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Decision Making Methodology to Assess Big Data Professional Education in Vocational and Technical Colleges: Forest HyperSoft Set Approach and Implementation

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Abstract: The rapid advancement of big data technologies has transformed industries, necessitating the development of specialized educational programs to equip students with relevant skills. Vocational and technical colleges play a crucial role in bridging the skill gap by offering big data professional education tailored to industry demands. However, assessing the quality and effectiveness of such programs remains a challenge due to the evolving nature of big data, the need for practical training, and alignment with industry requirements. This study proposes a comprehensive evaluation framework incorporating multiple criteria such as curriculum relevance, faculty expertise, infrastructure, industry collaboration, and student outcomes. By employing a Multi-Criteria Decision-Making (MCDM) approach, this research provides an in-depth analysis of big data education quality, ensuring that vocational institutions produce industry-ready graduates. We use two MCDM methods such as CRITIC method to compute the criteria weights and the VIKOR method to rank the alternatives. These methods are used with the Forest HyperSoft set to deal with criteria, sub criteria and sub-sub-criteria. We use five criteria and six alternatives in this study. These criteria are divided into Trees. Then we compute the criteria weights and rank the alternatives under each criterion. Then we obtain the rank of each criterion and combine these ranks into a final rank.

Keywords: Decision Making; Forest HyperSoft Set; Big Data; Education; Technical Colleges.

1. Introduction

In the era of digital transformation, big data has emerged as a critical component across various industries, influencing decision-making, automation, and business intelligence. As organizations increasingly rely on data-driven strategies, there is a growing demand for professionals equipped with big data skills, including data analytics, machine learning, and cloud computing. Vocational and technical colleges have recognized this trend and are offering specialized programs in big data to prepare students for industry-specific roles[1], [2]. However, the quality of these programs varies significantly, raising concerns about their effectiveness in meeting industry expectations. A systematic evaluation framework is necessary to assess whether these educational programs equip students with the competencies required in the evolving technological landscape.

Evaluating the quality of big data professional education in vocational and technical colleges involves multiple dimensions. A well-structured curriculum that aligns with industry standards, faculty expertise in both theoretical and practical applications, access to modern technological infrastructure, and strong industry collaborations are essential factors that determine the success of these programs. Additionally, student learning outcomes, employability rates, and exposure to real-world big data projects are crucial indicators of program effectiveness[3], [4]. Traditional educational evaluation methods may not be sufficient to capture the complexities of big data education, necessitating the use of advanced evaluation methodologies such as Multi-Criteria Decision-Making (MCDM) approaches.

A robust evaluation framework should consider not only the academic aspects of big data education but also the practical training opportunities and industry involvement. Many vocational colleges struggle with outdated curricula, limited faculty expertise in emerging technologies, and inadequate access to real-world datasets, which hinder the effectiveness of their programs. Furthermore, the lack of industry certifications, limited internship opportunities, and weak industry-academic partnerships can affect students' readiness for the job market[5], [6]. Therefore, a systematic assessment that integrates qualitative and quantitative criteria is essential to ensure the continuous improvement of big data professional education.

This study proposes a comprehensive evaluation framework that incorporates key criteria such as curriculum relevance, faculty competency, infrastructure support, industry linkages, and student performance outcomes. By employing MCDM techniques, the study aims to rank and compare different educational programs, identifying best practices and areas for improvement. The findings will provide valuable insights for policymakers, educators, and industry stakeholders in refining big data curricula, enhancing teaching methodologies, and strengthening industry-academic collaborations[7], [8].

Ultimately, improving the quality of big data professional education in vocational and technical colleges is crucial for producing a highly skilled workforce capable of driving digital innovation. As the demand for data professionals continues to rise, vocational institutions must adopt evidence-based strategies to enhance their educational offerings.[9], [10] This research contributes to the ongoing discourse on higher education quality assessment, offering practical recommendations to optimize big data training programs and ensure that graduates meet the evolving needs of the industry

The main contributions of this study are organized as follows:

We propose a MCDM approach by using two methods, such as CRITIC method to compute the criteria weights and the VIKOR method to rank the alternatives.

The decision matrix is created by opinions of three experts and decision makers who have experience in the related field.

We employ the Forest HyperSoft set to divide the criteria as levels and each criterion present as TreeSoft set. Then we compute the criteria weights and ranking the alternatives in each criterion.

Finally, we combined the rank of the alternatives as a final rank. We show the rank of alternative stable under different criteria.

The rest of this study is organized as follows: Section 2 shows the steps of the CRITIC methodology to compute the criteria weights and the VIKORB methodology to rank the alternatives. Also, this section shows the ideal of the Forest HyperSoft to divide each criterion as Tree. Section 3 shows the results of the proposed approach. Section 5 shows the conclusions of this study.

2. Forest HyperSoft Set with CRITIC and VIKOR Methods

This section shows the steps of the CRITIC method to compute the criteria weights and the VIKOR method to rank the alternatives. We use the Forest HyperSoft set to classify the different criteria into different TreeSoft. Ans in each TreeSoft we rank the alternatives and compute the criteria weights. Finally, we combined the rank of the alternatives to select the best one.

Forest HyperSoft Set

Let U be a universe of discourse and H non-empty set of U, and A be a set of criteria, each of this criterion has different levels.

Level 1 refers to the sub criteria values

Level 2 refers to the sub-sub-criteria values.

Level 3 refers to the sub-sub-sub-criteria values.

Each of the criteria refers to the TreeSoft set and all these TreeSoft set can be combined to obtain the Forest HyperSoft Set[11], [12].

Fig 1 shows the example of the Forest HyperSoft set with different TreeSoft set by different level with values.

