Edu Komputika 12 (1) (2025)

Edu Komputika Journal

https://journal.unnes.ac.id/journals/edukom/

Energy Supply Chain Optimization: Design of a Transportation Vendor Assessment System Using the Simple Additive Weighting Method

Rendy Bagus Pratama✉ and Ragil Nurhawanti

Logistics Oil and Gas, Polytechnic Energy and Mineral Akamigas, Cepu, Indonesia

Article Info

Article History:
Received: 8 November 2025
Revised: 30 Desember 2025
Accepted: 31 Desember 2025

Keywords:
Decision Support System, SAW Method

Abstract

In the energy logistics sector, which demands high speed and efficiency, fuel transportation vendor selection is a strategic decision that significantly impacts operational smoothness. To transform the cumbersome manual selection process into digital precision, a study developed a Vendor Management Information System based on the Simple Additive Weighting (SAW) method. This system is designed to provide objective decision-making support by analyzing 2024 performance data through eight key evaluation criteria, including service quality, price, and fleet availability. After going through a normalization and weighting process in the decision matrix, the system determined Vendor A1 (PT. X) as the best provider with the highest score. The data is descriptive quantitative in nature, where the data collection process involved respondents from three departments within the company who are experts in the field of procurement, with proof of ownership of procurement certification for goods and services. A total of 23 respondents served as the basis for SAW data processing, and 5 people served as references for creating criteria for weighting in the method. This automation logic was then technically mapped through Data Flow Diagrams (DFDs) and Entity-Relationship Diagrams (ERDs) to ensure an integrated workflow. The implementation of this system marks a significant shift towards digital efficiency, which not only minimizes human error and increases transparency but also lays a strong foundation for the adoption of more sophisticated decision-making technologies in the future.

✉ Correspondence Address:
Jl. Gajah Mada No. 38, Mentul, Karangboyo, Kec. Cepu, Kab. Blora, Jawa Tengah, 58315
E-mail: rendybaguspratama@gmail.com

ISSN 2252-6811
E-ISSN 2599-297X

INTRODUCTION

Fuel distribution is the lifeblood of the national energy supply chain; the efficiency, reliability, and security of its distribution are key determinants of energy availability across the region. In this landscape, transportation vendor selection has become a strategic decision, not just an operational one, as vendors are strategic partners that determine the logistics performance, costs, and sustainability of the supply chain.

Ironically, this crucial selection process is often marred by subjective assessments, resulting in inefficiencies, inconsistencies, and the risk of bias—real threats to supply chain performance. Therefore, the need for a systematic, transparent, and data-driven approach becomes urgent. This is where the Simple Additive Weighting (SAW) method demonstrates its strength. Known for its simplicity and effectiveness in addressing both quantitative and qualitative criteria, SAW has proven to be a competitive and reliable solution for objective supplier evaluation.

As digital transformation permeates logistics, the integration of methodological decision-making (MCDM) into information systems is key to automation, accountability, and transparency. Recent advances demand digital decision support systems capable of improving traceability and reducing human error.

Based on this urgency, this research focuses on designing an SAW-based Vendor Management Information System for fuel transporter selection. The primary objectives are clear: to improve efficiency, increase transparency, and ensure objective and accountable decision-making in energy logistics management.

Integration of Big Data and IoT (Internet of Things). In the past, performance data of service providers (criteria in SAW) were entered manually based on monthly reports. Now, IoT technology allows data to be entered automatically and objectively. Telemetry & GPS: Data on timeliness (reliability) and driving behavior (safety) are pulled directly from vehicle sensors. Temperature & Pressure Sensors: For the transportation of specific fuels, cargo integrity data becomes a quality parameter that cannot be manipulated. Benefits: Scores in the SAW method become very accurate because they are based on actual field data (evidence-based).

Utilization of Artificial Intelligence (AI) for Weighting. One of the challenges of SAW is determining the weight for each criterion. AI technology can optimize this process. Machine Learning (ML) enables AI to analyze historical data on past distribution failures, determining which criteria have the most significant influence on risk. Performance Prediction: Before the contract is signed, AI can predict the performance of potential service providers based on market trends and weather/route data, which then becomes input values in the SAW matrix.

