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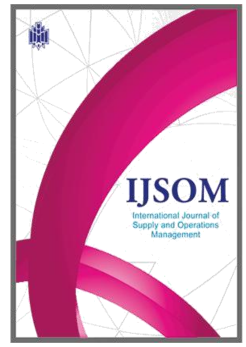

Supplier Selection in the Context of Industry 4.0 Using Hybrid DEA-SMART Method

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Abstract

In the era of Industry 4.0, choosing suppliers for online commerce is of utmost importance and calls for the application of efficient, data-centric techniques. Businesses are under increasing pressure to improve their supply chain management strategies and select the best suppliers in the online commerce environment of Industry 4.0. Traditional approaches, however, sometimes don't include a thorough assessment of suppliers across several dimensions. In order to close this gap, this paper proposes a new approach that combines Data Envelopment Analysis (DEA) with the Simple Multi-Attribute Rating Technique (SMART). The first phase is applying DEA to determine how effective suppliers are using the data that has been gathered. DEA offers a quantitative indicator of how efficiently providers convert their inputs into outputs. This combination score enables rating suppliers while simultaneously considering multi-attribute evaluation and quantifying efficiency assessment, then using a number of different criteria, providers are evaluated using the SMART approach. The findings of this analysis help to improve supplier selection procedures in the context of online commerce, which falls under the purview of Industry 4.0.

Keywords: Supplier selection; Industry 4.0; Data Envelopment Analysis; Simple Multi-Attribute Rating Technique.

1. Introduction

Industry, a part of an economy, produces highly automated and mechanized materials. Since the beginning of industrial development, technological developments have led to changes in attitudes that are currently referred to as "industrial revolutions": mechanization (known as the first industrial revolution), a heavy dependence on electrical energy (known as the second industrial revolution), and the wide adoption of digitalization (referred to as the third industrial revolution). A new fundamental paradigm change in industrial production appears to be brought about by the combination of Internet technologies and future-oriented technologies in the field of "smart" objects (machines and goods), which is based on a highly advanced digitalization within factories (Arora et al., 2022). The fourth industrial revolution, often known as Industry 4.0, and the digitization of business are taking place as the 21st century gets underway (Azadi et al., 2023). The implementation of technological advances is essential to Industry 4.0 because they allow for the real-time collection and analysis of data, which gives the industrial system vital information. This was made possible by the development of the Internet of Things (IoT), cloud services, big data analytics, and the cyber-physical system concept of Industry 4.0 (Azadi et al., 2021). The foundation for Industry 4.0 supply chains (SCs) has been laid by developments in communication and information technology, which provide multiple opportunities for supply chain intelligence and autonomy. The earlier research has given considerable emphasis to the assessment and choice of sustainable suppliers as a crucial SC decision. This process has not yet been accomplished by industry 4.0

