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Integration of Hierarchical Clustering and Fuzzy-TOPSIS in Oil and Gas Industry for Supplier Sustainability Performance Evaluation

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ABSTRACT

This study evaluates the implementation of seven sustainability criteria using Request for Information (RFI) data, classifies contractors through Hierarchical Clustering, and identifies dominant clusters and criteria using the Fuzzy-TOPSIS method. A descriptive quantitative approach was applied, with 24 of 59 contractors providing complete responses. Hierarchical Clustering grouped contractors based on sustainability performance similarity, while Fuzzy-TOPSIS provided a comprehensive evaluation. Results show that Cluster 4 (37.5% of contractors) achieved the highest Closeness Coefficient Index (CCi), indicating the best sustainability performance, whereas Cluster 1 (8.3%) had the lowest CCi. Waste Management is the dominant criterion in Cluster 4, while Procedure & Policies is most significant in Cluster 1. These findings suggest that the integrated approach can support the company in identifying and prioritizing contractors for strategic engagement based on sustainability readiness.

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INTRODUCTION

Indonesia is committed to contributing to sustainability. With increasingly stringent government regulations and growing public awareness of environmental issues, companies that want to survive in the world market cannot simply ignore them [1]. In the energy market, the oil and gas sector is an industry that plays a vital role in the global economy as the world's main fuel supplier [2]. Based on this statement, it can be said that the case company is one of the players that help Indonesia achieve its commitments. According to Atstāja and Mukem [3], in order to be more efficient and have a greater impact on their performance, oil and gas companies in developing countries should implement Sustainable Supply Chain Management (SSCM) practices which are closer to circular business than Green Supply Chain Management (GSCM) practices, especially since their implementation can be affected by certain barriers and pressures involving the use of Quality, Health, and Safety (QHS). Delivered from Carter et al [4], SSCM activities include monitoring, supporting, and integrating sustainability performance criteria into contractor selection processes. Referring to company's 2023 Sustainability Report, the company's short-term plan to fulfill responsible sourcing practices is to select priority supply chain partners as an initial engagement on climate change-related disclosures.

Currently, the case company does not have a contractor evaluation process based on sustainability criteria. Such an evaluation process often faces challenges, such as the difficulty of collecting relevant data for sustainability evaluation [5], integrating diverse sustainability criteria, and the need to produce objective and accountable results, especially in accordance with the company's short-term plan. Therefore, this study aims to analyze the sustainability performance of the case company contractors based on seven criteria, group contractors with similar characteristics according to the optimal number of clusters, and determine the order of the dominant cluster and its main criteria.

Hierarchical Clustering was chosen because the dataset is small and less complex, making it more suitable than K-Means, which is generally used for large datasets and requires predefined cluster numbers. Although Abdalla [6] reported that K-Means achieved better entropy and purity when using cosine similarity on high-dimensional datasets, the same study also found that Hierarchical Clustering outperformed K-Means when Euclidean distance was applied. Given that the present research involves a small-scale dataset with limited categorical variables, Hierarchical Clustering is considered more appropriate due to its interpretability and suitability for exploratory grouping. According to Shukla [7], when training data using this method on large-scale data, the process required to train the data will take a lot of time and result in poor algorithm performance. Similarly, according to Ran, Xi, Lu, Wang, and Lu research results [8], this method requires a lot of time and memory, especially for handling large-scale problems. The results of the application of this method are expected to provide visualization in the form of grouping contractors based on the similarity of categories that have been met in each sustainability criterion using a dendrogram.