Blockchain for Transparency and AuditBias and data manipulation issues in vendor selection can be mitigated with Blockchain: Smart Contracts. Once a service provider is selected through the verified SAW system, a digital contract can be automatically formed. Immutable Records: The history of service provider evaluations and certifications is stored in an unchangeable digital ledger, ensuring that the selection process is truly transparent and accountable according to Good Corporate Governance (GCG) principles.

Cloud-Based Decision Support System (DSS): The transformation from desktop applications to Cloud-Native enables collaboration between departments (finance, operations, HSSE) in providing assessments. Interactive Dashboard: Visualization of SAW ranking results makes it easier for top management to intuitively compare candidates. Scalability: Enables the evaluation of hundreds of vendors across different regions simultaneously without physical infrastructure constraints.

RESEARCH METHODS

This study uses a descriptive quantitative approach to address the vendor selection problem for fuel carriers. The main challenge identified is the lack of a systematic and measurable evaluation framework, which often results in subjective, inconsistent, and inefficient decision-making (Evcioglu & Kabak, 2023; Fadilla et al., 2022).

Therefore, a multi-criteria decision-making (MCDM) method is needed to provide an objective and transparent evaluation process. Data collection involved developing a questionnaire with 23 respondents from three divisions. To develop the criteria, interviews were conducted with five experts from certified companies with at least two years of experience in the field.

The Simple Additive Weighting (SAW) method was chosen because of its ability to accommodate multiple evaluation criteria through simple steps: data normalization, criteria weighting, and calculating a final score for each vendor alternative. Previous studies have confirmed that SAW is effective in supplier evaluation and is comparable to other methods such as TOPSIS, AHP, and SMART (Purnomo & Setiawan, 2019; Mulliner et al., 2016; Shih et al., 2016).

The evaluation criteria applied in this study include quality, price, delivery, service, flexibility, fleet availability, performance history, and geographic location. Each criterion is classified as a benefit or cost attribute according to its nature (Boakai & Samanlioglu, 2023; Sustainable Supplier Selection, 2023).

Research data was collected through questionnaires distributed to relevant management personnel in 2024. This data was then used to construct a decision matrix, which was normalized to allow proportional comparisons between criteria. The normalized values were multiplied by their respective weights to calculate a final preference score. The vendor alternative with the highest score was designated as the most appropriate choice (Astuti et al., 2021; Fadilla et al., 2022).

Beyond quantitative calculations, this study also designed a Vendor Management Information System to automate the evaluation process. System modeling was performed using Data Flow Diagrams (DFDs) to represent process flows and Entity Relationship Diagrams (ERDs) to depict database structures. This modeling approach ensures clarity of entity relationships and systematic data flows, which are crucial for consistent and transparent decision-making (Silaen & Sibuea, 2020; Zhang et al., 2021).

Through this methodological approach, the expected outcomes include not only a structured calculation of vendor selection results but also the conceptual design of an information system that can serve as a reliable decision-support tool. This integration aligns with current trends in digital supply chain management and supports transparent, accountable, and data-driven decision-making (Zuhud et al., 2025; Chakraborty & Mateen, 2025).

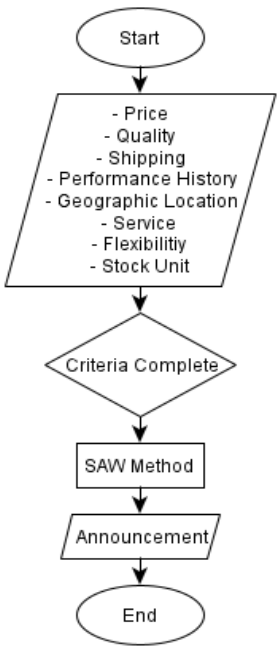

Figure 1. Flowchart of research

RESULT AND DISCUSSION

A. Simple Additive Weighting Method

The research results indicate that the application of the Simple Additive Weighting (SAW) method provides a structured and objective basis for selecting land-mode fuel transportation vendors. The process begins with the data preparation stage, in which historical vendor performance data collected from questionnaires distributed in 2024 is compiled. Eight evaluation criteria are employed, namely quality, price, delivery, service, flexibility, fleet availability, performance history, and geographic location. These criteria are then classified as either benefit or cost attributes. Each criterion is assigned a weight according to its level of importance to operational needs.