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SCs, where decentralized of supply chain participants and real-time information transparency, technical assistance, and connectivity are believed to be the core architectural elements. Actions for supplier evaluation and selection have an impact on almost every choice that needs to be made in the management of supply chains and networks. Although researchers and business leaders have focused a lot of attention on the significance of sustainability and environmental issues and their incorporation in SCs, there haven't been many practical attempts to incorporate sustainability concerns within the framework of Industry 4.0 SCs, and more primarily sustainable supplier evaluation and selection within this context. To clarify the research directions in this field, further research efforts are needed (Dabrowski, 2014). The manufacturing industries, in specific, are changing to prepare for the fourth Industrial Revolution, or Industry 4.0, in today's fiercely competitive and innovation-driven corporate climate. Supply chain strategy is vital for achieving an edge over the competition, and it does offer operational and strategic advantages to firms, regions, and nations, according to business leaders, academics, and policymakers. Businesses today must optimize their company operations and support the performance of their whole supply chain to compete in the market. Different factors should be defined and assessed considering various providers' features to choose the best source. As a result, this issue can be categorized as a multi-criteria decision-making problem (Erdogan et al., 2018). E-commerce has flourished since the introduction of the Internet. Because client needs are changing so quickly in the e-commerce era, the complexity and ease of dealing with procurement have become increasingly noticeable. There is consensus in the pertinent literature that choosing the right suppliers is a challenging task due to the sheer volume of criteria that must be considered. Therefore, there is an urgent need for a more structured and open approach to making purchasing decisions, particularly in supplier selection. (Frank et al., 2019). The supplier selection problem (SSP), which involves many criteria for evaluation, is fundamentally a multi-criteria decision-making problem. The Simple Multi Attribute Rating Technique (SMART) is one of the multi-criteria decision-making approaches that is particularly well suited for modeling quantitative criteria.It has found widespread application in a variety of fields, including selection, evaluation, planning and development, decision making forecasting, and other areas. The Simple Multi Attribute Rating Technique (SMART) is a method of multiple criteria decision making developed by Edwards in 1971. It is a compensatory method that aims to provide an easy way to implement the basic principles of Multi-Attribute Utility Theory (MAUT) (Ghadimi et al., 2019). The Simple Multi Attribute Rating Technique (SMART) is a popular multi-attribute decision-making (MADM) technique used to evaluate options based on multiple attributes or criteria. In this method, the decision-maker (DM) identifies the relevant attributes, assigns weights to each attribute based on their relative importance, scores each alternative on each attribute, and then chooses the alternative with the highest total score as the preferred option. The Simple Multi Attribute Rating Technique (SMART) employs a linear additive model, where the total value of an option is determined by the sum of the weighted performance scores for each criterion. This implies that the value of each attribute is multiplied by its respective weight and then added up to calculate the overall value of the alternative (Ghobakhloo, 2020). The SMART uses weights assigned to each attribute by the decision-maker to determine the hierarchy. In other words, the decision maker assigns weights to each criterion based on their individual judgment (Hwang et al., 1981). Despite the large number of providers, the selection procedure is very difficult because many of them do not satisfy all the requirements established by the business. Based on this, a determining model that aids in simplifying and improving the selection process is needed. To provide a proper assessment procedure, this research concentrates on the many criteria obtained from earlier studies. Additionally, this study used both the Simple Multi Attribute Rating Technique (SMART) and Data Envelopment Analysis (DEA) methodologies for its computations. This study uses the DEA Method to assess the effectiveness of suppliers. The efficiency of the provider's input variables is considered, and the best supplier is chosen using hybrid DEA-SMART approach. The effectiveness of our method is proven by offering a numerical example of a manufacturing business that identifies and selects suppliers in the context of an electronic marketplace and provides decision support services on this basis.

2. Literature Review

Industry 4.0 has changed how businesses produce, enhance, and distribute their goods. The Internet of Things (IoT), cloud computing, analytics, AI, and machine learning are among the cutting-edge technologies that manufacturers are incorporating into their manufacturing processes. These "smart" businesses have cutting-edge gauges, software that is embedded, and robotics that gather data, analyze it, and help with decision-making. When operational data from ERP, supply chain, customer service, and other corporate systems is linked with data from production processes, even greater value from previously segregated information is produced. (Javaid et al., 2022) figure out the barriers and solutions to the use of current technology in production processes to line with Industry 4.0 objectives. 22 barriers and