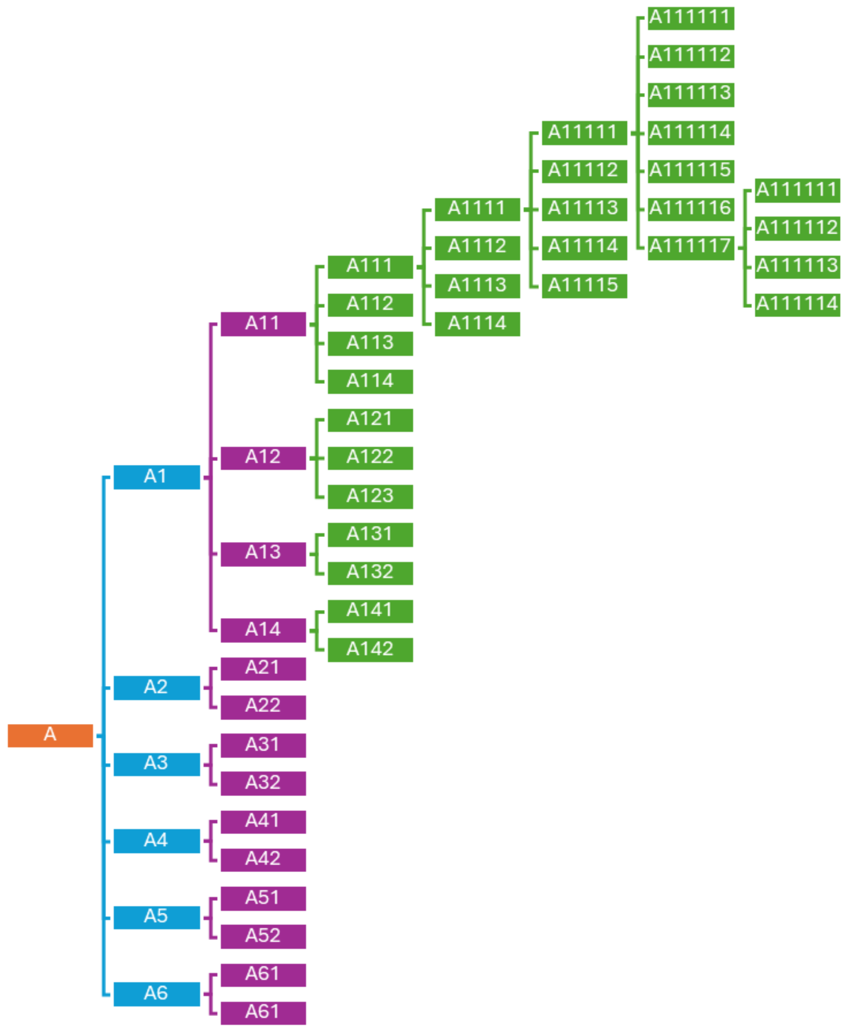

Fig 1. Example of Forest HyperSoft.

CRITIC Method

This part shows the steps of the CRITIC method to compute the criteria weights[13], [14].

Create the decision matrix.

$$F = \begin{bmatrix} f_{11} & \cdots & f_{1n} \\ \vdots & \ddots & \vdots \\ f_{m1} & \cdots & f_{mn} \end{bmatrix}; i = 1, \dots, m; j = 1, \dots, n \tag{1}$$

Normalize the decision matrix.

We can normalize the decision matrix for positive and negative criteria such as:

$$x_{ij} = \frac{f_{ij} - \min_i f_{ij}}{\max_i f_{ij} - \min_i f_{ij}} \tag{2}$$

$$x_{ij} = \frac{f_{ij} - \max_i f_{ij}}{\min_i f_{ij} - \max_i f_{ij}} \tag{3}$$

Compute the correlation coefficient μ_{jk}

Compute the standard deviation σ_j

Compute the C index

$$C_j = \sigma_j \sum_{k=1}^{n} \left(1 - \mu_{jk}\right) \tag{4}$$

Compute the criteria weights.

$$w_j = \frac{C_j}{\sum_{j=1}^{n} C_j} \tag{5}$$

VIKOR Method

The VIKOR Method is used to rank the alternatives[15], [16].

Normalize the decision matrix.

The decision matrix is normalized for positive and negative criteria such as:

$$y_{ij} = \frac{\max_i f_{ij} - f_{ij}}{\max_i f_{ij} - \min_i f_{ij}} \tag{6}$$

$$y_{ij} = \frac{\min_i f_{ij} - f_{ij}}{\min_i f_{ij} - \max_i f_{ij}} \tag{7}$$

Compute the weighted decision matrix.

$$d_{ij} = w_j y_{ij} \tag{8}$$

Compute the S and R indexes

$$S_i = \sum_{j=1}^{n} d_{ij} \tag{9}$$

$$R_i = \max_j d_{ij} \tag{10}$$

Compute the VIKOR index

$$G_i = \theta \times \left(\frac{S_i - \min_i S_i}{\max_i S_i - \min_i S_i}\right) + (1 - \theta) * \left(\frac{R_i - \min_i R_i}{\max_i R_i - \min_i R_i}\right) \tag{11}$$

Where θ value between 0 and 1. In this study we used the θ value with 0.5.

3. Results and Discussion

This section shows the implementation of the proposed approach. We display the results of the criteria weights and ranking the alternatives. This study uses the Forest HyperSoft set to deal with criteria and sub criteria. We divide the case study into five TreeSoft sets to deal with criteria and sub criteria with six alternatives as shown in Fig 2.