Table 1. Data Classification (Ci)

Data Classification	
C1	Quality (Quality of the conveyance, age, and condition of the conveyance)
C2	Price (Price quote)
C3	Delivery (Response speed in delivery time changes)
C4	Service (How well it responds to complaints, requests)
C5	Flexibility (Flexible in delivery time)
C6	Fleet Availability (Availability of fleet types according to user requests)
C7	Performance History (Good track record)
C8	Geographic Location (Far or close to total kilometers to supply and delivery points)

From each of these criteria, variables will be made. For each variable, a weight value will be given a weight value in the form of numbers. These numbers are free to be determined, for example, the range could be from 1-5, 1-100, or 0-1. In the study above, we will use a range of 1 to 5.

Table 2. Variable Weighting Results Criteria C1

C1 – Quality Criteria	
Quality	**Value**
Poor	1
Fair	3
Excellent	5

In this criterion, the weighting is divided into three values: low, medium, and high, with low points worth 1, medium points worth 3, and the highest points worth 5.

Table 3. Variable Weighting Results Criteria C2

C2 - Price Criteria	
Cost (Rp/Liter)	**Value**
70-80	2
81-90	3
>=91	4

In criterion 2, the focus of the assessment weighting is on the price of the product for which the group data has been classified.

Table 4. Variable Weighting Results Criteria C3

C3 – Delivery Criteria	
Time	**Value**
Slow	1
Fairly fast	3
Very fast	5

Vendor response and responsiveness efforts in meeting company needs based on the criteria in this table.

Table 5. Variable Weighting Results Criteria C4

C4 – Service Criteria	
Service	**Value**
Poor	1
Fair	3
Excellent	5

Assess the process load carried out during the procurement process based on 3 classes.

Table 6. Variable Weighting Results Criteria C5

C5 – Flexibility Criteria	
Flexibility	**Value**
Poor	1
Good	3
Excellent	5

Services from vendors related to fulfilling the procurement needs of goods required by the company.

Table 7. Variable Weighting Results Criteria C6

C6 – Fleet Availability Criteria	
Fleet Type	**Value**
<=1	1
2	3
>=3	5

Fleet required by the company for distributing fuel products.

Table 8. Variable Weighting Results Criteria C7

C7 – Performance History Criteria	
History	**Value**
Poor	1
Fair	3
Excellent	5

Vendor performance in the procurement process at other locations, how many times they have participated in the procurement process, and how long the procurement process has lasted.

Table 9. Variable Weighting Results Criteria C8

C8 – Geographic Location Criteria	
Distance (kilometer)	**Value**
<=30	2
31-40	3
>=41	4

Location factors are a determining factor in service, if in the future something happens outside of the plan and requires speed in service.

In this assessment, if a higher weight value of a variable indicates a better condition, then the criteria of quality, delivery, service, flexibility, fleet availability, and performance history are categorized as Benefit attributes. Conversely, if a smaller weight value is considered more advantageous, such as in the case of price and geographic location, these criteria are classified as Cost attributes.

For each criterion used, a weight value will be assigned. Decision-makers assign weight to each criterion based on its own considerations or, more commonly, on the results of surveys/questionnaires. In this case, the weighting is carried out on its own consideration, and the questionnaire data that have been collected before are used, and the results are obtained.

Table 10. Weight Value of Each Criterion

Weighted Value of Each Criterion (Ci)		
Criteria	**Weight**	**Simplified Weight**
Quality	15	0,15
Price	15	0,15
Shipping	10	0,1
Service	15	0,15
Flexibility	10	0,1
Fleet Availability	15	0,15
Performance History	10	0,1
Geographic Location	10	0,1
Total	**100**	**1**

In this case study, there are three fuel transporter vendors using land transportation modes, which serve as the alternatives. Each alternative is subsequently assigned variables corresponding to each evaluation criterion, reflecting the specific conditions and performance of the respective alternative.

