significant, even decisive, influence on the overall competitive and innovative capacity of the entire country. Due to the complex and multidimensional nature of innovation, the application of MCDM methodologies is of paramount importance. The necessity for MCDM arises from the fact that provincial innovation performance is measured through a diverse array of criteria that are often conflicting or contradictory. These indicators encompass institutional frameworks, human capital and R&D, infrastructure, and market sophistication, among others. For instance, a province might possess a transparent and effective governance system yet suffer from inadequate technical infrastructure; conversely, another region might boast modern facilities while its business development and human resources lag behind. MCDM techniques enable policymakers to systematically balance and aggregate these opposing factors, assigning rational weights to each criterion to produce a comprehensive, equitable, and objective assessment of each province's innovation output. Such results provide a robust foundation for efficient resource allocation, the formulation of tailored intervention policies, and the promotion of local socio-economic development.

3. Materials and Methods

This section delineates the procedural steps for determining criteria weights using several distinct methodologies.

To calculate the criteria weights using the LOPCOW (Logarithmic Percentage Change Objective Weighting) method, the following sequence of steps must be applied [28]:

Construct the Decision Matrix as per Eq. (1), where x_{ij} is the value of criterion *j* for alternative *i*. Here, *i* ranges from 1 to *m*, and *j* ranges from 1 to *n*, with *m* and *n* being the number of alternatives to be ranked and the number of criteria used to evaluate the alternatives, respectively.

$$\boldsymbol{X} = \begin{bmatrix} x_{11} & x_{12} & x_{1j} & x_{1n} \\ x_{21} & x_{22} & x_{2j} & x_{2n} \\ x_{i1} & x_{i2} & x_{ij} & x_{in} \\ x_{m1} & x_{m2} & x_{mj} & x_{mn} \end{bmatrix} \tag{1}$$

Normalize the Data using Eqs. (2) and (3). In these equations, B and C represent the benefit criteria (larger is better) and the cost criteria (smaller is better), respectively.

$$n_{ij} = \frac{x_{ij} - min(x_{ij})}{max(x_{ij}) - x_{ij}} \quad if \quad j \epsilon B \tag{2}$$

$$n_{ij} = \frac{max(x_{ij}) - x_{ij}}{max(x_{ij}) - min(x_{ij})} \quad if \quad j \epsilon C \tag{3}$$

Calculate the Standard Deviation of the criteria using Eq. (4).

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m}\left(x_{ij} - \frac{\sum_{i=1}^{m} x_{ij}}{m}\right)}{m}} \tag{4}$$

Calculate the *PVj* values for each criterion using Eq. (5).

$$PV_j = 100 \left| ln \frac{\sqrt{\frac{\sum_{i=1}^{m} n_{ij}^2}{m}}}{\sigma_j} \right| \tag{5}$$

Calculate the Weight for each criterion using Eq. (6).

$$w_j^{LOPCOW} = \frac{PV_j}{\sum_{j=1}^{n} PV_j} \tag{6}$$

To calculate the criteria weights using the SD (Standard Deviation) method, the following sequence of steps must be applied [29]:

Calculate the Standard Deviation for the criteria using Eq. (4).

Calculate the Weight of the criteria using Eq. (7).

$$w_j^{SD} = \frac{\sigma_j}{\sum_{j=1}^{n} \sigma_j} \tag{7}$$

The LOPCOW-SD method is a hybrid combination of the LOPCOW and SD methods, used to calculate the criteria weights according to Eq. (8) [41, 42].

$$w_j^{CO} = \frac{w_j^{LOPCOW} \cdot w_j^{SD}}{\sum_{j=1}^{n}\left(w_j^{LOPCOW} \cdot w_j^{SD}\right)} \tag{8}$$

To compare the three methods (LOPCOW, SD, and LOPCOW-SD), the ranking of the alternatives (provinces) will be performed using various MCDM methods. Subsequently, the comparison of the three weighting methods (LOPCOW, SD, and LOPCOW-SD) will be conducted based on the Spearman coefficient and the WSPE coefficient. Both the Spearman and WSPE coefficients serve as metrics to evaluate the degree of rank similarity among alternatives when different weighting methods or diverse ranking methodologies are applied. However, a fundamental distinction exists between these two indicators: the Spearman coefficient assesses the entire ranking list by assigning equal importance to every position [43]. In contrast, the WSPE coefficient typically assigns higher priority weights to the top-ranked alternatives, which progressively diminish for those in lower positions [44]. Utilizing both coefficients enables a comprehensive assessment of ranking stability, focusing not only on high-performing alternatives but also encompassing those in the middle and lower tiers. This dual approach ensures that the evaluation of provincial innovation efforts yields the most objective rankings possible. Consequently, it provides a solid foundation for the national government and local authorities to formulate appropriate policies aimed at enhancing innovation performance across all regions.

The Spearman Rank Correlation Coefficient is calculated as shown in Eq. (9). Here, *Di* represents the difference in the rank of alternative i when ranked by different MCDM methods, or when ranked by the same MCDM method but with criteria weights calculated by different weighting methods [45, 46].

$$S = 1 - \frac{6\sum_{i=1}^{m} D_i^2}{m(m^2-1)} \tag{9}$$

The WSPE coefficient is calculated as shown in Eq. (10). Here, $\sigma(i) - \rho(i)$ denotes the difference in the rank of alternative *i* when ranked by different MCDM methods, or when ranked by the same MCDM method but with criteria weights calculated by different weighting methods [45, 46].

$$WSPE = 1 - \frac{6}{m^4+m^3-m^2-m}\sum_{\alpha \in Z}[\sigma(i) - \rho(i)]^2(2m - 2 - \sigma(i) - \rho(i)) \tag{10}$$

4. Results and Discussion

In this section, the LOPCOW, SD, and LOPCOW-SD methodologies were implemented to determine criteria weights for evaluating innovation performance across several Vietnamese provinces; subsequently, MCDM techniques were applied to rank these provinces based on their innovation levels. Following this, the values of both Spearman and WSPE coefficients were computed to facilitate a comparative analysis of the weighting methods. The three primary objectives of these procedures include: identifying the most critical criteria within innovation efforts, distinguishing provinces with high versus low innovation performance, and conducting a comparative evaluation of the three weighting methodologies.