14 solutions were identified by the researchers using a thorough literature analysis. These were then ranked using the BWM and combined compromise solution (CoCoSo) approaches. The paper suggests a framework to assist managers in manufacturing firms in comprehending the challenges and strategically implementing the solutions to convert their systems into Industry 4.0-based systems. Also, (Kumar et al., 2016) intend to suggest an effective technique for choosing a cloud service provider that satisfies the user's Quality of Service (QoS) needs in the context of Industry 4.0. To deal with the complexity and ambiguity involved in the selection process, the study uses a *"fuzzy-based Analytic Hierarchy Process (fuzzy-AHP)"* as a decision-making tool. Meanwhile, (Trung and Thanh, 2022) intend to suggest a fuzzy linguistic MCDM model for the assessment and choice of industry 4.0-compliant digital marketing technologies. The methodology utilized in this research entails identifying the evaluation criteria and alternatives and employing two MCDM methods, SF-AHP and TOPSIS, to support the decision-making process. Besides, (Naveed et al., 2021) attempt to define the critical success factors (CSFs) of Cloud Enterprise Resource Planning (CERP), a key technology for reaching Industry 4.0. The study offers significant knowledge into how businesses may effectively execute CERP as part of their Industry 4.0 strategy using the *"Analytic Hierarchy Process (AHP) and Fuzzy Analytic Hierarchy Process (FAHP)"* approaches to figure out the ranking of the CSFs accountable for the achievement of the information management system (IMS). Likewise, In the framework of Industry 4.0, (Medić et al., 2018) seek to find the most suitable innovations in organization for manufacturing firms in developing nations. The researchers utilized the European Manufacturing Survey data to determine the weights of the criterion and the *"Fuzzy Analytic Hierarchy Process (FAHP)"* to rank the organizational innovations. Additionally, they ranked the organizational innovations using the *"Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE)"* method. Moreover, (Kumar et al., 2021) use a hybrid MCDM technique to investigate strategies for overcoming the obstacles to Industry 4.0. The SWARA-WASPAS method was adjusted for the study's evaluation of Industry 4.0's obstacles and prioritization of solutions for overcoming them.

Besides, (Erdogan et al., 2018) want to present an extensive strategy for choosing the most suitable Industry 4.0 implementation plan, which can assist firms in improving their effectiveness and competitiveness in today's competitive business environment. The methods used includes a methodical approach to identifying different Industry 4.0 implementation strategies, laying out criteria for choosing the best one, and using multi-criteria decision-making (MCDM) methods based on AHP-VIKOR methodologies to evaluate and contrast various implementation strategies. To deal with uncertainty in the selection process, fuzzy set theory is often used. Likewise, (Jamwal et al., 2021) propose to provide a framework for sustainability in Industry 4.0 for (Micro Small Medium enterprises) sector (MSMEs) in India. For the construction of the framework, the study employs a hybrid MCDM methodology based on the *"F-AHP and DEMATEL"* techniques.

The enablers of each enabler group are compared pairwise using F-AHP, and the relationships between the enablers are determined using DEMATEL. In addition, (Raj et al., 2020) seek to identify and study the obstacles to the deployment of Industry 4.0 in the manufacturing sector in various economic scenarios. The study makes use of a suggested approach that has four parts, including the identification of obstacles, the examination of how obstacles relate to one another, expert confirmation of the findings, and sensitivity analysis. The Grey-DEMATEL approach is used in the study to examine the connections between the obstacles.

(Medić et al., 2018) explore the deployment of advanced digital technologies in manufacturing firms and assess their impact in the context of Industry 4.0 in transition nations (i.e., Slovenia, Croatia, and Serbia). The approaches utilized in this study include Fuzzy Analytic Hierarchy Process (FAHP) to generate criteria weights and Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) to rank sophisticated digital technologies. Additionally, (Ucal Sari and Ak, 2022) use fuzzy data envelopment analysis to assess machine efficiency in Industry 4.0. The Data Envelopment Analysis (DEA), Cronbach Alpha reliability analysis, and traditional DEA methods were used in this study's approach. The study also employs the Interval DEA (IDEA) technique as the way to measure efficiency. In the era of Industry 4.0, (Pishdar et al., 2021) evaluate the sustainability performance of third-party logistics service providers (3PLs) that are contemplating circular economy methods. The study compares the sustainability performance of 17 3PLs in terms of various factors using an interval type-2 fuzzy super-slack-based measure network DEA technique. Similarly, (Azadi et al., 2021) investigate a novel DEA model to assess the viability of CSPs (Cloud Service Providers) in the context of Industry 4.0. Data Envelopment Analysis (DEA), a nonparametric methodology that considers numerous inputs and multiple outputs, was utilized in this work to analyze the performance of a group of peer entities. Also, (Azadi et al., 2021) compare internal finance to external funding and examine the significance of financing for manufacturers investing in Industry 4.0 technology. The researchers provide a novel data envelopment analysis (DEA) model that considers economic, environmental, and social elements to analyze the sustainability of financial resources. Also, (Arora et al., 2022) evaluate, and rate Industry 4.0 technologies based on their relative efficiencies in dealing with hurdles in the agricultural supply chain. Analytic Hierarchy Process (AHP) and Data Envelopment Analysis (DEA), two multi-criteria decision-making methodologies, are combined in the AHP-DEA framework used in this study. While DEA is used to assess the relative effectiveness of the alternatives, AHP is used to create a hierarchy of pair-wise comparison and resolve conflicts while achieving the desired aim.