Table 11. The Circumstances of Each Alternative C1 – C4

Alternatif	**Criteria**			
	C1	**C2**	**C3**	**C4**
A1	Excellent	75	Fast	**Excellent**
A2	Fairly Good	115	Fairly fast	**Fairly Good**
A3	**Excellent**	**82**	**Fast**	**Fairly Good**

The results obtained from the 4 criteria are further processed into 3 classes.

Table 12. The Circumstances of Each Alternative C5 – C8

Alternatif	Criteria			
	C5	C6	C7	C8
A1	Excellent	4	Fairly Good	36,1
A2	Good	1	Excellent	63,5
A3	Good	2	Excellent	34,5

From the table above, it is then converted into a weight value according to each variable that has been made before.

Table 13. The Weight Value of Each Alternative Criterion C1 – C4

Alternatif	Criteria			
	C1 (+)	C2 (-)	C3 (+)	C4 (+)
A1	5	2	5	5
A2	3	4	3	3
A3	5	3	5	3

The results obtained from the 4 criteria are further processed into 3 classes.

Table 14. The Weight Value of Each Alternative Criterion C5 – C8

Alternatif	Criteria			
	C5 (+)	C6 (+)	C7 (+)	C8 (-)
A1	5	5	3	**3**
A2	3	1	5	**4**
A3	**3**	**3**	**5**	**3**

The results obtained from the 4 criteria are further processed into 3 classes. Furthermore, the table above will be formed into a decision matrix as follows.

5 2 5 5 5 5 3 3
3 4 3 3 3 1 5 4
5 3 5 3 3 3 5 3

From this decision matrix, the normalization process of the decision matrix X is carried out with the following calculations.

Table 15. Decision Matrix Data

R11		**R12**	
R21	Max (5,3,5)	**R22**	Min (2,4,3)
R31		**R32**	

R11 is the element in the first row and first column with a value of 5. Since this column represents criterion C1 of the Benefit type, the maximum value is determined, namely Max {5,3,5} = 5. The maximum value is divided by R11 (5/5), resulting in a normalized value of 1.0.

R21 is the element in the second row and first column with a value of 3. As this column also belongs to criterion C1 of the Benefit type, the column maximum is 5. The calculation 3/5 yields a normalized value of 0.6.

R31 is the element in the third row and first column with a value of 5. Since it is part of criterion C1 of the Benefit type, the maximum column value remains 5. The calculation 5/5 results in a normalized value of 1.0.

R12 is the element in the first row and second column with a value of 2. As this column represents criterion C2 of the Cost type, the column minimum is used, namely 2. The calculation 2/2 produces a normalized value of 1.0.

R22 is the element in the second row and second column with a value of 4. Since this column is part of criterion C2 of the Cost type, the minimum value is 2. The calculation 2/4 produces a normalized value of 0.5.

R32 is the element in the third row and second column with a value of 3. As it belongs to criterion C2 of the Cost type, the column minimum of 2 is applied. The calculation 2/3 results in a normalized value of 0.7.

Table 16. Decision Matrix Data

R13		**R14**	
R23	Max (5,3,5)	R24	Max (5,3,3)
R33		R34	

R13 is the element in the first row and third column with a value of 5. As this column corresponds to criterion C3 of the Benefit type, the maximum value of 5 is used. The calculation 5/5 yields a normalized value of 1.0.

R23 is the element in the second row and third column with a value of 3. Since this column is part of criterion C3 of the Benefit type, the maximum column value of 5 is applied. The calculation 3/5 results in a normalized value of 0.6.

R33 is the element in the third row and third column with a value of 5. As this column is also part of criterion C3 of the Benefit type, the maximum column value of 5 is applied. The calculation 5/5 results in a normalized value of 1.0.

R14 is the element in the first row and fourth column with a value of 5. Since this column represents criterion C4 of the Benefit type, the column maximum of 5 is used. The calculation 5/5 produces a normalized value of 1.0.

R24 is the element in the second row and fourth column with a value of 3. As this column is part of criterion C4 of the Benefit type, the maximum column value of 5 is applied. The calculation 3/5 results in a normalized value of 0.6.