Table 1 consolidates the innovation data for 2024 concerning thirteen provinces within the Mekong Delta, which represents one of the seven key economic regions of Vietnam [21]. According to the Ministry of Science and Technology of Vietnam, seven parameters were used to assess the innovation performance of the provinces:

C1: Institutions.
C2: Human Capital and Research.
C3: Infrastructure.
C4: Market Sophistication.
C5: Business Sophistication.
C6: Knowledge, Creative, and Technological Outputs.
C7: Impact on Production, Business, and Society.

Table 1
Innovation index of selected provinces in Vietnam [21]

Province	C1	C2	C3	C4	C5	C6	C7
Can Tho	62.38	44.5	60.76	46.1	22.57	43.98	45.54
long An	55.78	19.75	53.11	38.31	45.72	39.27	39.48
Ben Tre	56.39	33.86	32.02	21.99	17.49	30.49	41.83
Hau Giang	64.66	17.84	56.82	21.45	14.72	15.29	49.7
Dong Thap	64.84	28.39	50.43	22.54	14.74	24.27	38.44
Ca Mau	66.48	25.2	40.65	25.68	16.6	27.71	32.57
Tien Giang	45.07	16.74	43.1	28.98	14.2	31.45	39.03
Vinh Long	44.08	32.07	51.09	25.7	15.32	21.42	40.88
Tra Vinh	71.5	16.54	35.36	36.25	9.31	28.39	32.2
Bac Lieu	30.59	26.56	54.89	23.72	9.06	18.7	44.66
An Giang	28.3	25.65	46.41	25.95	20.77	32.66	28.43
Soc Trang	48.06	22.25	53.3	25.89	19.12	18.85	33.04
Kien Giang	29.75	15.45	57.17	41.46	15.65	12.95	37.65

From the data in Table 1, it is observed that Tra Vinh province has the largest C1 value, Can Tho has the largest values for C2, C3, C4, and C6, Long An has the largest C5 value, and Hau Giang has the largest C7 value. This highlights the necessity of calculating weights for the criteria before proceeding with the ranking of the alternatives (provinces) to evaluate innovation performance.

Applying the equations from Section 2, the standard deviation (SD) and weights were calculated, and from these, the rankings of the criteria were determined, as summarized in Table 2.

It is apparent that, although both the LOPCOW and SD methods rely on the standard deviation values of the criteria, calculating the criteria weights yields significant differences. When using the SD method to determine weights, the descending order of priority for the criteria is C1 > C6 > C5 > C3 > C2 > C4 > C7. This order perfectly matches the descending order of the criteria's standard deviation values. In contrast, when using the LOPCOW method, the descending order of priority is C5 > C1 > C2 > C4 > C6 > C3 > C7.

Table 2
Standard deviation, weights, and rank of criteria

Method		C1	C2	C3	C4	C5	C6	C7
σ	value	14.39	8.04	8.45	7.84	8.79	8.82	5.80
	rank	1	5	4	6	3	2	7
LOPCOW	weight	0.1575	0.1475	0.1287	0.1431	0.1631	0.1422	0.118
	rank	2	3	6	4	1	5	7
SD	weight	0.2316	0.1294	0.136	0.1262	0.1415	0.142	0.0933
	rank	1	5	4	6	3	2	7
LOPCOW-SD	weight	0.2509	0.1313	0.1203	0.1242	0.1587	0.1388	0.0758
	rank	1	4	6	5	2	3	7

This difference is explained by the fact that the criteria weights calculated by the SD method are based directly and solely on the criteria's standard deviation value. In contrast, when using the LOPCOW method, the standard deviation is only one component of the criteria weights, which are also influenced by other computations within the LOPCOW methodology (refer back to Section 2).

It should be noted that C1 (Institutions), which has the largest standard deviation, is identified as the most important criterion when using the SD method and is the second most important when using the LOPCOW method. This suggests that C1 is indeed one of the most critical parameters for assessing innovation level (in this case study). Conversely, regardless of whether the LOPCOW or SD method is used for weighting, C7 (Impact on Production, Business, and Society) is consistently identified as the criterion with the lowest priority, and it is also the parameter with the lowest standard deviation. Consequently, the LOPCOW-SD method, being a combination of the other two, also determined that C1 is the most prioritized parameter and C7 is the least prioritized parameter.

A question arises: since all three methods calculate criteria weights based on standard deviation, why are the weights and the resulting ranks of these weights inconsistent when using LOPCOW, SD, and LOPCOW-SD? Therefore, which of these three methods is the most effective for calculating the criteria weights? To answer this, Tables 3 through 5 summarize the ranks of the alternatives when evaluated by eight different MCDM methods: MOORA, MARCOS, COCOSO, ROV, PIV, RAM, TOPSIS, and CRADIS, corresponding to the three cases where weights were calculated by LOPCOW, SD, and LOPCOW-SD, respectively. Eight methodologies, MOORA, MARCOS, COCOSO, ROV, PIV, RAM, TOPSIS, and CRADIS were selected due to their distinct mathematical frameworks for ranking alternatives. The MOORA method is based on calculating a composite score for each alternative by subtracting the sum of normalized cost criteria from the sum of normalized benefit criteria [47]. MARCOS relies on utility functions determined in relation to both ideal and anti-ideal solutions [48]. The COCOSO approach ranks alternatives by integrating different aggregation strategies, including weighted sum and weighted product, to derive a final compromise solution [49]. The ROV method calculates rankings by identifying the best and worst performance values of alternatives for each specific criterion [50]. PIV focuses on assessing the deviations between an alternative's value and the peak performance value of each criterion to formulate its evaluation [51]. The RAM technique employs an aggregation function based on a radical expression, where the radicand represents benefit criteria and the index corresponds to cost criteria [52]. TOPSIS is predicated on evaluating the shortest geometric distance to the positive ideal solution and the farthest distance from the negative ideal solution [53]. Finally, CRADIS operates based on the distance between the normalized weighted values of an alternative and the ideal/anti-ideal benchmarks [54]. The simultaneous deployment of these diverse methodologies aims to generate innovation assessment results and weighting method comparisons that achieve the highest degree of objectivity.