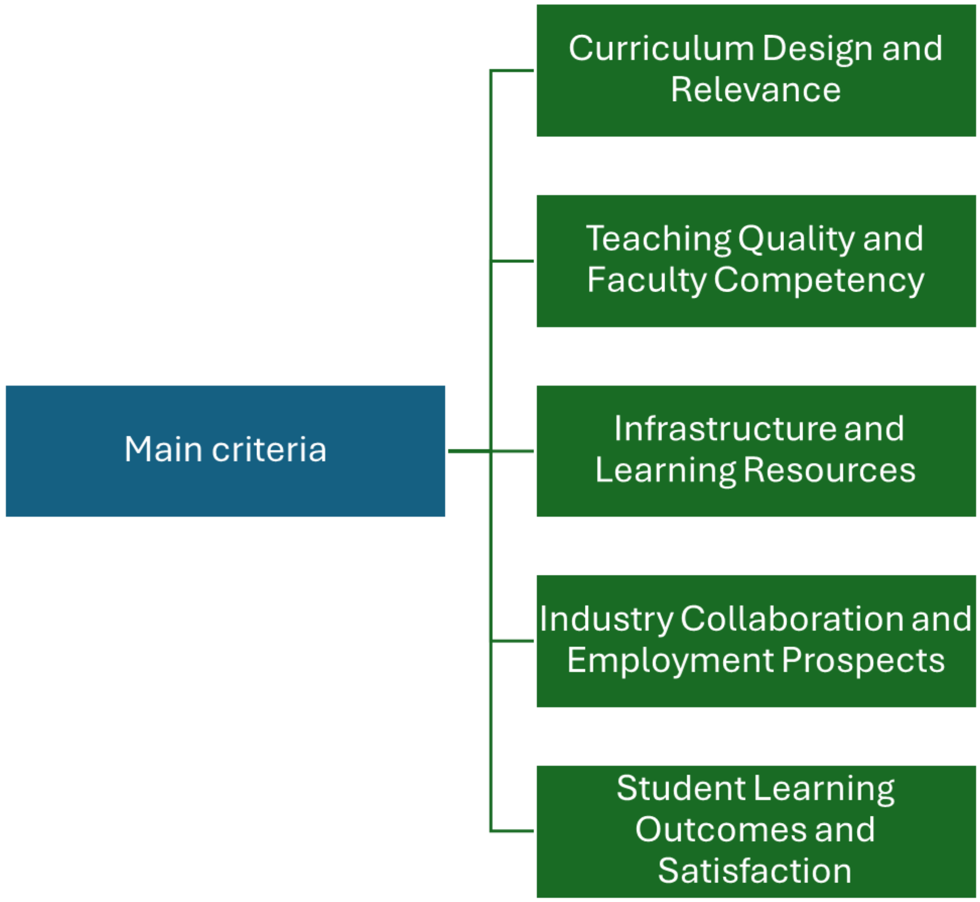

Fig 2. The main criteria.

Curriculum Design and Relevance

We use the first criterion. We divide the first criterion into TreeSoft set with criteria and sub criteria as shown in Fig 3.