R34 is the element in the third row and fourth column with a value of 3. As this column corresponds to criterion C4 of the Benefit type, the maximum value of 5 is used. The calculation 3/5 produces a normalized value of 0.6.

Table 17. Decision Matrix Data

R15		**R16**	
R25	Max (5,3,3)	R26	Max (5,1,3)
R35		R36	

R15 is the element in the first row and fifth column with a value of 5. Since this column represents criterion C5 of the Benefit type, the column maximum of 5 is used. The calculation 5/5 results in a normalized value of 1.0.

R25 is the element in the second row and fifth column with a value of 3. As this column belongs to criterion C5 of the Benefit type, the maximum column value of 5 is applied. The calculation 3/5 produces a normalized value of 0.6.

R35 is the element in the third row and fifth column with a value of 3. Since this column is also part of criterion C5 of the Benefit type, the maximum column value of 5 is used. The calculation 3/5 yields a normalized value of 0.6.

R16 is the element in the first row and sixth column with a value of 5. Because this column represents criterion C6 of the Benefit type, the maximum column value of 5 is applied. The calculation 5/5 produces a normalized value of 1.0.

R26 is the element in the second row and sixth column with a value of 1. As this column corresponds to criterion C6 of the Benefit type, the maximum column value of 5 is used. The calculation 1/5 results in a normalized value of 0.2.

R36 is the element in the third row and sixth column with a value of 3. Since this column also represents criterion C6 of the Benefit type, the maximum column value of 5 is used. The calculation 3/5 yields a normalized value of 0.6.

Table 18. Decision Matrix Data

R17		**R18**	
R27	Max (3,5,5)	R28	Min (3,4,3)
R37		R38	

R17 is the element in the first row and seventh column with a value of 3. Since this column represents criterion C7 of the Benefit type, the column maximum of 5 is used. The calculation 3/5 results in a normalized value of 0.6.

R27 is the element in the second row and seventh column with a value of 5. As this column corresponds to criterion C7 of the Benefit type, The maximum column value of 5 is applied. The calculation 5/5 produces a normalized value of 1.0.

R37 is the element in the third row and seventh column with a value of 5. Because this column also represents criterion C7 of the Benefit type, the maximum column value of 5 is used. The calculation 5/5 results in a normalized value of 1.0.

R18 is the element in the first row and eighth column with a value of 3. Since this column represents criterion C8 of the Cost type, the minimum column value of 3 is used. The calculation 3/3 yields a normalized value of 1.0.

R28 is the element in the second row and eighth column with a value of 4. Because this column belongs to criterion C8 of the Cost type, the column minimum of 3 is applied. The calculation 3/4 results in a normalized value of 0.8.

R38 is the element in the third row and eighth column with a value of 3. As this column corresponds to criterion C8 of the Cost type, the minimum column value of 3 is used. The calculation 3/3 produces a normalized value of 1.0.

After performing the calculations on all values in the decision matrix as described above, the normalized matrix (R) is obtained as follows:

$$R = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 0{,}6 & 1 \\ 0{,}6 & 0{,}5 & 0{,}6 & 0{,}6 & 0{,}6 & 0{,}2 & 1 & 0{,}8 \\ 1 & 0{,}7 & 1 & 0{,}6 & 0{,}6 & 0{,}6 & 1 & 1 \end{bmatrix}$$

$$W = (0{,}15 \mid 0{,}15 \mid 0{,}1 \mid 0{,}15 \mid 0{,}1 \mid 0{,}15 \mid 0{,}1 \mid 0{,}1)$$

Then :

$$A1 = (0{,}15x1) + (0{,}15x1) + (0{,}1x1) + (0{,}15x1) + (0{,}1x1) + (0{,}15x1) + (0{,}1x0{,}6) + (0{,}1x1) = 1{,}0$$

$$A2 = (0{,}15x0{,}6) + (0{,}15x0{,}5) + (0{,}1x0{,}6) + (0{,}15x0{,}6) + (0{,}1x0{,}6) + (0{,}15x0{,}2) + (0{,}1x1) + (0{,}1x0{,}8) = 0{,}6$$

$$A3 = (0{,}15x1) + (0{,}15x0{,}7) + (0{,}1x1) + (0{,}15x0{,}6) + (0{,}1x0{,}6) + (0{,}15x0{,}6) + (0{,}1x1) + (0{,}1x1) = 0{,}8$$