Table 3
Ranks of alternatives with LOPCOW criteria weights

Province	MOORA	MARCOS	COCOSO	ROV	PIV	RAM	TOPSIS	CRADIS
Can Tho	1	1	1	1	1	1	2	1
long An	2	2	2	2	2	2	1	2
Ben Tre	3	4	10	5	3	3	3	4
Hau Giang	8	7	8	4	8	8	9	7
Dong Thap	4	3	3	3	4	4	6	3
Ca Mau	5	5	5	7	5	5	4	5
Tien Giang	11	9	7	9	11	11	11	9
Vinh Long	6	6	4	6	6	6	8	6
Tra Vinh	9	8	9	8	9	9	7	8
Bac Lieu	13	13	11	12	13	13	13	13
An Giang	7	11	13	13	7	7	5	11
Soc Trang	10	10	6	10	10	10	10	10
Kien Giang	12	12	12	11	12	12	12	12

Table 4
Ranks of alternatives with SD criteria weights

Province	MOORA	MARCOS	COCOSO	ROV	PIV	RAM	TOPSIS	CRADIS
Can Tho	1	1	1	1	1	1	2	1
long An	2	2	2	2	2	2	1	2
Ben Tre	4	5	10	7	4	4	4	5
Hau Giang	7	7	8	4	7	7	7	7
Dong Thap	3	3	3	3	3	3	5	3
Ca Mau	5	4	4	5	5	5	3	4
Tien Giang	10	10	9	10	10	10	11	10
Vinh Long	8	8	5	8	8	8	9	8
Tra Vinh	6	6	6	6	6	6	6	6
Bac Lieu	13	13	11	12	13	13	13	13
An Giang	11	11	12	13	11	11	8	11
Soc Trang	9	9	7	9	9	9	10	9
Kien Giang	12	12	13	11	12	12	12	12

Table 5
Ranks of alternatives with LOPCOW-SD criteria weights

Province	MOORA	MARCOS	COCOSO	ROV	PIV	RAM	TOPSIS	CRADIS
Can Tho	1	1	1	1	1	1	2	1
long An	2	2	2	2	2	2	1	2
Ben Tre	5	5	10	7	5	4	4	5
Hau Giang	7	7	8	5	7	7	7	7
Dong Thap	4	3	3	3	4	5	5	3
Ca Mau	3	4	4	4	3	3	3	4
Tien Giang	10	10	9	10	10	11	11	10
Vinh Long	8	8	5	8	8	8	10	8
Tra Vinh	6	6	6	6	6	6	6	6
Bac Lieu	13	13	11	13	13	13	13	13
An Giang	11	11	12	12	11	10	8	11
Soc Trang	9	9	7	9	9	9	9	9
Kien Giang	12	12	13	11	12	12	12	12

It is observed that for each weighting method, the rank of the alternatives varies when ranked by different MCDM methods. This is attributed to the difference in the algorithms of the MCDM methods and has been documented in many studies [55]. However, it is also noted that regardless of the weighting method used and the MCDM method applied for ranking, Can Tho and Long An are consistently identified as the two provinces with the highest innovation performance among the 13 provinces considered. Conversely, provinces such as Tien Giang, Bac Lieu, An Giang, Soc Trang, and Kien Giang are consistently identified as having poor innovation performance in most cases, irrespective of the weighting or ranking method used.

For provinces with good innovation performance, such as Can Tho and Long An, local authorities need to continue investing heavily in science and technology, upgrading digital infrastructure, and acting as a "locomotive" to share experiences. Furthermore, the government should pilot breakthrough innovation policies here for potential replication. Residents in these provinces benefit from a dynamic work environment, smart public services, and higher incomes, and they need to proactively acquire digital skills and boldly engage in entrepreneurship to maintain their leading position. Conversely, for provinces with lower innovation performance, administrative reform must be prioritized. Resources should be focused on resolving fundamental bottlenecks like digital infrastructure, and a search for comparative advantages in niche sectors such as high-tech agriculture should be pursued. The government should implement specialized support programs for capital and human resources to bridge the gap. Residents in these provinces will see improved quality of public services and job opportunities; in return, they need to proactively enhance their skills, participate in learning, and actively contribute feedback to build a more business-friendly local government to jointly drive change.

Thus, this study has achieved its main objectives, including identifying the most and least important criteria for innovation. The provinces assessed as having the best and poorest innovation performance have also been identified. The next objective of this research is to evaluate the effectiveness of the three weighting methods: LOPCOW, SD, and LOPCOW-SD. Tables 6 through 8 summarize the values of the Spearman coefficient and the WSPE coefficient between the MCDM methods, corresponding to the three cases where the criteria weights were calculated by the three different methods.

Comparing the LOPCOW and SD methods reveals that SD demonstrates a superior advantage over LOPCOW. The minimum value of the Spearman coefficient when using LOPCOW weights is 0.5030 (between TOPSIS and COCOSO), which is significantly lower than 0.7433, the minimum Spearman coefficient value when using SD weights (also between TOPSIS and COCOSO). Similarly, the minimum WSPE value when using LOPCOW weights is 0.6919 (between TOPSIS and COCOSO), also significantly lower than 0.8442, the minimum WSPE value when using SD weights (between TOPSIS and COCOSO). For the LOPCOW method, the average Spearman coefficient and the average WSPE coefficient across the MCDM methods are 0.8568 and 0.9147, respectively, both lower than the corresponding values when using the SD method for weighting, which are 0.9323 and 0.9557, respectively. All these data lead to a robust conclusion that the SD method, when used to calculate criteria weights, ensures a higher stability in the ranking of alternatives across different MCDM methods compared to the LOPCOW method. More succinctly, the SD method is affirmed to be more effective than the LOPCOW method.