Table 1. The studies examined in the literature

Authors	Methodology	Purpose
Javaid, M. et al. (2022)	**BWM & CoCoSo**	Evaluating the barriers and solutions to the use of current technology in production processes to line with Industry 4.0 objectives.
Kumar, R et al. (2016)	**Fuzzy - AHP**	Suggesting an effective technique for choosing a cloud service provider that satisfies the user's Quality of Service needs in the context of Industry 4.0.
Trung, N. Q. et al. (2022)	**SF-AHP & TOPSIS**	Providing a fuzzy linguistic MCDM model for the assessment and choice of industry 4.0-compliant digital marketing technologies.
Naveed, Q. N. et al. (2021)	**AHP & FAHP**	Attempting to define the critical success factors of Cloud Enterprise Resource Planning, a key technology for reaching Industry 4.0.
Medi, N. et al. (2018)	**FAHP & PROMETHEE**	seek to find the most suitable innovations in organization for manufacturing firms in developing nations.
Kumar, V., et al. (2021)	**SWARA-WASPAS**	Investigating the strategies for overcoming the obstacles to Industry 4.0.
Erdogan, M. et al. (2018)	**AHP-VIKOR**	Presenting an extensive strategy for choosing the most suitable Industry 4.0 implementation plan, which can assist firms in improving their effectiveness and competitiveness in today's competitive business environment.
Jamwal et al. (2021)	**FAHP-DAMATEL**	Propose to provide a framework for sustainability in Industry 4.0 for Micro Small Medium enterprises sector in India.
Raj, A., et al. (2020)	**Grey-DAMATEL**	Seek to identify and study the obstacles to the deployment of Industry 4.0 in the manufacturing sector in various economic scenarios.
Ucal Sari, I., & Ak, U. (2022)	**DEA**	Use fuzzy data envelopment analysis to assess machine efficiency in Industry 4.0.
Pishdar, M. et al. (2021)	**DEA**	Evaluating the sustainability performance of third-party logistics service providers (3PLs) that are contemplating circular economy methods in the context of industry 4.0.
Azadi, M. et al. (2021)	**DEA**	investigate a novel DEA model to assess the viability of Cloud Service Providers in the context of Industry 4.0.
Azadi, M. et al. (2021)	**DEA**	Compare internal finance to external funding and examine the significance of financing for manufacturers investing in Industry 4.0 technology.
Arora, C. et al. (2022)	**AHP-DEA**	Evaluate and rate Industry 4.0 technologies based on their relative efficiencies in dealing with hurdles in the agricultural supply chain.

The literature study demonstrates a deficit in our knowledge of supplier selection in the context of Industry 4.0, particularly in e-commerce. There is a lack of precise advice on choosing suppliers who are prepared for this period of digital transformation, even while current research provides insightful analyses of Industry 4.0's larger landscape. This study fills this knowledge void by emphasizing industry 4.0's supplier selection techniques, notably in e-commerce. Our research intends to offer helpful tips for supply chain experts, stakeholders, and e-commerce companies navigating this challenging market.

3. Methodology

3.1 Simple Multi Attribute Rating Technique (SMART)

The Simple Multi-Attribute Rating Technique (SMART) is a method of multiple criteria decision making. The SMART uses weights assigned to each attribute by the decision-maker to determine the hierarchy. In other words, the decision maker assigns weights to each criterion based on their individual judgment. The weights reflect the relative importance of each attribute in the decision-making process. The alternatives are then evaluated on each attribute using a predetermined scale, and the scores are combined using the assigned weights to determine the overall value of each alternative. By using this approach, SMART simplifies the decision-making process by breaking down the problem into smaller, more manageable pieces (Siregar et al., 2017; Trung et al., 2022).