B. Data Flow Diagram (DFD)

Using the SAW method, the raw data is transformed into a decision matrix, then normalized and multiplied by the weights of each criterion to produce a final score for each vendor. The calculation results indicate that Vendor A1 (PT. AB) achieved the highest overall score, thus being recommended as the most appropriate choice. These quantitative results do not stand alone but serve as the core decision-making logic integrated into the designed Vendor Management Information System.

As shown in Figure 2, before entering the data processing stage using the SAW method, data for each criterion must be met, and all data must be present in each criterion post. Once all criteria are met and the criteria class assignments are appropriate, the SAW calculation stage can proceed. The data matrix will be calculated, and the result will be a decision from the SAW method regarding which vendor best aligns with the established criteria.

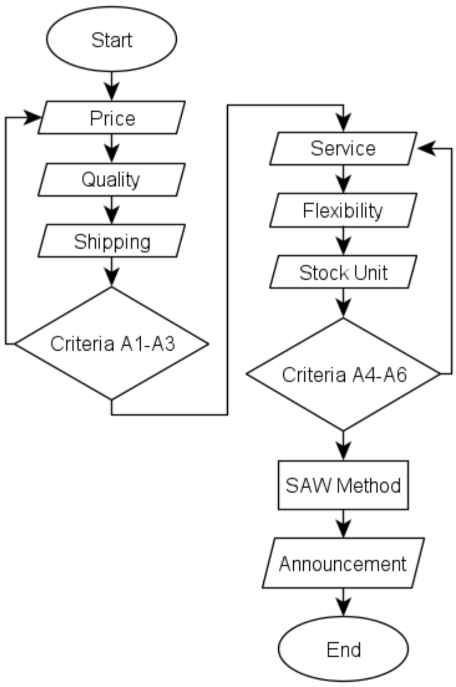

Figure 2. Flowchart diagram

The integration of the SAW algorithm into the system design ensures that vendor evaluation can be performed automatically and consistently. In the conceptual framework, the system workflow modeled through Flowcharts and Data Flow Diagrams (DFD) illustrates each stage of the SAW calculation. At the Level 0 DFD, inputs such as vendor data and evaluation criteria are processed by the system's calculation module, which executes the SAW steps ranging from normalization to weighted summation. The output of this process is a ranked vendor recommendation presented to decision-makers.

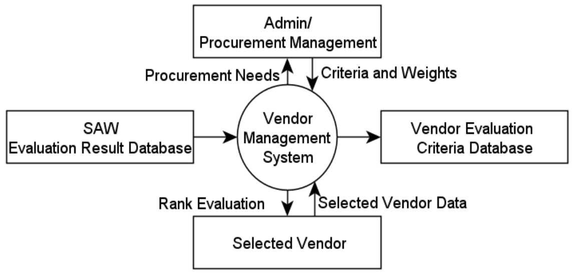

Figure 3. Data flow diagrams level 0

Level 1 Data Flow Diagram (DFD) provides a more detailed breakdown of the sub-processes within the system. At this level, the main process depicted in the Level 0 DFD is decomposed into several specific components to ensure that the workflow is clearly defined and systematically structured. The sub-processes illustrated include.

Data Input – This stage involves entering and storing vendor data and evaluation criteria into the system. The input data include quality, price, delivery, service, flexibility, fleet availability, performance history, and geographic location. These inputs serve as the foundation for all subsequent calculations.

Data Evaluation – Once the data are entered, the system validates the information and ensures compliance with the required format and criterion weights. At this stage, criteria are also classified as either benefit or cost attributes.

SAW calculation – the core process of the system, where the decision matrix is normalized by criteria type, multiplied by assigned weights, and aggregated to obtain a final score for each vendor.