In accordance with the research title, this research integrates the Hierarchical Clustering method with Fuzzy Technique for Order Preference by Similarity to Ideal Solution (Fuzzy-TOPSIS). The role of Fuzzy-TOPSIS is to identify the most dominant cluster and the most prominent performance criteria in each cluster. As one of the most important Multiple Criteria Decision Making (MCDM) methods, this approach provides knowledge about the distance between the positive ideal solution (PIS) and the negative ideal solution (NIS) to determine alternatives [9]. Previous studies have predominantly employed comparative methods such as AHP, TOPSIS, or fuzzy logic as stand-alone evaluation tools for supplier sustainability performance. While AHP is useful for structuring decision hierarchies, it often relies heavily on subjective judgments, and TOPSIS can be sensitive to normalization processes that affect ranking results. Similarly, fuzzy logic is effective in handling linguistic and categorical data but lacks robustness when not integrated with complementary techniques. As highlighted in recent studies [10] [11], the integration of these methods with clustering or ranking approaches is necessary to generate more reliable and comprehensive decisions. Building on this gap, the present study positions its contribution by integrating Hierarchical Clustering and Fuzzy-TOPSIS, enabling both the mapping of contractors into meaningful sustainability clusters and the prioritization of their performance in a single framework. The use of Fuzzy-TOPSIS is particularly relevant, as the dataset consists of categorical scales represented numerically, which require conversion into fuzzy numbers to better capture the uncertainty inherent in qualitative judgments.

RESEARCH METHOD

Sustainability is a holistic concept that has become one of the global issues that has received great attention, especially in industries that have significant environmental, social, and economic impacts—the triple bottom line (TBL)—and has been integrated into the corporate strategy of many organizations [12]. While existing literature often focuses on ranking methods, recent studies highlight the growing importance of grouping contractors according to their capabilities [13]. This research method, based on Figure 1. Research Methodology Flowchart, is divided into several process flows delivered as follows.

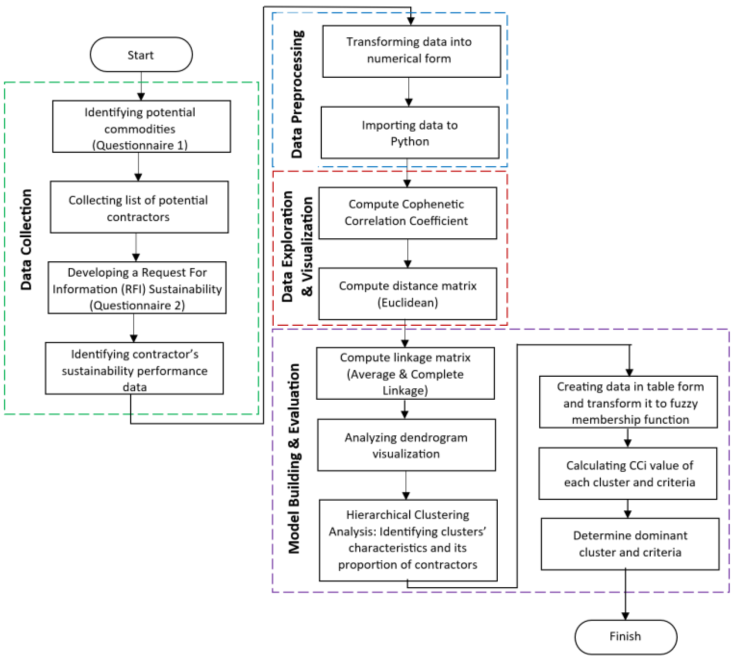

Figure 1. Research Methodology Flowchart

Data Collection

Data collection was the initial stage in conducting this research which was done by distributing questionnaire 1 and questionnaire 2. These two questionnaires were used to identify potential contractors and the sustainability performance of each contractor. Questionnaire 2, called the Sustainability RFI, was formulated using the seven sustainability criteria based on TBL. These data were collected from July 2024 to September 2024.

Data Preprocessing

The collected data was transformed into numerical format to simplify the processing stage with Hierarchical Clustering. Once converted, the data was imported into Google Colab Python to start data processing. The Hierarchical Clustering method provided output in the form of a dendrogram that showed how the performance of contractors with one another was similar. Before generating the dendrogram, the Elbow Method, supported by the Knee Locator, was utilized to identify the optimal cluster count that accurately represented the data. One study also stated that methods such as the Davies–Bouldin Index (DBI) or the Elbow Method should be used to determine the optimal number of clusters based on the data employed [14]. Further details of this process will be elaborated in the subsequent explanation.