- Process involved in SMART:

STEP 1: Define the decision problem and identify the criteria that are relevant to the decision.

STEP 2: Assign weights to each criterion by allocating values in the range of 1 to 100 for each criterion based on their level of importance.

STEP 3: Normalize each criterion by dividing its weight by the sum of weights of all criteria using the given formula.

$$\textbf{Normalization} = \frac{w_j}{\sum w_j}$$

- where $\mathbf{w_j}$ is weight of criteria and $\sum \mathbf{w_j}$ is total wight for all criteria.

STEP 4: Find the utility value for converting the criterion value of each attribute to the raw data value by utilizing the formula provided:

$$\textbf{Ui (ai)} = \frac{c_{out} - c_{min}}{c_{\max} - c_{min}}$$

- where **Ui (ai)** is utility value of first criteria to the last criteria, $\mathbf{C_{max}}$ is value of maximum criteria and $\mathbf{C_{min}}$ is value of minimum criteria, $\mathbf{C_{out}}$ is value criterion to the last criteria.

STEP 5: Calculating the final value of each criterion by combining the normalized value of the raw data criteria with the weight-normalized value criteria, followed by multiplying them using the formula below:

$$\text{U}(\text{a}_i) = \sum_{j=1}^{m} w_j\, u_i(a_i), \quad \text{i}= 1, 2,\dots,\text{m}$$

3.2 Data Envelopment Analysis (DEA)

DEA is a non-parametric method used to evaluate the relative efficiency of decision-making units (DMUs) based on their inputs and outputs. The main idea behind DEA is to compare the performance of DMUs that have similar inputs and outputs but operate under different conditions or constraints. DMUs can be any entity that consumes resources (inputs) to produce goods or services (outputs), such as hospitals, banks, schools, or manufacturing plants. DEA evaluates the efficiency of DMUs by comparing their input-output relationships to the best performing DMU (the "efficient frontier"). The efficient frontier is a set of DMUs that represent the best combination of inputs and outputs, given the constraints or conditions faced by each DMU. DEA assumes that each DMU has a unique set of inputs and outputs, and that the performance of each DMU can be represented by a set of input-output ratios. So, DEA then determines the relative efficiency of each DMU by comparing its input-output ratios to those of the efficient frontier. The DMUs that have a ratio of 1 are referred to as efficient and the units that have a ratio less than 1 are less efficient compared to the most efficient units (Ucal Sari and Ak, 2022).

- Process involved in DEA:

STEP 1: Choose the decision-making units (DMUs) that desire to compute efficiency scores for.

STEP 2: Determining the data inputs and outputs for DMUs.

STEP 3: After determining inputs and outputs, calculate DMUs efficiency score using DEA formula provided below:

$$E_k = \text{Max} \sum_{r=1}^{p} u_r y_{rk}$$
s.t
$$\sum_{i=1}^{z} v_i x_{ik} = 1$$
$$\sum_{r=1}^{p} u_r y_{rk} - \sum_{i=1}^{z} v_i x_{ik} \leq 0$$
$$u_r \geq 0, r=1,\dots,p$$
$$v_i \geq 0, i=1,\dots,z$$

- which $\mathbf{E_k}$ is efficiency, score, $\mathbf{y_{rk}}$ is, output r for,DMU_k , $\mathbf{x_{ik}}$ is, input i for,DMU_k , $\mathbf{u_r}$ is, weight devoted to output r, $\mathbf{v_i}$ is, weight devoted to input i, **n** is # of DMUs, **p** is # of, outputs and **z** is # of, inputs.

STEP 4: After obtaining formula and implementing it for each of DMU's, using LINGO software obtain efficiency score.

STEP 5: Rank the DMUs based on efficiency scores.

3.3 Hybrid DEA-SMART Approach for Suppliers Selection

Step 1: Choose the, decision-making units (DMUs) that desire to compute efficiency scores for.

Step 2: Determining the data inputs and, outputs for DMUs.