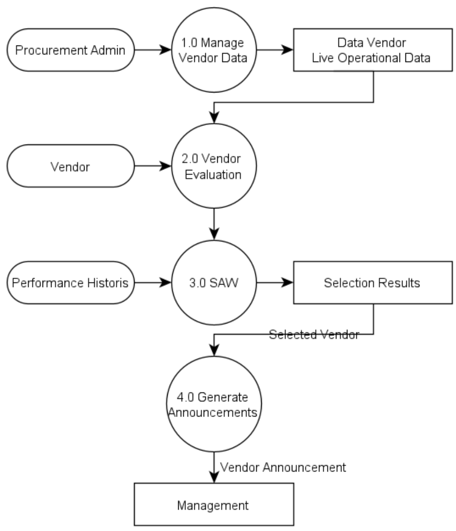

Figure 4. Data flow diagrams (DFD) level 1

Vendor Selection Results – Based on the calculations, the system produces a total score for each vendor and generates a ranking. The output is then presented in the form of reports or recommendations that can be directly utilized by decision-makers.

Through this hierarchical modeling, the logical structure of the system is explained more transparently. The relationships between each stage are clearly illustrated, which not only facilitates further system development but also ensures that the vendor evaluation process runs systematically, consistently, and accountably.

C. Entity Relationship Diagram (ERD)

The Entity Relationship Diagram (ERD) illustrates the data entities involved in the system, along with their attributes and interrelationships. The main entities modeled in this study include Vendor, Criteria, Evaluation, and Selection Results.

Vendor stores basic information about the fuel transportation service providers, such as company identity and the characteristics of their fleet. Criteria represent the assessment aspects used in the selection process, including quality, price, delivery accuracy, service, flexibility, fleet availability, performance history, and geographic location.

Evaluation is the entity that links vendors with criteria. Each vendor is assessed based on all existing criteria, resulting in scores or values for each evaluation aspect. The Selection Results entity records the final values after all calculations are completed, including the ranking of vendors based on the SAW method.

The relationships among these entities form a well-structured relational database, ensuring that each vendor evaluation can be traced back to the corresponding vendor and criteria. With this design, the system maintains data consistency (avoiding conflicting duplicates) and supports decision traceability, enabling management to understand the calculation basis and the rationale behind whether a vendor is selected or not.

The core logic of vendor selection is based on the application of the Simple Additive Weighting (SAW) method. This process begins with the construction of a decision matrix, followed by data normalization based on the type of criteria (benefit or cost). The normalized values are then multiplied by their respective weights to produce a final score for each vendor. The vendor with the highest score is selected as the most suitable option. What was previously a manual and time-consuming process can now be automated through the system, making it more efficient, minimizing human errors, and enhancing decision accuracy.

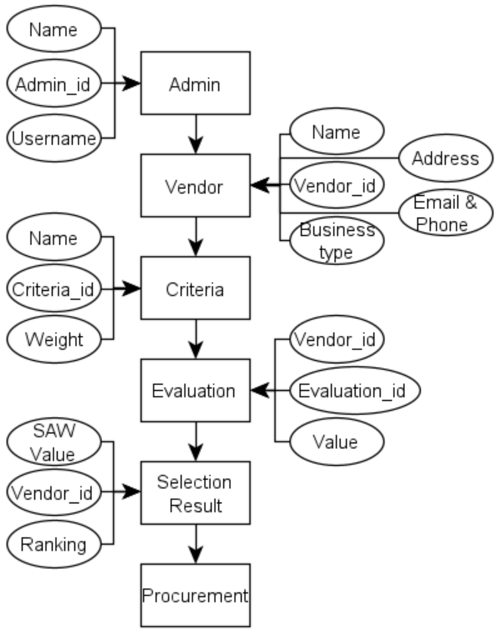

Figure 5. Entity relationship diagrams (ERD)

Compared to manual evaluation, the system provides faster, more consistent, and more accountable results. Each decision generated includes a clear audit trail, allowing management to justify vendor selections more transparently. Furthermore, the system is designed to be scalable, meaning it can be further developed to incorporate other multi-criteria decision-making (MCDM) methods such as TOPSIS or AHP, depending on future organizational needs.

This study demonstrates that the designed system has significant potential as a reliable decision support tool in energy logistics management. It aligns with the demands of transparency, accountability, and efficiency in today's digital era.