Data Exploration and Visualization

This stage initiateed how the Hierarchical Clustering method started. In determining the appropriate method, the Cophenetic Correlation Coefficient (CCC) was used. The function is to calculate the inter-cluster linkage with a choice of methods, such as single linkage, average linkage, complete linkage, or Ward's Method [15]. The method with the highest CCC value is the best method to use on the data. The corresponding formulas are presented as follows [16]:

$$CCC = \left[\frac{\sum_{i<j}^{k}(d_{ij} - d*_{ij})}{\sum_{i<j}^{k} d^2{}_{ij}}\right]^{\frac{1}{2}} \qquad ...(1)$$

After the CCC value was calculated, the next step was to calculate the distance between data points using the Euclidean method. The Euclidean method was used because it effectively reduced the influence of outliers in the sample space, encouraged more rational merging, and got better results than other distance measurements [17]. The following is the calculation formula:

$$d_{ij} = \sqrt{\sum_{k=1}^{p}(x_{ik} - x_{jk})^2} \qquad ...(2)$$

whereas:

d_{ij} values of the original distance matrix.

d^*_{ij} values of the matrix of shrinking distances.

Model Building and Evaluation

This section outlines the main stages of data processing through to completion. The process began by calculating the linkage matrix that best represented the data. This study compares the Complete Linkage and Average Linkage methods, as Average Linkage yields the highest CCC value, while Complete Linkage (the second highest CCC value) provides better visualization. Here are the respective formulas [16]:

Average Linkage [18]

$$D = \frac{\sum x_{p \in C_i}, x_{q \in C_j} D(x_p, x_q)}{|C_i||C_j|} \qquad ...(3)$$

Complete Linkage

$$D(I, J) = \max(D_{ij}),\ i \in I,\ j \in J \qquad ...(4)$$

Afterwards, the dendrogram from each method was generated, illustrating the distribution of contractors across clusters. This study further analyzed the characteristics of each cluster to provide a deeper understanding of their composition to proceed to the calculation stage of the second method. To support data processing through the Fuzzy-TOPSIS method, the dendrogram visualization was transformed into tabular format (Table 5 to **Table 9**). Subsequently, each dataset was converted into fuzzy membership functions based on its level of relevance to sustainability. The weights for each are presented in the following table.

Table 1. Transformation of Fuzzy Membership Function [19]

Rank	Sub-Criteria Grade	Membership Function
Very Low (VL)	1	(0.00, 0.10, 0.25)
Low (L)	2	(0.15, 0.30, 0.45)
Medium (M)	3	(0.35, 0.50, 0.65)
High (H)	4	(0.55, 0.70, 0.85)
Very High (VH)	5	(0.75, 0.90, 1.00)

Table 1 shows the conversion of categorical assessment data into triangular fuzzy numbers. This step is needed in the Fuzzy-TOPSIS method to represent subjective evaluations and uncertainty throughout the assessment process. The calculation process was carried out through several stages as follows:

1. Form a fuzzy decision matrix based on the evaluation results from the questionnaire.
2. Normalization of decision matrix to equalize the rating scale between criteria; Beneficial and Non-beneficial.

   Beneficial Criteria

   $r_{ij} = \left(\frac{\mathrm{aij}}{c*j}, \frac{\mathrm{bij}}{c*j}, \frac{\mathrm{cij}}{c*j}\right)$, whereas $c*_j$ = max{c_{ij}}

   Non-beneficial Criteria

   $r_{ij} = \left(\frac{aj^-}{aij}, \frac{aj^-}{bij}, \frac{aj^-}{cij}\right)$, whereas a_j^- = min{a_{ij}}
3. Weighting the fuzzy decision matrix by multiplying the normalized fuzzy value by the weight of each criterion, where the weight is determined based on the level of relevance of the criterion to sustainability.
4. Determining the Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS).

   Positive Ideal Solution **(A^+):** $A^+ = (v^+_1, v^+_2, \ldots, v^+_n)$, whereas $v^+_j = \max\{v_{ij3}\}$

   Negative Ideal Solution (A^-):

   $A^- = (v^-_1, v^-_2, \ldots, v^-_n)$,

   whereas $v^-_j = \min\{v_{ij1}\}$
5. Calculate the distance to the two values.

The results of the above calculations will be used to calculate Di^*, Di^-, and Closeness Coefficient Index (CCi). The function of the CCi value is to determine the relative closeness of each alternative, in this case including clusters and dominant criteria, to the ideal solution. The formula is presented as follows.

$$CCi = \frac{Di^-}{(Di^- + Di^*)}$$

The higher the CCi value (close to 1), the closer an alternative is to the positive ideal solution (PIS), which will be discussed in the next section.