Step 3: After determining inputs and outputs, Calculate DMU's efficiency score using DEA mathematical formula. After obtaining formula and implementing it for each of DMU's, using LINGO software obtain efficiency score.

$$E_k = \text{Max} \sum_{r=1}^{p} u_r y_{rk}$$
s.t
$$\sum_{i=1}^{z} v_i x_{ik} = 1$$
$$\sum_{r=1}^{p} u_r y_{rk} - \sum_{i=1}^{z} v_i x_{ik} \leq 0 \qquad (3)$$
$$u_r \geq 0, r=1,\dots,p$$
$$v_i \geq 0, i=1,\dots,z$$

Step 4: To make a hybrid model, Assess the criteria for DMU's (attributes) , attributes in rows as A_i and criteria in columns as C_j to evaluate decision matrix.

A_i (i=1,2,...,z)
C_j (j=1,2,..,p)
$$Y = \begin{bmatrix} y_{11} & \cdots & y_{1p} \\ \vdots & \ddots & \vdots \\ y_{z1} & \cdots & y_{zp} \end{bmatrix}$$

Step 5: Using SMART approach, find the raw data.

$$\text{Ui (ai)} = \frac{c_{out} - c_{min}}{c_{\max} - c_{min}} \qquad (3.1)$$

Step 6: assign weights to each criterion by allocating values in the range of 1 to 100 for each criterion.

Step 7: Normalize each criterion weight by dividing its weight by the sum of weights of all criteria using the given formula:

$$\text{Normalization} = \frac{w_j}{\sum w_j} \qquad (3.2)$$

Step 8: Calculating the final weighted value of each criterion by combining the raw value,of criteria with the,weight-normalized value criteria, followed by multiplying them using the formula below:

$$U(a_i) = \sum_{j=1}^{m} w_j \, u_i(a_i), \quad i= 1, 2,\dots,m \qquad (3.3)$$

Step 9: Normalizing the final weighted value.

$$U(a_i)' = \frac{w_j}{\Sigma w_j} \times 100 \tag{3.4}$$

Step 10: To evaluate a hybrid model, multiplying the, efficiency scores of all DMU's with the final weighted value of the criteria, a hybridized efficiency score is produced.

$$E_{k'} = E_k \times U(a_i)' \tag{3.5}$$

Step 11: Rank the DMU's based on their hybridized, efficiency score.

3.4. Case Study

This section provides supplier selection in an B2B e-commerce setting in the context of industry 4.0 (Yoon and Hwang, 1981). The study was carried out using 4 criteria and 4 decision-making units, as shown in Fig.2. For businesses involved in B2B manufacturing e-commerce, selecting suppliers is a crucial and difficult issue. In this study, we provide an integrated data envelopment analysis and a simple multi-attribute ranking technique for the selection of suppliers based on several criteria. The efficiency score of each supplier is determined using the data envelopment analysis (DEA) in the proposed DEA-SMART approach, and the weights of each criterion are then computed using Simple Multi Attribute Rating Technique (SMART). A numerical example illustrates how to use the suggested way to compare the ranking order changes between the DEA method and the hybrid DEA-SMART method.