Comparing the minimum Spearman coefficient, the minimum WSPE coefficient, the average Spearman coefficient, and the average WSPE coefficient when using the SD and LOPCOW-SD methods, the differences are found to be negligible. Specifically:

i. The minimum Spearman coefficient is 0.7433 for SD and 0.7324 for LOPCOW-SD.
ii. The minimum WSPE coefficient is 0.8442 for SD and 0.8375 for LOPCOW-SD.
iii. The average Spearman coefficient is 0.9323 for SD and 0.9389 for LOPCOW-SD.
iv. The average WSPE coefficient is 0.9557 for SD and 0.9609 for LOPCOW-SD.

All these values indicate that the SD and LOPCOW-SD methods are of equivalent effectiveness. However, these findings have only been verified through the evaluation of innovation performance across thirteen provinces. Whether such results remain consistent when the number of provinces under assessment is altered must be scrutinized through sensitivity analysis. This investigation constitutes the content presented in the subsequent section of this paper.

Table 6
Spearman and WSPE coefficients between MCDM methods with LOPCOW weights

Method	Spearman						
	MARCOS	COCOSO	ROC	PIV	RAM	TOPSIS	CRADIS
MOORA	0.9345	0.6559	0.8143	1.0000	1.0000	0.9454	0.9345
MARCOS		0.8088	0.9454	0.9345	0.9345	0.8307	1.0000
COCOSO			0.8034	0.6559	0.6559	0.5030	0.8088
ROC				0.8143	0.8143	0.6614	0.9454
PIV					1.0000	0.9454	0.9345
RAM						0.9454	0.9345
TOPSIS							0.8307
min				0.5030			
Average				0.8568			
Method	**WSPE**						
	MARCOS	COCOSO	ROC	PIV	RAM	TOPSIS	CRADIS
MOORA	0.9682	0.8077	0.9042	1.0000	1.0000	0.9529	0.9682
MARCOS		0.8838	0.9647	0.9682	0.9682	0.8834	1.0000
COCOSO			0.8646	0.8077	0.8077	0.6919	0.8838
ROC				0.9042	0.9042	0.7877	0.9647
PIV					1.0000	0.9529	0.9682
RAM						0.9529	0.9682
TOPSIS							0.8834
min				0.6919			
Average				0.9147			

Table 7
Spearman and WSPE coefficients between MCDM methods with SD weights

Method	Spearman						
	MARCOS	COCOSO	ROC	PIV	RAM	TOPSIS	CRADIS
MOORA	0.9945	0.8416	0.9345	1.0000	1.0000	0.9399	0.9945
MARCOS		0.8744	0.9454	0.9945	0.9945	0.9454	1.0000
COCOSO			0.8744	0.8416	0.8416	0.7433	0.8744
ROC				0.9345	0.9345	0.8416	0.9454
PIV					1.0000	0.9399	0.9945
RAM						0.9399	0.9945
TOPSIS							0.9454
min				0.7433			
Average				0.9323			
Method	**WSPE**						
	MARCOS	COCOSO	ROC	PIV	RAM	TOPSIS	CRADIS
MOORA	0.9941	0.8980	0.9541	1.0000	1.0000	0.9549	0.9941
MARCOS		0.9274	0.9647	0.9941	0.9941	0.9611	1.0000
COCOSO			0.9203	0.8980	0.8980	0.8442	0.9274
ROC				0.9541	0.9541	0.9031	0.9647
PIV					1.0000	0.9549	0.9941
RAM						0.9549	0.9941
TOPSIS							0.9611
min				0.8442			
Average				0.9557			

Table 8
Spearman and WSPE coefficients between MCDM methods with LOPCOW-SD weights

Method	Spearman						
	MARCOS	COCOSO	ROC	PIV	RAM	TOPSIS	CRADIS
MOORA	0.9945	0.8689	0.9672	1.0000	0.9891	0.9508	0.9945
MARCOS		0.8744	0.9727	0.9945	0.9782	0.9399	1.0000
COCOSO			0.8908	0.8689	0.8143	0.7324	0.8744
ROC				0.9672	0.9345	0.8853	0.9727
PIV					0.9891	0.9508	0.9945
RAM						0.9727	0.9782
TOPSIS							0.9399
min				0.7324			
Average				0.9389			
Method	WSPE						
	MARCOS	COCOSO	ROC	PIV	RAM	TOPSIS	CRADIS
MOORA	0.9933	0.9207	0.9741	1.0000	0.9929	0.9717	0.9933
MARCOS		0.9274	0.9808	0.9933	0.9800	0.9588	1.0000
COCOSO			0.9415	0.9207	0.8815	0.8375	0.9274
ROC				0.9741	0.9494	0.9254	0.9808
PIV					0.9929	0.9717	0.9933
RAM						0.9823	0.9800
TOPSIS							0.9588
min				0.8375			
Average				0.9609			

5. Sensitivity Analysis

Sensitivity analysis is a vital procedure when solving MCDM problems and can be implemented through various approaches, such as modifying criteria weights, varying the number of alternatives to be ranked, or adjusting the quantity and nature of criteria [27]. This study adopts the approach of varying the number of alternatives to generate diverse scenarios [27]. Originally, 13 provinces were evaluated; to introduce randomness into the scenarios, the following three cases were established:

Scenario 1 (S1): Removed the first province, Can Tho, from the list.

Scenario 2 (S2): Removed the middle-ranked province (position 7 in Table 1), Tien Giang, from the list.

Scenario 3 (S3): Removed the final province in Table 1, Kien Giang, from the list.

For each scenario, the LOPCOW, SD, and LOPCOW-SD methods were reapplied to calculate criteria weights, followed by the re-execution of MOORA, MARCOS, COCOSO, ROV, PIV, RAM, TOPSIS, and CRADIS for ranking. The Spearman and WSPE coefficients were also recalculated from scratch.

In S1, after excluding Can Tho, the standard deviations and criteria weights were consolidated in Table 9. Figures 1, 2, and 3 illustrate the provincial rankings corresponding to weights derived from the LOPCOW, SD, and LOPCOW-SD methods, respectively. The mean values for the Spearman and WSPE coefficients are summarized in Table 10.