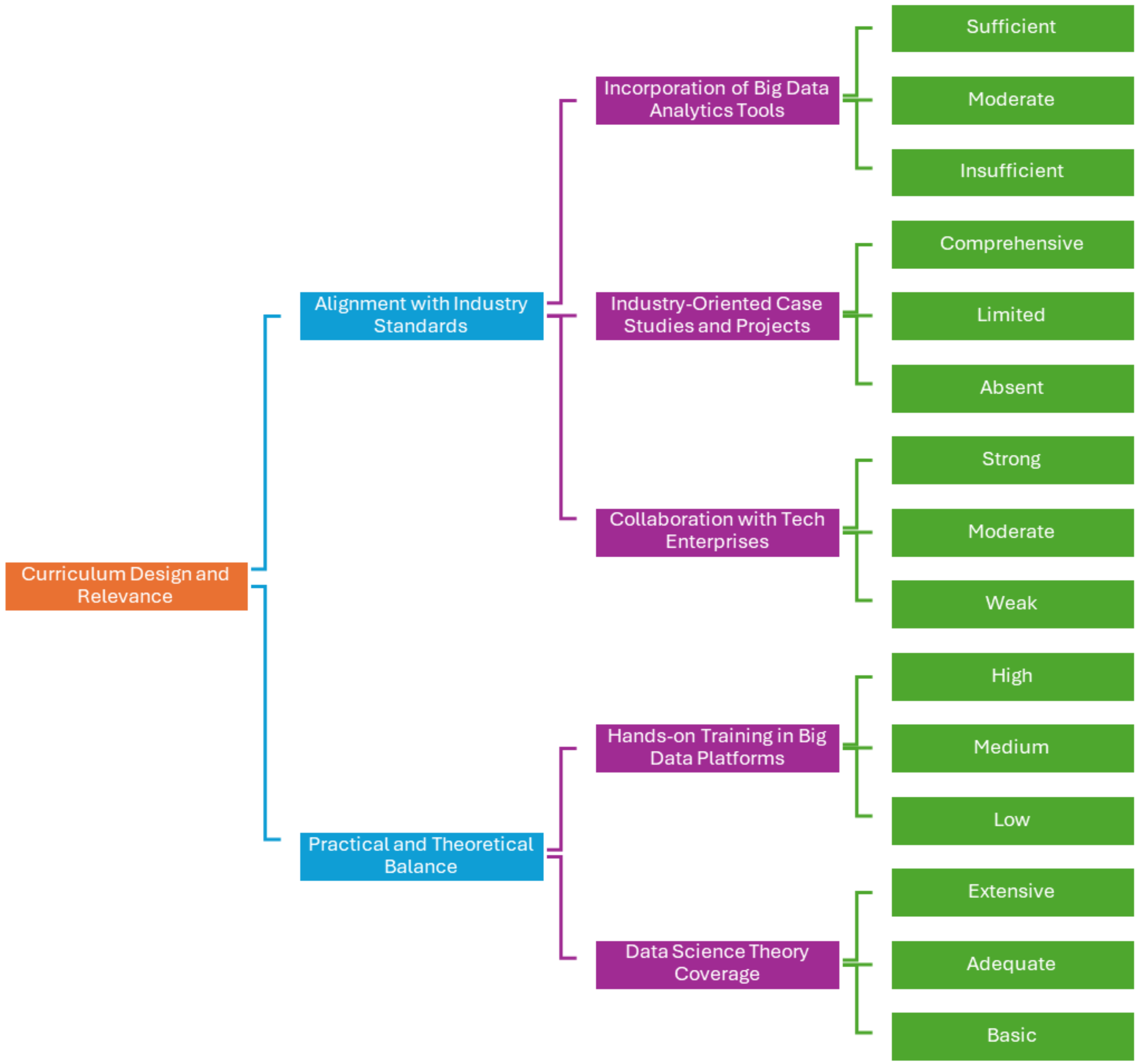

Fig 3. The sub criteria of first criterion.

This criterion has two sub criteria and each sub criteria has three and two sub criteria. Then we select the best values in this criterion as: $A_{1111} \times A_{1121} \times A_{1131} \times A_{1211} \times A_{1221}$. Then we apply the CRITIC and VIKOR method in these values.

In the CRITIC Method, we built the decision matrix between the criteria and alternatives using scale between 0.1 to 0.9. Then we combine these values into a single matrix.

Eq. (2) is used to normalize the decision matrix as shown in Table 1.

Then we compute the correlation coefficient μ_{jk}

Then we compute the standard deviation σ_j

Then we compute the C index using Eq. (4).

Then we compute the criteria weights using Eq. (5) as shown in Table 2.

Table 1. Normalized decision matrix by CRITIC Method.

	A_{1111}	A_{1121}	A_{1131}	A_{1211}	A_{1221}
R_1	-0.64552	0	-0.41557	-1	-0.73879
R_2	-0.39687	-0.58297	-0.89855	-0.83666	-1
R_3	0	-0.49227	-1	-0.6022	-0.91322
R_4	-0.91058	-0.53765	0	0	-0.25005
R_5	-1	-1	-0.4413	0	0
R_6	-0.95536	-0.91023	-0.96618	-0.51135	-0.45661

Table 2. The criteria weights.

	A_{1111}	A_{1121}	A_{1131}	A_{1211}	A_{1221}
Criteria	0.263924	0.197501	0.156383	0.194405	0.187787

In the VIKOR Method, we start with the combined decision matrix between the criteria and alternatives.

We normalize the decision matrix using Eq. (6) as shown in Table 3.

Then we compute the weighted decision matrix using Eq. (8) as shown in Table 4.

Then we compute the S and R indexes using Eqs. (9 and 10).

Then we compute the VIKOR index using Eq. (11). We use the value of θ with 0.5

Table 3. Normalized decision matrix by VIKOR Method.

	A_{1111}	A_{1121}	A_{1131}	A_{1211}	A_{1221}
R_1	0.354484	1	0.584427	0	0.261214
R_2	0.603126	0.417025	0.10145	0.163344	0
R_3	1	0.507733	0	0.397795	0.086778
R_4	0.089416	0.462345	1	1	0.749951
R_5	0	0	0.558702	1	1
R_6	0.044642	0.089766	0.033817	0.488654	0.543389

Table 4. Weighted normalized decision matrix by VIKOR Method.

	A_{1111}	A_{1121}	A_{1131}	A_{1211}	A_{1221}
R_1	0.093557	0.197501	0.091395	0	0.049053
R_2	0.159179	0.082363	0.015865	0.031755	0

R_3	0.263924	0.100278	0	0.077334	0.016296
R_4	0.023599	0.091313	0.156383	0.194405	0.140831
R_5	0	0	0.087372	0.194405	0.187787
R_6	0.011782	0.017729	0.005288	0.094997	0.102042

Teaching Quality and Faculty Competency

We divide this criterion into TreeSoft set with criteria and sub criteria as shown in Fig 4.