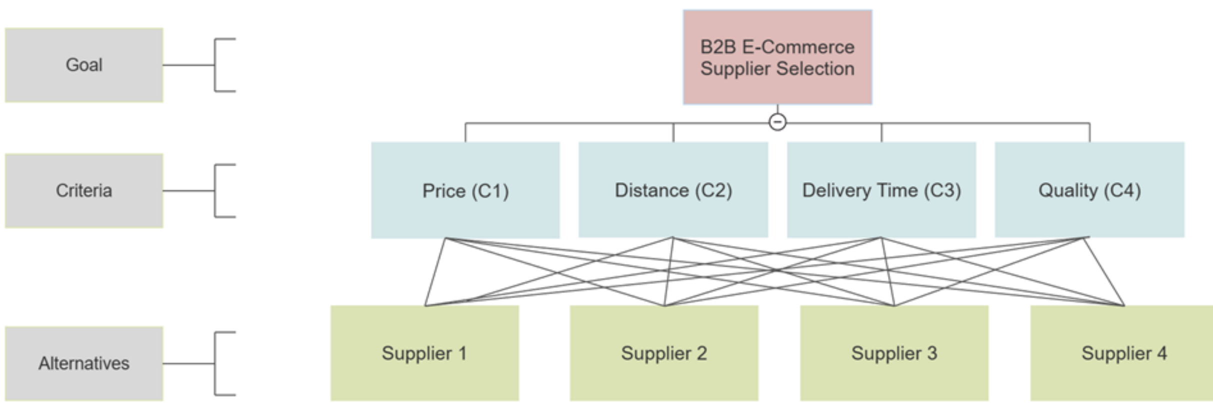

Figure 1. Alternatives and criteria's hierarchical chart

A brief description and clarification of all criteria are provided in Table 2.

Table 2. Description of criteria

Criteria	Description
Price	Monetary value or cost assigned to a product or service.
Distance	The actual distance that needs to be covered for goods or services to be transported from the supplier's location to the company's location.
Delivery time	The time taken from the placement of the order to the receipt of the products or completion of the requested services.
Quality	The level of excellence or how well the supplier's offerings meet the company's requirements or standards.

The following data is acquired through investigation and with the support of findings from additional pertinent studies, as indicated in the study, and is based on specified criteria and Decision-Making Units (DMUs) as detailed in Table 3 (Yoon and Hwang, 1981).

Table 3. Collected data according to criteria and DMU's

DMU's	Input Variable		Output Variable	
Suppliers	Price (I_1)	Distance (I_2)	Delivery Time (O_1)	Quality (O_2)
S1	53	39	0.84	0.92
S2	56	35	0.68	0.85
S3	46	47	0.93	0.74
S4	49	57	0.83	0.89

After gathering the data provided in Table 3, we created a mathematical model. By utilizing the LINGO software, we computed the efficiency score for each supplier according to Equation (3). The outcomes of the efficiency score calculation, which were achieved through the implementation of the Data Envelopment Analysis (DEA) technique, can be observed in Table 5.

$$\begin{aligned}
&E_1 = \text{Max } 0.84u_1 + 0.92u_2\\
&\text{s.t.}\\
&53v_1 + 39v_2 = 1\\
&0.84u_1 + 0.92u_2 - 53v_1 - 39v_2 <= 0\\
&0.68u_1 + 0.85u_2 - 56v_1 - 35v_2 <= 0\\
&0.93u_1 + 0.74u_2 - 46v_1 - 47v_2 <= 0\\
&0.83u_1 + 0.89u_2 - 49v_1 - 57v_2 <= 0\\
&U_1 >= 0\\
&U_2 >= 0\\
&V_1 >= 0\\
&V_2 >= 0
\end{aligned}$$

$$\begin{aligned}
&E_2 = \text{Max } 0.68u_1 + 0.85u_2\\
&\text{s.t.}\\
&56v_1 + 35v_2 = 1\\
&0.84u_1 + 0.92u_2 - 53v_1 - 39v_2 <= 0\\
&0.68u_1 + 0.85u_2 - 56v_1 - 35v_2 <= 0\\
&0.93u_1 + 0.74u_2 - 46v_1 - 47v_2 <= 0\\
&0.83u_1 + 0.89u_2 - 49v_1 - 57v_2 <= 0\\
&U_1 >= 0\\
&U_2 >= 0\\
&V_1 >= 0\\
&V_2 >= 0
\end{aligned}$$

$$\begin{aligned}
&E_3 = \text{Max } 0.93u_1 + 0.74u_2\\
&\text{s.t.}\\
&46v_1 + 47v_2 = 1\\
&0.84u_1 + 0.92u_2 - 53v_1 - 39v_2 <= 0\\
&0.68u_1 + 0.85u_2 - 56v_1 - 35v_2 <= 0\\
&0.93u_1 + 0.74u_2 - 46v_1 - 47v_2 <= 0\\
&0.83u_1 + 0.89u_2 - 49v_1 - 57v_2 <= 0\\
&U_1 >= 0\\
&U_2 >= 0\\
&V_1 >= 0\\
&V_2 >= 0
\end{aligned}$$