RESULT AND DISCUSSION

The questionnaire was developed based on seven sustainability criteria defined by the company, all of which are relevant to the triple bottom line (TBL) dimensions: Company Accreditation, Per-mits Due to Sustainability, Equipment, Ma -terials/Sourcing, Personnel, Procedures &

Policies, and Waste Management, as shown in Table 2.

Table 2. How the seven criteria represent the triple bottom line of sustainability.

Triple Bottom Lines (TBL)	Criteria	Description
Environment	*Permits Due to Sustainability* (PS)	Possession of legal documents related to the environment, such as Amdal or UKL-UPL.
	Equipment (EQ)	Use of equipment and technologies that support environmental standards, such as Euro 5 and low-emission technologies.
	Material/Sourcing (MS)	Policies on procurement of environmentally friendly materials and conservation of natural resources.
	Waste Management (WM)	Responsible waste management.
Social	*Personnel* (PN)	Worker empowerment programs, HSE campaigns, regular training, and programs for local communities.
Economy	*Company Accreditation* (CA)	Certifications and accreditations that support business competitiveness with compliance to sustainability standards.
	Procedure & Policies (PP)	Policies and procedures that support operational sustainability, including performance monitoring and auditing.

Based on the responses obtained from the distribution of Questionnaire 2, which contains contractor sustainability performance data, a categorization process is conducted to streamline clustering. The details of the sustainability performance data conversion are outlined in Table 3.

Table 3. Sustainability performance categories data.

Criteria		Category
CA	1	ISO
	2	ISO, API, SMK3
	3	ISO and SA8000
	4	ISO and SMK3
	5	ISO and API
	6	ISO, SMK3, PROPER
	7	ISO, SMK3, HSEP
	8	ISM CODE
	9	Does not implement at all
PS	1	Amdal/RKL-RPL
	2	UKL-UPL

Criteria		Category
	3	Amdal and UKL-UPL
	4	HB Management System (HMS)
	5	Sea Transportation Business License (SIUPAL) and International Convention for the Prevention of Pollution from Ships (MARPOL)
	6	Business Identification Number (NIB)
	7	General procedure of waste management
	8	Does not implement at all
EQ	1	Emission test or minimize scope 1, 2, & electricity emissions
	2	Has an environmental license
	3	SILO
	4	HSE system monitoring
	5	Managing ISO
	6	SILO, emission test, environmental license
	7	Does not implement at all
MS	1	Monitor contractor performance, campaign water conservation, reduce water usage
	2	Resource management and CIB procedure
	3	Certification
	4	OHS standards, BKB control, quality and environmental policies
	5	Material Safety Data Sheet (MSDS) and campaign
	6	Quality, Health, Safety, and Environmental Management System (QHSEMS) and campaign
	7	Equipment calibration and maintenance
	8	HSE monitoring
	9	Does not implement at all
PN	1	Company Social Responsibility (CSR), campaign, HSE training
	2	The HB Foundation, HB Charitable Foundation, Energy to Hero, Journey to ZERO
	3	Safety meeting, training matrix, HSE monthly program
	4	Recruitment SOP, Manpower Planning SOP, sharing session
	5	Does not implement at all or the case company's responsibility
PP	1	Performance monitoring, inspections, audits
	2	Journey to ZERO, OHS procedures, equipment inspections
	3	HSE Patrol
	4	QC procedures
	5	Training
	6	Does not implement at all
WM	1	Hazardous waste disposal site
	2	Third party
	3	Hazardous waste disposal site and third party
	4	Social License to Operate (SLO), third party

Criteria		Category
	5	Hazardous waste certification
	6	The Waste Data App
	7	Standards for handling waste, spills, chemicals and waste management procedures
	8	Quality Standard Operating Procedure (QSOP)
	9	The 3R program (office waste management)
	10	Does not implement at all

This data conversion represents each contractor numerically, enabling analysis using Hierarchical Clustering. Contractors are grouped based on similar sustainability scores, ensuring those in the same cluster share comparable characteristics.