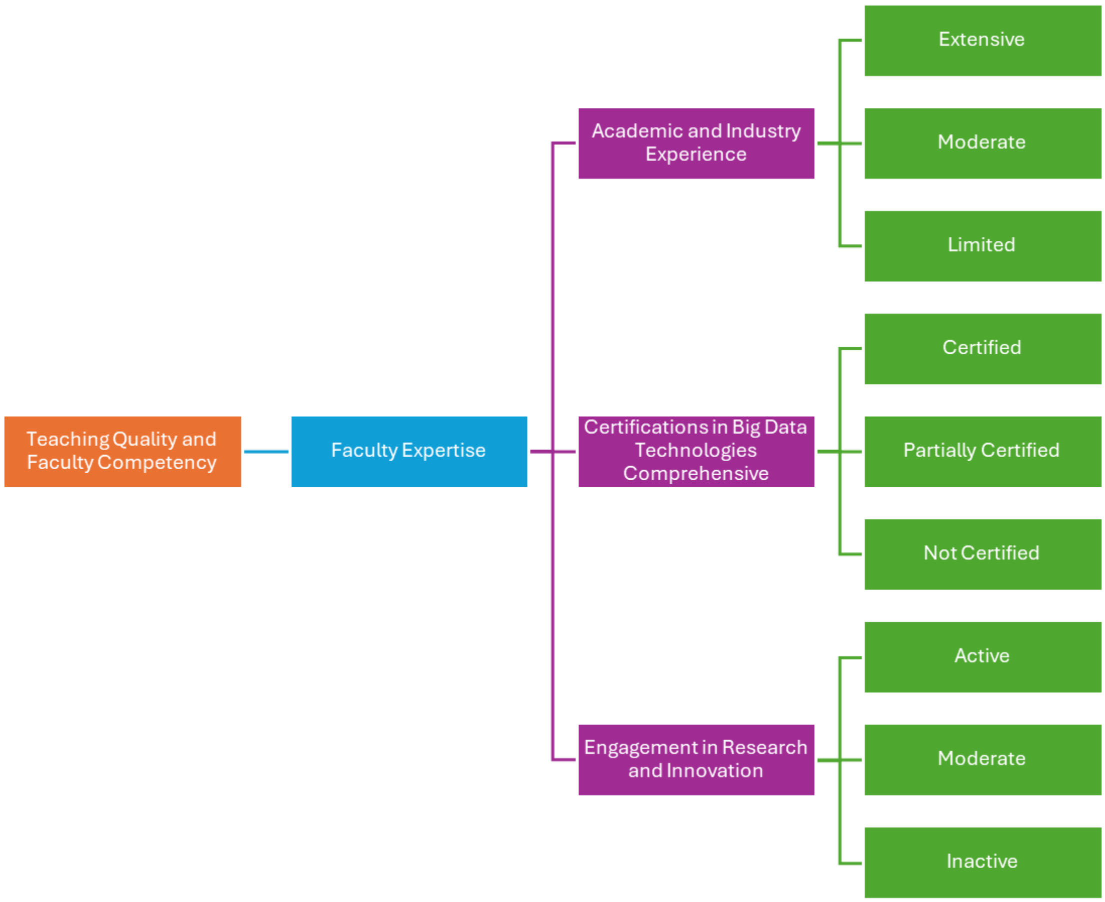

Fig 4. The sub criteria of second criterion.

This criterion has one sub criterion and each sub criteria has three sub criteria. Then we select the best values in this criterion as: $A_{2111} \times A_{2121} \times A_{2131}$. Then we apply the CRITIC and VIKOR method in these values.

In the CRITIC Method, we built the decision matrix between the criteria and alternatives using scale between 0.1 to 0.9. Then we combine these values into a single matrix.

Eq. (2) is used to normalize the decision matrix as shown in Table 5.

Then we compute the correlation coefficient μ_{jk}

Then we compute the standard deviation σ_j

Then we compute the C index using Eq. (4).

Then we compute the criteria weights using Eq. (5) as shown in Table 6.

Table 5. Normalized decision matrix by CRITIC Method.

	A_{2111}	A_{2121}	A_{2131}
R_1	0	0	-0.75015
R_2	-1	-0.95434	-0.78936
R_3	-0.63648	-0.77229	-0.84184
R_4	-0.22736	-0.63653	0
R_5	-0.54713	-1	-0.38242
R_6	-0.47823	-0.86332	-1

Table 6. The criteria weights.

	A_{2111}	A_{2121}	A_{2131}
Criteria	0.220868	0.322615	0.456517

In the VIKOR Method, we start with the combined decision matrix between the criteria and alternatives.

We normalize the decision matrix using Eq. (6) as shown in Table 7.

Then we compute the weighted decision matrix using Eq. (8) as shown in Table 8.

Then we compute the S and R indexes using Eqs. (9 and 10).

Then we compute the VIKOR index using Eq. (11). We use the value of θ with 0.5

Table 7. Normalized decision matrix by VIKOR Method.

	A_{2111}	A_{2121}	A_{2131}
R_1	1	1	0.249852
R_2	0	0.0457	0.210639
R_3	0.3635	0.2277	0.158157
R_4	0.7726	0.3635	1
R_5	0.4529	0	0.617581
R_6	0.5218	0.1367	0

Table 8. Weighted normalized decision matrix by VIKOR Method.

	A_{2111}	A_{2121}	A_{2131}

R_1	0.2209	0.3226	0.114062
R_2	0	0.0147	0.09616
R_3	0.0803	0.0735	0.072201
R_4	0.1707	0.1173	0.456517
R_5	0.1	0	0.281936
R_6	0.1152	0.0441	0

Infrastructure and Learning Resources

We divide this criterion into TreeSoft set with criteria and sub criteria as shown in Fig 5.