Data from Table 9 reveals that the hierarchy of criteria based on standard deviation decreases as follows: C1 > C5 > C3 > C6 > C4 > C2 > C7, which is entirely consistent with the SD method results. Conversely, the LOPCOW method yielded a hierarchy of C5 > C1 > C4 > C6 > C3 > C2 > C7. This discrepancy, as explained in Section 4, arises because the SD method relies solely on standard deviation, whereas LOPCOW incorporates standard deviation as just one of several computational components. Furthermore, C1 exhibited the highest standard deviation and weight in both SD and LOPCOW-SD, while ranking second in LOPCOW, confirming its status as a primary criterion. C7, having the lowest standard deviation, consistently received the minimum weight across all three methods, cementing its position as the lowest priority factor.

Table 9
Criteria weights in scenario S1

Method	C1	C2	C3	C4	C5	C6	C7
σ	14.6103	5.9716	8.0336	6.4721	9.0490	7.5446	5.6773
LOPCOW	0.1675	0.1272	0.1285	0.1391	0.1732	0.1390	0.1254
SD	0.2547	0.1041	0.1401	0.1128	0.1578	0.1315	0.0990
LOPCOW-SD	0.2890	0.0897	0.1219	0.1063	0.1851	0.1239	0.0841

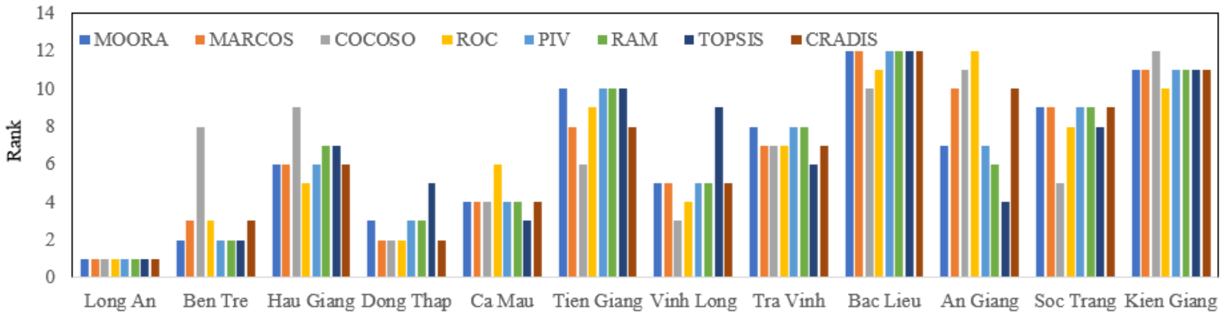

Fig. 1. Provincial rankings in scenario S1 using the LOPCOW method for criteria weighting

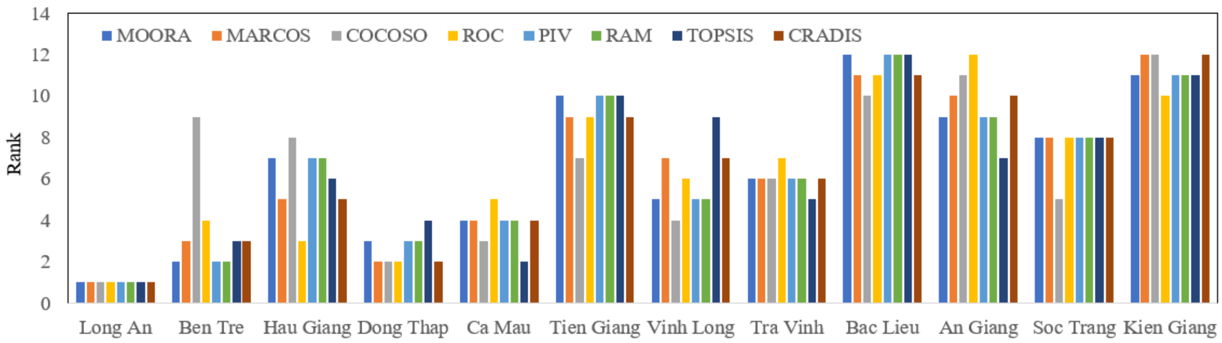

Fig. 2. Provincial rankings in scenario S1 using the SD method for criteria weighting

Observing Figures 1 to 3, Long An consistently secured the top rank across all weighting methods. In contrast, Tien Giang, Bac Lieu, An Giang, Soc Trang, and Kien Giang remained identified as low-performing provinces in terms of innovation, mirroring the results found in Section 4.

According to Table 10, the mean Spearman coefficient was highest under the LOPCOW-SD weighting method, followed by SD and LOPCOW. This hierarchy remained consistent when comparing the mean WSPE values. These results suggest that in S1, LOPCOW-SD ensures higher ranking stability for alternatives compared to SD, with LOPCOW being the least stable. Overall, S1 reinforces that LOPCOW-SD and SD outperform the LOPCOW method.

For scenario S2, after excluding Tien Giang province from the list of alternatives to be ranked, the standard deviations and criteria weights were calculated and summarized in Table 11. Figures 4, 5, and 6 illustrate the provincial rankings corresponding to cases where criteria weights were determined using the LOPCOW, SD, and LOPCOW-SD methods, respectively. Additionally, the average values of the Spearman and WSPE coefficients were calculated and are summarized in Table 12.

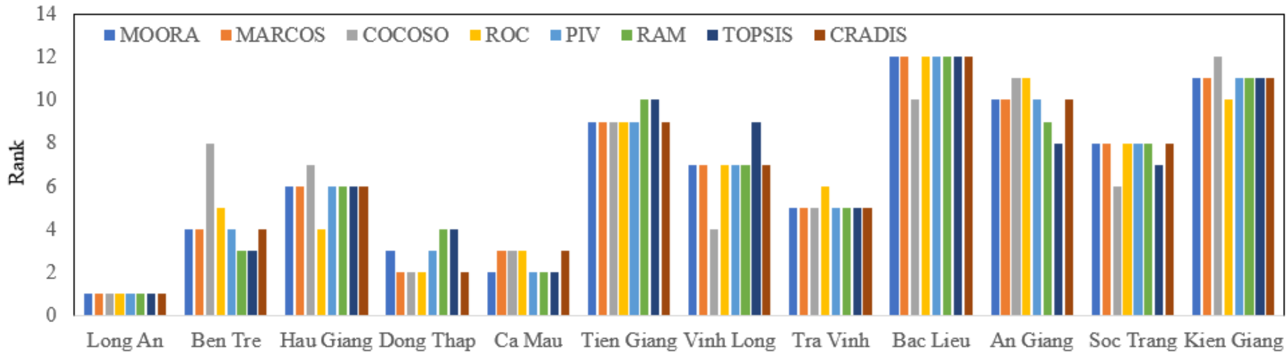

Fig. 3. Provincial rankings in scenario S1 using the LOPCOW-SD method for criteria weighting