The impact of Industry 4.0 on sustainability performance is not always direct but can be moderated by key factors, such as organizational readiness, technology readiness, regulatory actions, and stakeholder engagement [20]. In the oil and gas industry, supplier evaluation faces challenges such as limited local suppliers, additional costs of regulatory compliance and the need to develop capacity to meet international standards [21]. To overcome these challenges, this research proposes an evaluation approach based on Hierarchical Clustering and Fuzzy-TOPSIS. Both methods are expected to support the company's efforts to improve the sustainability of its supply chain, while encouraging the development of local suppliers that are more competitive and in line with global standards. Another advantage is that evaluating supplier performance can lead companies to reduce fixed and variable costs in the industry and simultaneously increase revenue [22].

Hierarchical Clustering calculations in this study were conducted using Python on Google Colab. The Average Linkage method achieved the highest Cophenetic Correlation Coefficient (CCC) of 0.768, while Complete Linkage scored 0.692 (Table 4). A higher CCC indicates better preservation of the data's hierarchical structure [16]. Although the obtained CCC values are below the commonly suggested threshold of 0.80–0.90, previous studies (e.g., [23] [24]) have reported similar CCC ranges, where achieving very high CCC values is often difficult. In this context, the chosen method is still considered acceptable, as it provided more interpretable and balanced clustering results compared to alternative linkage methods.

Table 4. Cophenetic Correlation Coefficient calculation results in Python.

Method	CCC Result
Ward	0.559
Single Linkage	0.617
Complete Linkage	0.692
Average Linkage	0.768

Although the elbow method **Figure 2** initially suggested six clusters, the Average Linkage method produced one cluster with only a single contractor, making the

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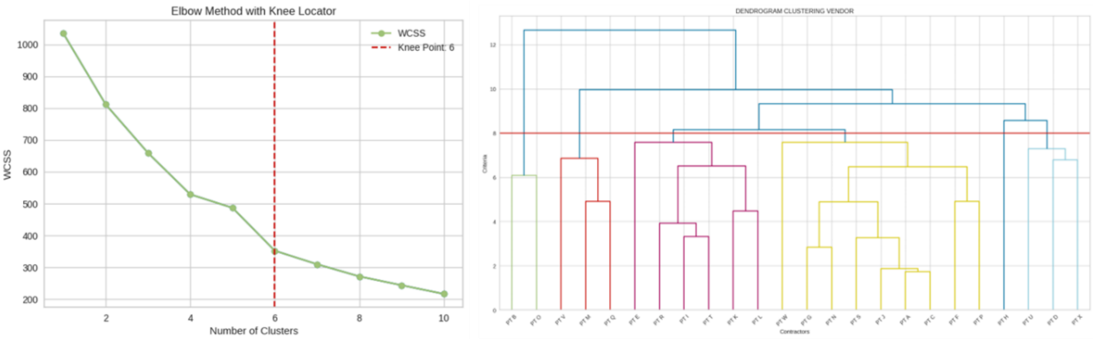
grouping less practical. To address this issue, we applied the Complete Linkage method (which had the second-highest Cophenetic Correlation Coefficient), and it produced five well-balanced clusters that better represented the underlying data structure, based on the elbow method for the Complete Linkage method as illustrated in **Figure 3**. The Complete Linkage method formed five distinct clusters, each grouping contractors with similar criteria categories. Cluster 1 is indicated by green, Cluster 2 by red, Cluster 3 by purple, Cluster 4 by yellow, and Cluster 5 by light blue. This method was chosen for its consistency in clustering, making the results more representative for evaluating sustainability performance. The clustering pattern also provides a clearer understanding of similarities among contractors. This information can support decision-makers in identifying groups with comparable sustainability characteristics.



(a) **(b)**

Figure 2. (a) Elbow Method result, (b) Dendrogram visualization of Average Linkage.

The clustering pattern shows clear category dominance within each cluster. The clustering results indicate that Cluster 4 has the highest number of contractors, totalling 9, followed by Cluster 2 with 6 contractors, Cluster 5 with 4 contractors, Cluster 3 with 3 contractors, and Cluster 1 with the fewest, consisting of only 2 contractors. The dendrogram results have also been presented in tabular form (Table 5 – Table 9) to facilitate a clearer understanding of the distribution and similarity of characteristics among contractors. The color gradation in the contractor column represents the degree of similarity between contractors, while red-colored cells indicate that the contractor does not fulfill the corresponding criterion at all.