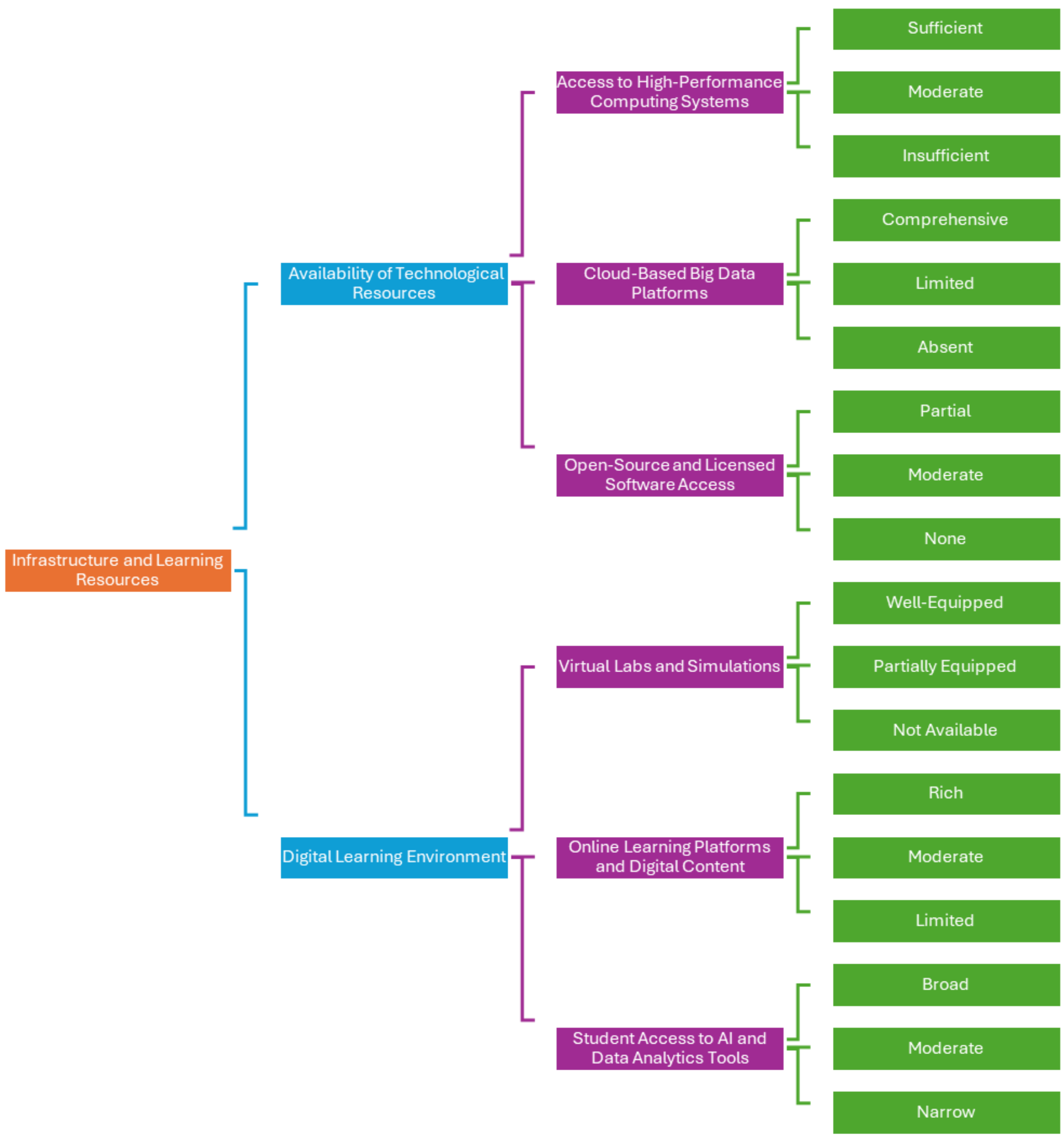

Fig 5. The sub criteria of third criterion.

This criterion has two sub criteria and each sub criteria has three and two sub criteria. Then we select the best values in this criterion as: $A_{3111} \times A_{3121} \times A_{3131} \times A_{3211} \times A_{3221} \times A_{3231}$. Then we apply the CRITIC and VIKOR method in these values.

In the CRITIC Method, we built the decision matrix between the criteria and alternatives using scale between 0.1 to 0.9. Then we combine these values into a single matrix.

Eq. (2) is used to normalize the decision matrix as shown in Table 9.

Then we compute the correlation coefficient μ_{jk}

Then we compute the standard deviation σ_j

Then we compute the C index using Eq. (4).

Then we compute the criteria weights using Eq. (5) as shown in Table 10.

Table 9. Normalized decision matrix by CRITIC Method.

	A_{3111}	A_{3121}	A_{3131}	A_{3211}	A_{3221}	A_{3231}
R_1	0	-1	0	0	-0.18494	-1
R_2	-0.28175	0	-0.09972	-0.26309	0	-0.34886
R_3	-0.68096	-0.74358	-0.42709	-0.52617	-0.45426	0
R_4	-0.62025	-0.6515	-0.37731	-0.7279	-0.39801	-0.53556
R_5	-0.62007	-0.60533	-1	-0.69722	-0.42614	-0.39396
R_6	-1	-0.97077	-1	-1	-1	-0.60625

Table 10. The criteria weights.

	A_{3111}	A_{3121}	A_{3131}	A_{3211}	A_{3221}	A_{3231}
Criteria	0.137941	0.181304	0.163361	0.134714	0.099207	0.283472

In the VIKOR Method, we start with the combined decision matrix between the criteria and alternatives.

We normalize the decision matrix using Eq. (6) as shown in Table 11.

Then we compute the weighted decision matrix using Eq. (8) as shown in Table 12.

Then we compute the S and R indexes using Eqs. (9 and 10).

Then we compute the VIKOR index using Eq. (11). We use the value of θ with 0.5

Table 11. Normalized decision matrix by VIKOR Method.

	A_{3111}	A_{3121}	A_{3131}	A_{3211}	A_{3221}	A_{3231}
R_1	1	0	1	1	0.815056	0

R_2	0.718249	1	0.900281	0.736914	1	0.651143
R_3	0.319042	0.256421	0.572906	0.473828	0.545735	1
R_4	0.379751	0.348497	0.622692	0.272098	0.601986	0.464443
R_5	0.379932	0.394672	0	0.302777	0.573861	0.606042
R_6	0	0.029235	0	0	0	0.393749

Table 12. Weighted normalized decision matrix by VIKOR Method.

	A_{3111}	A_{3121}	A_{3131}	A_{3211}	A_{3221}	A_{3231}
R_1	0.137941	0	0.163361	0.134714	0.080859	0
R_2	0.099076	0.181304	0.147071	0.099272	0.099207	0.184581
R_3	0.044009	0.04649	0.093591	0.063831	0.054141	0.283472
R_4	0.052383	0.063184	0.101724	0.036655	0.059721	0.131657
R_5	0.052408	0.071556	0	0.040788	0.056931	0.171796
R_6	0	0.0053	0	0	0	0.111617

Industry Collaboration and Employment Prospects

We divide this criterion into TreeSoft set with criteria and sub criteria as shown in Fig 6.