Table 10
Average values of the coefficients in scenario S1

Weight method	Spearman	WSPE
LOPCOW	0.8364	0.6166
SD	0.8761	0.6788
LOPCOW-SD	0.9389	0.7852

Table 11
Criteria weights in scenario S2

Method	C1	C2	C3	C4	C5	C6	C7
σ	14.8595	7.9941	8.6224	8.1620	9.0729	9.0627	6.0344
LOPCOW	0.1575	0.1449	0.1281	0.1436	0.1627	0.1439	0.1194
SD	0.2329	0.1253	0.1351	0.1279	0.1422	0.1420	0.0946
LOPCOW-SD	0.2523	0.1249	0.1191	0.1264	0.1591	0.1406	0.0777

It is observed that in scenario S2, the ranking of criteria based on standard deviation and weight values calculated via the SD method is perfectly consistent, specifically, decreasing in the order of C1 > C5 > C6 > C3 > C4 > C2 > C7. Additionally, the weight of C1 is found to be the highest when calculated using the LOPCOW-SD method and ranks second when using the LOPCOW method. This indicates that in this scenario, C1 is also evaluated as the most important criterion. Meanwhile, considering both standard deviation values and weights calculated by the three different methods, criterion C7 is consistently assessed as having the lowest priority.

Observations from Figures 4, 5, and 6 also reveal that in scenario S2, Can Tho and Long An provinces are consistently evaluated as the two provinces with the highest innovation performance. Meanwhile, Bac Lieu, An Giang, Soc Trang, and Kien Giang provinces are consistently identified as those with poor innovation performance. These results remain consistent with the findings obtained in Section 4 and in scenario S1 of this Section 5.

Based on the data in Table 12, it is observed that the average Spearman coefficient value is highest when criteria weights are calculated using the LOPCOW-SD method, followed by the SD method, and finally the LOPCOW method. This ranking is perfectly consistent when comparing these three methods based on the average WSPE coefficient values. These results indicate that in this scenario, employing the LOPCOW-SD method for criteria weighting ensures higher stability in the ranking of alternatives when using MCDM methods compared to the SD method, with the LOPCOW method ranking last. In summary, this scenario confirms that both LOPCOW-SD and SD methods achieve higher efficiency than the LOPCOW method.

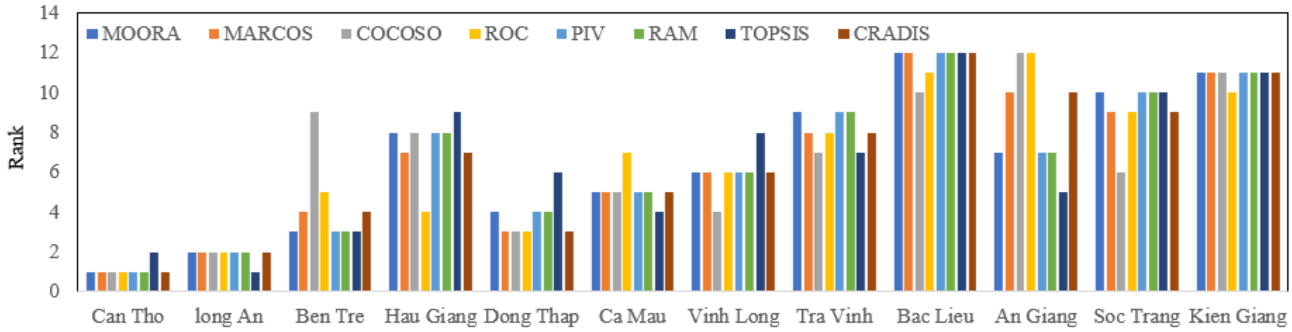

Fig. 4. Provincial rankings in scenario S2 using the LOPCOW method for criteria weighting

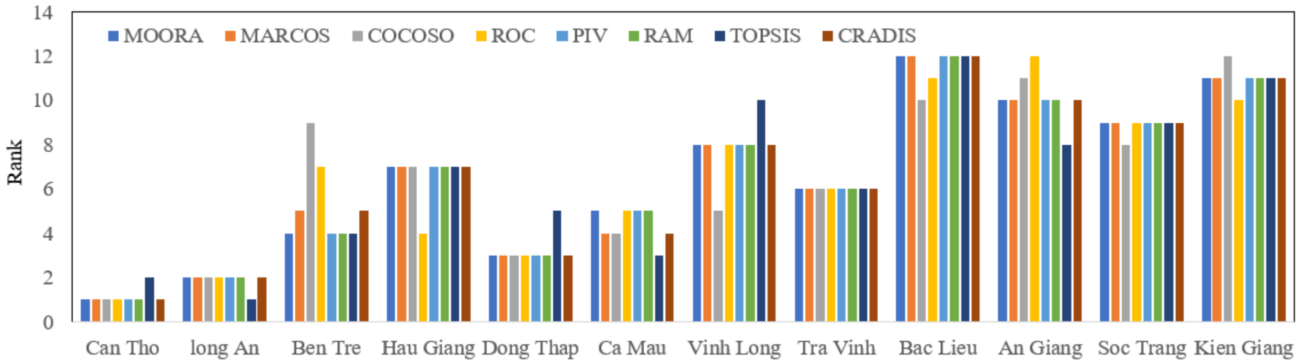

Fig. 5. Provincial rankings in scenario S2 using the SD method for criteria weighting