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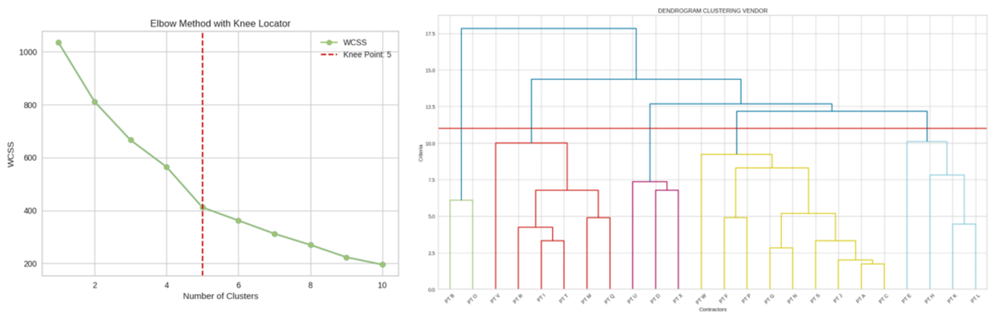

(a) (b)

Figure 3. (a) Elbow Method result, (b) Dendrogram visualization of Complete Linkage.

From Table 5 to Table 9, we can see how contractors are grouped into five clusters. To better understand the nature of each group, the following section explains the sustainability performance of contractors in each cluster based on the evaluated criteria. Cluster 1, comprising two contractors, demonstrates the lowest level of sustainability compliance. One contractor fails to meet any sustainability criteria, while the other (PT O) meets only four, and with minimal fulfillment. Environmental licensing within this cluster is limited to an NIB, and waste management practices rely merely on basic 3R principles without adherence to stringent sustainability standards. Overall, Cluster 1 reflects the weakest sustainability performance among all identified groups.

Table 5. Cluster 1.

CLUSTER 1 = 2 Contractors							
CONTRACTOR\CRITERIA	**CA**	**PS**	**EQ**	**MS**	**PN**	**PP**	**WM**
PT B	9	8	7	9	5	6	10
PT O	9	6	7	9	1	2	9

Cluster 2, consisting of six contractors, exhibits more diverse sustainability characteristics. While most contractors also hold ISO certification (CA: category 1), their PS compliance varies, with some relying only on basic licenses such as NIB. They generally conduct emission tests and maintain ISO standards (EQ), and their MS practices are reflected through sustainability campaigns and OHS compliance. CSR programs, HSE training, and audits (PN and PP: category 1) are also consistently implemented. Nevertheless, waste management (WM: category 7) remains limited to general handling without detailed procedures.

Table 6. Cluster 2.

CLUSTER 2 = 6 Contractors							
CONTRACTOR\CRITERIA	**CA**	**PS**	**EQ**	**MS**	**PN**	**PP**	**WM**
PT V	1	8	2	9	1	6	10
PT R	1	2	5	6	1	1	7
PT I	2	2	3	4	1	3	7

PT T	1	1	1	5	1	1	7
PT M	1	6	1	7	4	1	7
PT Q	1	7	2	5	1	1	10

Cluster 3, consisting of three contractors, shows lower levels of sustainability compliance, particularly in PS and EQ criteria where most requirements are not fulfilled. None of the contractors have implemented PS, and two did not meet EQ standards. Nevertheless, all contractors in this cluster hold ISO certification, and two also possess SMK3 and SA8000 certifications. Subcontractor monitoring, CSR programs, and HSE training (MS, PN, PP: category 1) are generally implemented, although only two contractors carried out inspections and audits under PP. Waste management practices vary, with handling done either internally or through third-party collaboration, reflecting significant gaps in overall sustainability performance.

Table 7. Cluster 3.

CLUSTER 3 = 3 Contractors							
CONTRACTOR\CRITERIA	**CA**	**PS**	**EQ**	**MS**	**PN**	**PP**	**WM**
U	4	8	7	1	1	6	1
D	3	8	2	1	1	1	2
X	1	8	7	5	1	1	3

Cluster 4, consisting of nine contractors, represents the largest group and generally demonstrates relatively strong sustainability practices. Most contractors in this cluster have implemented environmental permitting, emission reduction practices, subcontractor monitoring, water conservation initiatives, and CSR/HSE programs. However, waste management activities are still largely dependent on third-party services, indicating limited direct involvement in waste handling practices.