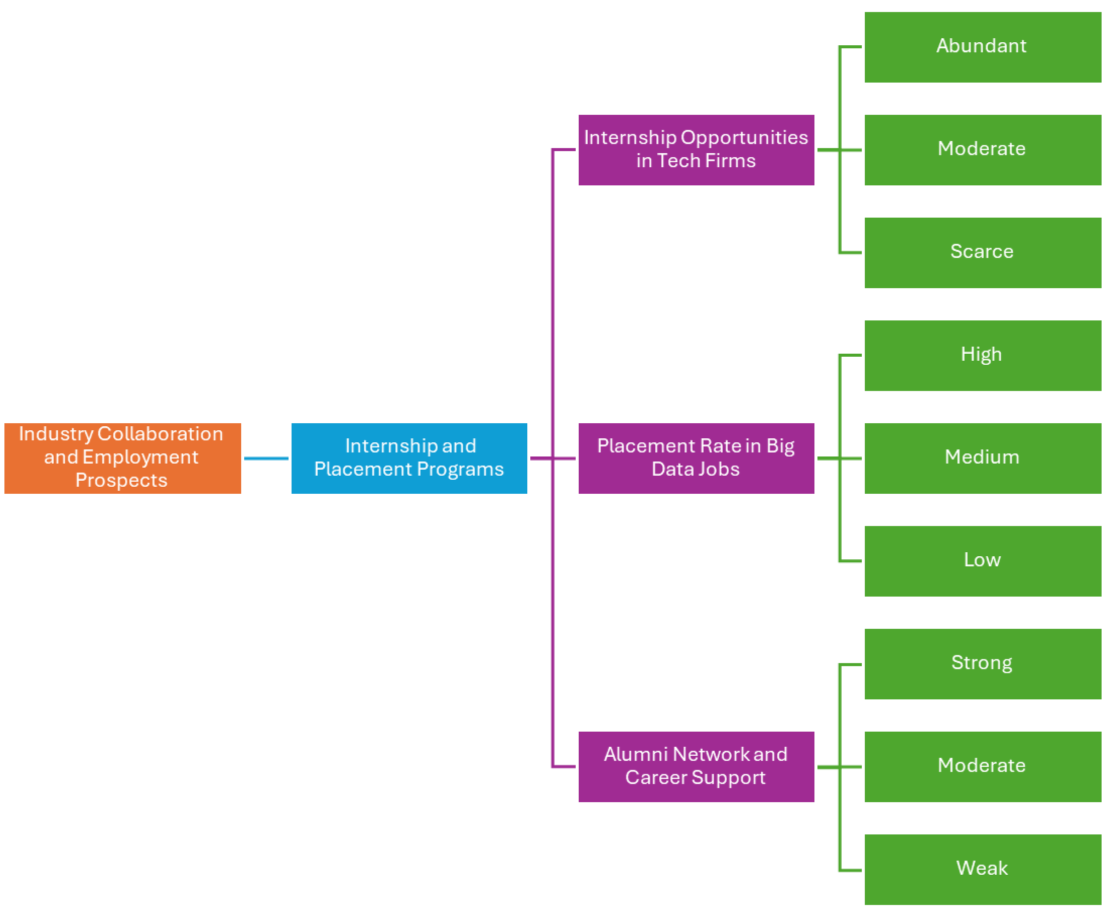

Fig 6. The sub criteria of the fourth criterion.

This criterion has two sub criteria and each sub criteria has three and two sub criteria. Then we select the best values in this criterion as: $A_{4111} \times A_{4121} \times A_{4131}$. Then we apply the CRITIC and VIKOR method in these values.

In the CRITIC Method, we built the decision matrix between the criteria and alternatives using scale between 0.1 to 0.9. Then we combine these values into a single matrix.

Eq. (2) is used to normalize the decision matrix as shown in Table 13.

Then we compute the correlation coefficient μ_{jk}

Then we compute the standard deviation σ_j

Then we compute the C index using Eq. (4).

Then we compute the criteria weights using Eq. (5) as shown in Table 14.

Table 13. Normalized decision matrix by CRITIC Method.

	A_{4111}	A_{4121}	A_{4131}
R_1	-1	0	-0.83337
R_2	0	-0.80409	-0.19333
R_3	-0.00014	-0.56571	-0.63175
R_4	-0.52992	-0.37719	0
R_5	-0.97077	-0.9101	-0.45674
R_6	-0.92473	-1	-1

Table 14. The criteria weights.

	A_{4111}	A_{4121}	A_{4131}
Criteria	0.364783	0.36631	0.268908

In the VIKOR Method, we start with the combined decision matrix between the criteria and alternatives.

We normalize the decision matrix using Eq. (6) as shown in Table 15.

Then we compute the weighted decision matrix using Eq. (8) as shown in Table 16.

Then we compute the S and R indexes using Eqs. (9 and 10).

Then we compute the VIKOR index using Eq. (11). We use the value of θ with 0.5

Table 15. Normalized decision matrix by VIKOR Method.

	A_{4111}	A_{4121}	A_{4131}
R_1	0	1	0.166627
R_2	1	0.195908	0.806668
R_3	0.999863	0.434291	0.368255
R_4	0.470082	0.622812	1
R_5	0.029235	0.089902	0.543257
R_6	0.075273	0	0

Table 16. Weighted normalized decision matrix by VIKOR Method.

	A_{4111}	A_{4121}	A_{4131}
R_1	0	0.36631	0.044807
R_2	0.364783	0.071763	0.216919
R_3	0.364733	0.159085	0.099026
R_4	0.171478	0.228142	0.268908
R_5	0.010664	0.032932	0.146086
R_6	0.027458	0	0

Student Learning Outcomes and Satisfaction

We divide this criterion into TreeSoft set with criteria and sub criteria as shown in Fig 7.