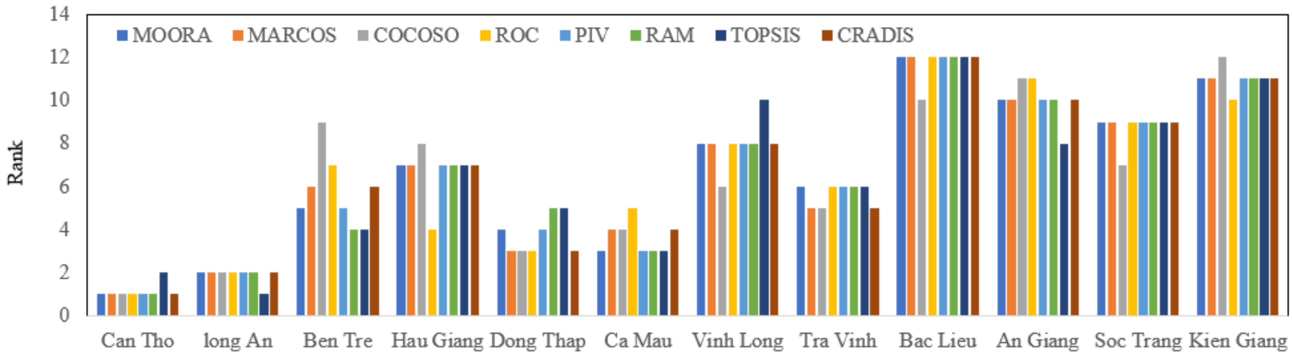

Fig. 6. Provincial rankings in scenario S2 using the LOPCOW-SD method for criteria weighting

Table 12
Average values of the coefficients in scenario S2

Weight method	Spearman	WSPE
LOPCOW	0.8626	0.7083
SD	0.9311	0.8496
LOPCOW-SD	0.9351	0.8631

In scenario S3, after excluding Kien Giang province from the list of alternatives to be ranked, the standard deviations and criteria weights were calculated in the same manner as S1 and S2, as summarized in Table 13. Figures 7, 8, and 9 illustrate the provincial rankings corresponding to the cases where criteria weights were determined using the three methods. Additionally, the average values of the Spearman and WSPE coefficients were calculated and are summarized in Table 14.

Table 13
Criteria weights in scenario S3

Method	C1	C2	C3	C4	C5	C6	C7
σ	13.4972	7.8636	8.4317	7.3361	9.1186	8.2177	6.0264
LOPCOW	0.1531	0.1466	0.1310	0.1454	0.1644	0.1398	0.1198
SD	0.2231	0.1300	0.1394	0.1213	0.1507	0.1358	0.0996
LOPCOW-SD	0.2359	0.1316	0.1261	0.1218	0.1711	0.1311	0.0824

Once again, in this scenario, it is observed that the decreasing priority of the criteria based on their weight values calculated by the SD method is consistent with their standard deviation values, specifically, in the order of C1 > C5 > C3 > C6 > C2 > C4 > C7. This implies that C1 ranks first while C7 ranks last. Furthermore, in this scenario, criterion C1 is found to rank first when weights are calculated using the LOPCOW-SD method and second when using the LOPCOW method, whereas criterion C7 consistently ranks last in all cases. Thus, this scenario also confirms that C1 is the most important criterion, while C7 is the least important.

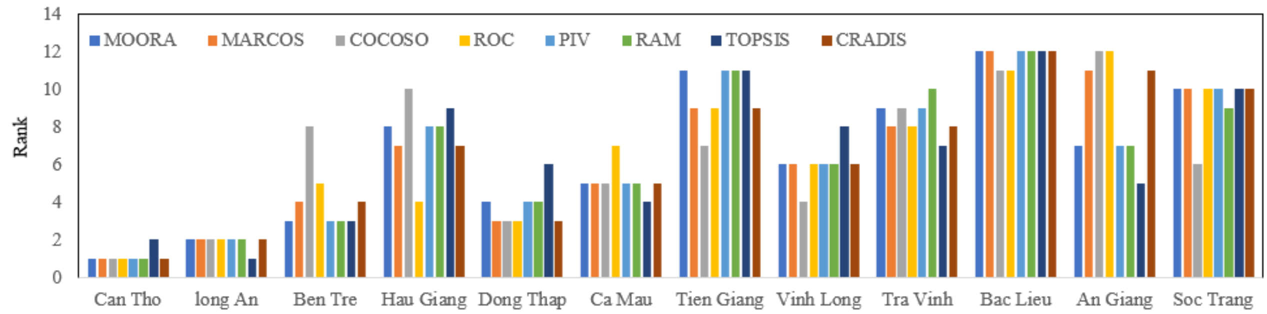

Fig. 7. Provincial rankings in scenario S3 using the LOPCOW method for criteria weighting

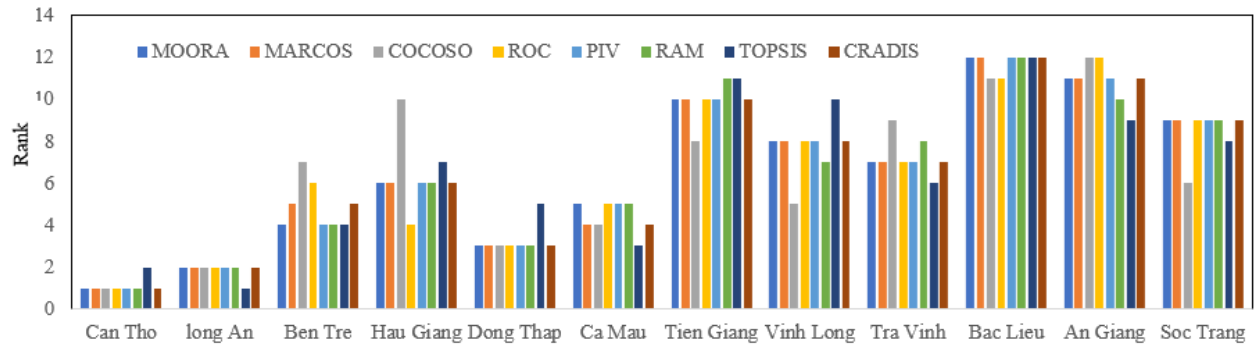

Fig. 8. Provincial rankings in scenario S3 using the SD method for criteria weighting