Table 8. Cluster 4.

CLUSTER 4 = 9 Contractors							
CONTRACTOR\CRITERIA	**CA**	**PS**	**EQ**	**MS**	**PN**	**PP**	**WM**
PT W	1	3	7	1	3	5	7
PT F	2	4	1	1	2	2	6
PT P	5	2	1	1	5	1	7
PT G	1	2	5	2	3	1	4
PT N	1	2	5	2	1	3	4
PT S	1	2	2	1	1	4	2
PT J	1	3	1	1	1	1	2
PT A	1	1	1	1	1	1	2
PT C	1	2	2	1	1	1	1

Cluster 5, with four contractors, mostly includes those holding ISO certification, with one contractor also receiving a PROPER award. These contractors require UKL/UPL for operations and hold additional permits like SIUPAL and MARPOL. Environmental compliance within this cluster varies; some meet emission standards, while others have not implemented them. Sustainability initiatives mainly align with standard requirements, such as CSR programs, HSE training, and regular audits, although waste management practices are still basic, focusing on hazardous waste certification and standard disposal procedures.

Table 9. Cluster 5.

CLUSTER 5 = 4 Contractors							
CONTRACTOR\CRITERIA	**CA**	**PS**	**EQ**	**MS**	**PN**	**PP**	**WM**
PT E	1	2	7	9	1	1	3
PT H	8	5	7	3	3	1	5
PT K	6	1	6	5	1	1	7
PT L	7	2	4	8	1	3	8

Nevertheless, all contractors in this cluster hold ISO certification, and two also possess SMK3 and SA8000 certifications. Subcontractor monitoring, CSR programs, and HSE training (MS, PN, PP: category 1) are generally implemented, although only two contractors carried out inspections and audits under PP. Waste management practices vary, with handling done either internally or through third-party collaboration, reflecting significant gaps in overall sustainability performance.

The subsequent stage involves calculating sustainability performance using the Fuzzy-TOPSIS method. In this process, the categorical data on sustainability performance is transformed into fuzzy membership functions as presented in **Table 2**. This conversion is conducted based on the weighted relevance of each category to sustainability. This approach is comparable to the structured evaluation in which expert judgment was used to assign weights to multiple criteria—such as Price, Service, Quality, and Reliability [25]. Similarly, this study applies Fuzzy-TOPSIS to incorporate expert-based weighting in evaluating sustainability performance across seven defined criteria.

The ranking in **Table 10** was obtained through the standard stages of the Fuzzy-TOPSIS method. After normalizing and weighting the decision matrix, the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) were determined. The Euclidean distances of each cluster to FPIS (Di*) and to FNIS (Di^-) were then calculated. The Closeness Coefficient Index (CCi) was derived using the formula $CCi = Di^- / (Di^* + Di^-)$, as outlined in the methodology section. Based on these calculations, Cluster 4 achieved the highest CCi value of 0.803, indicating the strongest sustainability performance, while Cluster 1 showed the lowest CCi value of 0.107, reflecting the weakest performance.

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Table 10. Ranking of dominant clusters.

Cluster	Di^*	Di^-	CCi	Rank
CLUSTER 4	1.144	4.665	0.803	1
CLUSTER 2	2.571	2.931	0.532	2
CLUSTER 3	3.418	2.3671	0.409	3
CLUSTER 5	3.596	2.150	0.374	4
CLUSTER 1	4.815	0.577	0.107	5

Additionally, analyses were conducted to determine the dominant criteria in each cluster, with the results presented in Table 11. The dominant criteria is indicated by the highest CCi value, which are highlighted in green. Based on the analysis, Clusters 1, 2, and 5 are primarily characterized by Procedures & Policies (PP), with CCi values of 0.829, 0.921, and 1, respectively. In contrast, Cluster 3 (CCi = 1) and Cluster 4 (CCi = 0.946) are dominated by Waste Management (WM).

Table 11. Dominant criteria of each cluster.