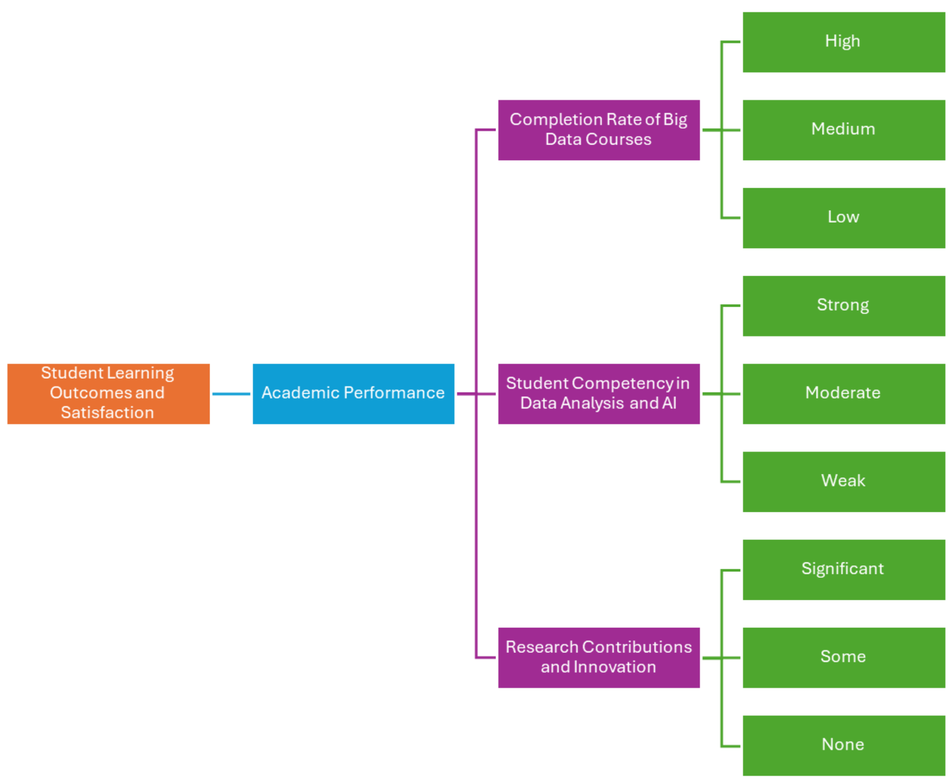

Fig 7. The sub criteria of the fifth criterion.

This criterion has two sub criteria and each sub criteria has three and two sub criteria. Then we select the best values in this criterion as: $A_{5111} \times A_{5121} \times A_{5131}$. Then we apply the CRITIC and VIKOR method in these values.

In the CRITIC Method, we built the decision matrix between the criteria and alternatives using scale between 0.1 to 0.9. Then we combine these values into a single matrix.

Eq. (2) is used to normalize the decision matrix as shown in Table 17.

Then we compute the correlation coefficient μ_{jk}

Then we compute the standard deviation σ_j

Then we compute the C index using Eq. (4).

Then we compute the criteria weights using Eq. (5) as shown in Table 18.

Table 17. Normalized decision matrix by CRITIC Method.

	A_{5111}	A_{5121}	A_{5131}
R_1	-0.52278	0	-0.28758
R_2	-0.69336	-0.5001	-1
R_3	-1	-0.91322	-0.57494
R_4	0	-1	-0.47506
R_5	-0.43166	0	-0.86229
R_6	-0.69305	-0.8839	0

Table 18. The criteria weights.

	A_{5111}	A_{5121}	A_{5131}
Criteria	0.256628	0.410091	0.33328

In the VIKOR Method, we start with the combined decision matrix between the criteria and alternatives.

We normalize the decision matrix using Eq. (6) as shown in Table 19.

Then we compute the weighted decision matrix using Eq. (8) as shown in Table 20.

Then we compute the S and R indexes using Eqs. (9 and 10).

Then we compute the VIKOR index using Eq. (11). We use the value of θ with 0.5

Table 19. Normalized decision matrix by VIKOR Method.

	A_{5111}	A_{5121}	A_{5131}
R_1	0.477219	1	0.71242

R_2	0.306645	0.499902	0
R_3	0	0.086778	0.425065
R_4	1	0	0.524941
R_5	0.568342	1	0.13771
R_6	0.306952	0.116095	1

Table 20. Weighted normalized decision matrix by VIKOR Method.

	A_{5111}	A_{5121}	A_{5131}
R_1	0.122468	0.410091	0.237435
R_2	0.078694	0.205005	0
R_3	0	0.035587	0.141666
R_4	0.256628	0	0.174952
R_5	0.145853	0.410091	0.045896
R_6	0.078773	0.04761	0.33328

In the final, we obtain the ranks of the alternative in each criterion as shown in Table 21. Then we combine these ranks into final ranks.

Table 21. Ranks of alternatives.

	A_1	A_2	A_3	A_4	A_5	Final Rank
R_1	4	2	3	4	1	4
R_2	5	5	1	2	5	5
R_3	3	4	2	3	6	3
R_4	1	1	4	1	4	1
R_5	2	3	5	5	2	2
R_6	6	6	6	6	3	6

5. Conclusions

The evaluation of big data professional education in vocational and technical colleges is a critical step in ensuring that graduates possess the necessary skills to thrive in a data-driven economy. This study highlights the importance of a multi-dimensional assessment framework that considers curriculum relevance, faculty expertise, technological infrastructure, industry collaborations, and student outcomes. By leveraging MCDM methodologies, the research provides a structured approach to ranking and improving educational programs, allowing institutions to align their training with industry requirements.

This study used two MCDM methods such as CRITIC method to compute the criteria weights and the VIKOR method to rank the alternatives. We used the Forest HyperSoft set to divide each criterion as a Tree, then in each tree we compute the criteria weights and ranking the alternatives.

Then we combined these ranks into a final rank. The results show alternative 6 is the best and alternative 4 is the worst.

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