CONCLUSION

Ultimately, this study confirms that we have successfully bridged the gap between error-prone manual processes and the need for digital objectivity in energy logistics. The design of a Vendor Management Information System, firmly rooted in the precision of the Simple Additive Weighting (SAW) method, has proven to be not only a viable approach but a transformative breakthrough.

This conceptual system is a digital architecture that transforms mountains of evaluation data into a structured, automated workflow, neatly captured through Data Flow Diagrams (DFDs) and supported by a solid data foundation in Entity Relationship Diagrams

(ERDs). This ensures that every vendor selection decision—from criteria to final score—takes place within a transparent and consistent framework.

The implementation of SAW in this system yields more than just numbers; it provides real-time recommendations that eliminate subjective bias and drastically reduce the potential for human error. Moreover, the system is designed with a forward-thinking vision: it is a scalable blueprint, ready to adopt the complexity of more advanced MCDM methods such as TOPSIS or AHP in the future.

Overall, this system serves as a strategic foundation for organizations committed to aligning their procurement practices with the modern era. It is a response to competitive market demands, a tangible manifestation of digital transformation that empowers energy logistics management with smart, data-driven, and accountable decisions.

REFERENCES

Astuti, D., et al. (2021). Performance Evaluation of Logistics Using SAW and SMART Methods. Journal of Logistics and Supply Chain Management, 3(2), 58–64.

Biswanghri, & Das, S. (2023). Application of MCDM Approach for Vendor Selection in LED Light Industry. In Computational Intelligence in Data Science (pp. 521–535). Springer.

Boakai, S., & Samanlioglu, F. (2023). An MCDM approach to third party logistics provider selection. International Journal of Logistics Systems and Management, 44(3), 351–370.

Chakraborty, S., & Mateen, A. (2025). Guest editorial: Global supply chain transformation using digital technologies in the post-pandemic era. Journal of Global Operations and Strategic Sourcing.

Evcioglu, M., & Kabak, Ö. (2023). Supplier selection in supply chain network using MCDM methods. Sigma Journal of Engineering and Natural Sciences, 41(4), 1082–1097.

Fadilla, A. N., Rosyidi, C. N., & Jauhari, W. A. (2022). Supplier selection and order allocation in a pharmaceutical wholesaler using BWM, TOPSIS, and MOLP. Indonesian Journal of Industrial Engineering, 23(2), 101–112.

Khan, S. A. R., et al. (2020). A hybrid MCDM approach for sustainable supplier selection: Evidence from the automotive industry. Sustainability, 12(4), 1528.

Key Innovations Shaping Digital Supply Chains in 2025. (2025). Jusda Global. Retrieved from https://www.jusdaglobal.com/en/article/key-innovations-digital-supply-chains-2025

Putranto, I. D., & Maulina, D. (2023). Sistem Pendukung Keputusan dengan Metode SMART untuk Menentukan Guru Terbaik. JACIS: Journal Automation Computer Information System, 3(2), 92–102.

Sarhir, O. (2025). Enhancing Supply Chain Resilience with Metaverse and ChatGPT Technologies. arXiv preprint arXiv:2501.14777.

Silaen, A. M., & Sibuea, M. L. (2020). Penerapan Data Flow Diagram (DFD) dalam Perancangan Sistem Informasi Akademik. Jurnal Teknologi dan Sistem Informasi, 1(2), 60–68.

Sustainable Supplier Selection through Multi-Criteria Decision Making (MCDM) Approach: A Bibliometric Analysis. (2023). Machines, 11(4), 96.

Zhang, J., Brintrup, A., Calinescu, A., Kosasih, E., & Sharma, A. (2021). Supply Chain Digital Twin Framework Design: An Approach of SCOR Model and System of Systems. arXiv preprint arXiv:2107.09485.

Zuhud, A., et al. (2025). A Theoretical Framework for Graph-based Digital Twins for Supply Chain Management and Optimization. arXiv preprint arXiv:2504.03692.

Key Innovations Shaping Digital Supply Chains in 2025. (2025). Jusda Global. Retrieved from https://www.jusdaglobal.com/en/article/key-innovations-digital-supply-chains-2025