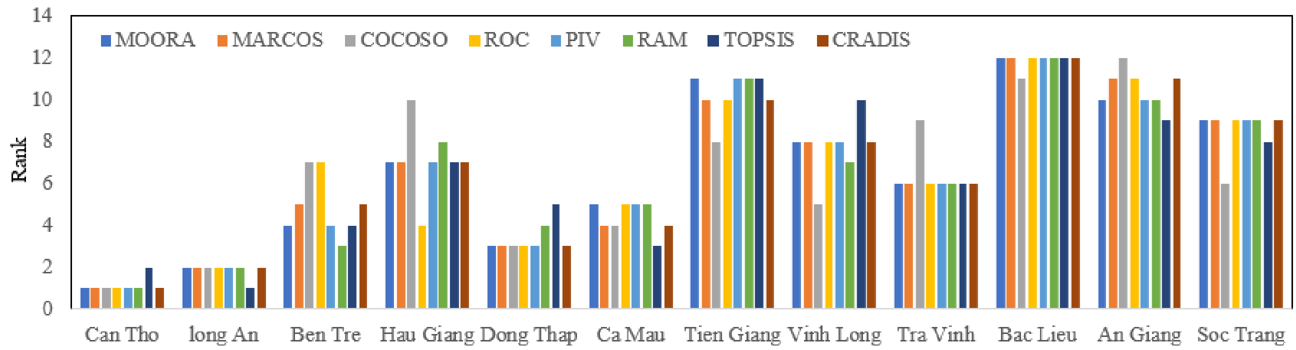

Fig. 9. Provincial rankings in scenario S3 using the LOPCOW-SD method for criteria weighting

According to the data in Table 14, it is observed that in scenario S3, based on the average Spearman coefficient values, the SD method is evaluated higher than the LOPCOW-SD method, with the LOPCOW method ranking last. This ranking is also consistent when comparing these three methods based on the average WSPE coefficient values. In summary, this scenario further confirms that both LOPCOW-SD and SD methods are more effective than the LOPCOW method in ensuring the stability of the ranking of alternatives when they are ranked using different methods.

Table14
Average values of the coefficients in scenario S3

Weight method	Spearman	WSPE
LOPCOW	0.8444	0.6993
SD	0.9208	0.8311
LOPCOW-SD	0.9131	0.8168

Based on the results obtained in Section 4 and the sensitivity analysis in Section 5, this study has achieved the following objectives. First, among the seven criteria used by the Vietnamese Ministry of Science and Technology to assess innovation performance, Institutions (C1) was identified as the most critical parameter. This finding provides important orientations for both local and central governments in improving the ranking of innovation efforts. Next, this study determined that among the 13 surveyed provinces in Vietnam, Can Tho and Long An are the top performers in innovation efficiency. Conversely, provinces such as Tien Giang, Bac Lieu, An Giang, Soc Trang, and Kien Giang were identified as having poor innovation indices. Leading provinces must continue to invest heavily in Science, Technology, and digital infrastructure while serving as role models for sharing experiences. Meanwhile, the Government should pilot breakthrough policies to replicate the innovation models of these provinces in other regions. Citizens in these localities need to proactively enhance their digital and entrepreneurial skills to maintain their position. In contrast, underperforming provinces should prioritize administrative reform and focus on resolving fundamental bottlenecks, such as Institutions (C1). For these provinces, the government needs specific support programs, while citizens must proactively improve their expertise and actively contribute to building business-friendly governance to collectively drive change. Finally, this research demonstrates that in determining criteria weights, the SD and LOPCOW-SD methods are more effective than the LOPCOW method. This offers a significant orientation for policymakers in criteria weighting when evaluating innovation indices.

6. Conclusions

The evaluation of innovation performance among localities plays a fundamental role, providing an objective data foundation for the government to allocate resources and develop appropriate socio-economic development policies aligned with each province's potential. Furthermore, assessment helps localities identify their strengths and weaknesses, thereby promoting improvements in the investment environment, enhancing productivity, and ultimately yielding practical benefits that improve the quality of life for local residents. This study evaluated the innovation efforts of 13 provinces in Vietnam, employing three methods for criteria weighting: LOPCOW, SD (Standard Deviation), and LOPCOW-SD, the latter being a combination of the first two. The following conclusions were drawn:

1. Among the seven parameters used to assess provincial innovation performance, Institutions (C1) was confirmed to be the most important parameter, while Impact on Production-Business and Society (C7) was determined to be the least important.

2. Among the 13 provinces surveyed, Can Tho and Long An were identified as the two provinces with the highest innovation performance. Conversely, provinces with poor rankings included Tien Giang, Bac Lieu, An Giang, Soc Trang, and Kien Giang. This finding holds significant implications for the government, local authorities, and residents in terms of the appropriate actions that need to be implemented.

3. Using the SD method and the LOPCOW-SD method to calculate criteria weights ensures a higher stability in the provincial rankings compared to the LOPCOW method, when the provinces are ranked by different MCDM methods.

4. This study only evaluated the innovation performance of 13 provinces within a single economic region of Vietnam using seven specific criteria. Therefore, expanding the survey scale to include more provinces and considering a broader set of criteria to characterize innovation efficiency will be one of the key research directions in the near future. The determination of C1 as the most important criterion and C7 as the least important is only confirmed to be valid within the context of the current problem; it cannot represent all innovation assessment problems when applied to different contexts, such as varying survey scales, different target subjects, or alternative weighting methods, etc. This implies that, in the future, mathematical methods must be selected, and specific studies must be conducted for each particular case. Furthermore, incorporating expert opinions on the importance of criteria to rank provincial innovation performance in a way that aligns with the practical situation of each locality is also a task that needs to be implemented soon.

Funding
Funded by the EU NextGenerationEU through the Recovery and Resilience Plan for Slovakia under the project Smart Transformation and Innovation Consortium Slovakia (STICS) No. 09102-03-V01-00011.

Conflicts of Interest
The authors declare no conflicts of interest.

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