	CLUSTER 1			**CLUSTER 2**			**CLUSTER 3**			**CLUSTER 4**			**CLUSTER 5**		
	di*	**di-**	**CCi**	**di***	**di-**	**CCi**	**di***	**di-**	**CCi**	**di***	**di-**	**CCi**	**di***	**di-**	**CCi**
CA	0.468	0.040	0.079	0.557	0.281	0.335	0.407	0.168	0.292	0.796	0.527	0.398	0.405	0.560	0.580
PS	0.140	0.484	0.775	0.767	0.318	0.293	0.466	0.318	0.405	1.306	0.000	0.000	0.857	0.000	0.000
EQ	0.498	0.020	0.039	0.380	0.462	0.548	0.471	0.105	0.182	0.562	0.763	0.576	0.519	0.413	0.444
MS	0.468	0.040	0.079	0.540	0.301	0.358	0.178	0.403	0.694	0.148	1.162	0.887	0.490	0.458	0.483
PN	0.328	0.176	0.348	0.572	0.291	0.337	0.436	0.169	0.279	0.853	0.465	0.353	0.539	0.329	0.379
PP	0.087	0.421	0.829	0.071	0.827	0.921	0.249	0.456	0.647	0.110	1.296	0.922	0.000	0.857	1.000
WM	0.326	0.179	0.355	0.440	0.397	0.474	0.000	0.564	1.000	0.071	1.244	0.946	0.284	0.624	0.687

This suggests that contractors in Clusters 3 and 4 prioritize waste management, while those in Clusters 1, 2, and 5 focus more on sustainability policies. If the case company aims to select contractors based on specific sustainability criteria, the dominant criteria in each cluster can serve as a key consideration. Contractors in Clusters 3 and 4 demonstrate strength in waste management (WM), whereas those in Clusters 1, 2, and 5 place greater emphasis on sustainability policies (PP).

Compared to previous studies that mainly applied AHP, TOPSIS, or clustering methods in isolation, this research contributes by integrating Hierarchical Clustering and Fuzzy-TOPSIS to address categorical and subjective sustainability data, which were often overlooked. The results show that while Average Linkage yielded higher CCC, Complete Linkage produced more interpretable clusters, referring to the study by [8], that aligned with contractors' sustainability profiles. Cluster 4 demonstrated superior performance largely due to strong compliance in high-weighted criteria such as Permits, Waste Management, and Policies, whereas Cluster 1 scored lowest because of weak implementation in these areas, consistent with [20], who emphasized that under many real-life conditions, crisp data are inadequate to fully capture human judgment. This finding reinforces that sustainability performance is not evenly distributed, but strongly influenced by key weighted criteria, highlighting the importance of combining clustering and fuzzy decision-making. Thus, the study strengthens the existing knowledge framework—while previous studies such as [26] have implemented combinations like K-Means and TOPSIS to deal with large-scale, numerical data—by showing how integrated methods can provide more representative classification and prioritization, offering both methodological novelty and practical insight for supplier evaluation in the oil and gas industry.

CONCLUSION

Since the company's efforts contradicted their short-term plans, the data processing and analysis in this study were conducted to address this gap. The findings of this study reveal variations in the implementation of sustainability criteria among contractors, with Equipment (EQ) identified as the least fulfilled criterion, while Procedures & Policies (PP) and Waste Management (WM) emerged as the dominant factors influencing performance. The integration of Hierarchical Clustering (Complete Linkage) and Fuzzy-TOPSIS successfully grouped contractors into five clusters and prioritized their sustainability performance, with Cluster 4 achieving the highest Closeness Coefficient Index (0.803) and Cluster 1 the lowest (0.107). However, this research has certain limitations. Hierarchical Clustering may be less effective for large-scale datasets, and the analysis was not differentiated by contractors' fields of work, which could influence the sustainability priorities of each group. Future research should therefore explore clustering based on contractors' specific work categories, align the evaluation framework with company needs; enabling more tailored and strategic decision-making in sustainability-oriented contractor selection. It may also explore alternative linkage methods in hierarchical clustering. Although Average Linkage showed a higher Cophenetic Correlation Coefficient (CCC), it resulted in less practical clustering. In contrast, Complete Linkage yielded more interpretable and balanced clusters. Therefore, further comparison of clustering techniques is recommended to improve accuracy and relevance in sustainability evaluations.

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