$$\begin{aligned}
&E_4 = \text{Max } 0.83u_1 + 0.89u_2\\
&\text{s.t.}\\
&49v_1 + 57v_2 = 1\\
&0.84u_1 + 0.92u_2 - 53v_1 - 39v_2 <= 0\\
&0.68u_1 + 0.85u_2 - 56v_1 - 35v_2 <= 0\\
&0.93u_1 + 0.74u_2 - 46v_1 - 47v_2 <= 0\\
&0.83u_1 + 0.89u_2 - 49v_1 - 57v_2 <= 0\\
&U_1 >= 0\\
&U_2 >= 0\\
&V_1 >= 0\\
&V_2 >= 0
\end{aligned}$$

After constructing the mathematical model using Equation (3), we proceeded to methodically solve the subsequent equations denoted as E1, E2, E3, and E4 utilizing Lingo software. By means of this thorough analysis, we ascertained the effectiveness measurements for each equation, as outlined in Table 4.

Table 4. Evaluation of efficiency score

Suppliers	Price (I_1)	Distance (I_2)	Delivery Time (O_1)	Quality (O_2)	Efficiency Score
S1	53	39	0.84	0.92	1.00
S2	56	35	0.68	0.85	1.00
S3	46	47	0.93	0.74	1.00
S4	49	57	0.83	0.89	1.00

Following the calculation of efficiency scores, the SMART approach is used to find the best provider, assuming that all suppliers obtained a computed score of 1.00. The first critical step in starting this process is standardizing the data, which is currently available at multiple scales. This standardization technique starts with determining the lowest and highest values for each criterion in the dataset. Following that, we calculate the raw data as shown in Table 5 for each provider and criterion using Equation (3.1). To simplify the process, we initially identified the minimum and maximum

values for each criterion, as illustrated in Table 5. Subsequently, we applied Equation 3.1 to calculate the Ui(ai) value for each entry in the table.
As an illustration, consider the calculation for Supplier 1: $\text{Ui(ai)} = \frac{53-46}{10} = 0.70$

Table 5. Evaluation of raw data

Suppliers	Price (I_1)	Distance (I_2)	Delivery Time (O_1)	Quality (O_2)
S1	53	39	0.84	0.92
S2	56	35	0.68	0.85
S3	46	47	0.93	0.74
S4	49	57	0.83	0.89
Min Value	46	35	0.68	0.74
Max Value	56	57	0.93	0.92
Max-Min Value	10	22	0.25	0.18
S1	0.70	0.18	0.64	1
S2	1.00	0	0.00	0.61
S3	0	0.55	1.00	0
S4	0.3	1.00	0.60	0.83

As shown in Table 6, allocating weights to each criterion is performed by assigning values ranging from 1 to 100 using the Simple Multi Attribute Rating Technique. Furthermore, Equation (3.2) is used to achieve weight normalization. It is vital to highlight that the decision maker's judgment is used to determine the weight allocated to each criterion. It is essential to emphasize that the weights assigned to each criterion are based on the judgment of the decision maker. According to the SMART method, the decision maker's judgment plays a crucial role in determining these weights.

Table 6. Weight and normalized weight of each criterion

Criteria	Weight	Normalized-Weight
C1	40	0.4
C2	20	0.2
C3	10	0.1
C4	30	0.3
Sum	100	1

The eventual weighted value for each criterion is calculated by multiplying the raw value of the criteria by their weighted values. The values derived from equations (3.3) and (3.4) are then computed to produce the final scores. Table 7 displays the total cumulative values of the criteria as calculated by the Simple Multi Attribute Rating Technique.
As an illustration, consider the calculation for Supplier 1: $\text{U(ai)} = \big((0.4 \times 0.70) + (0.2 \times 0.18) + (0.1 \times 0.65) + (0.3 \times 1)\big) = 0.68$

$$U(ai)' = \frac{w_j}{\sum w_j} = \frac{0.68}{2.1} = 0.32 \times 100 = 32$$

Table 7. Evaluation of final score using SMART method

DMU's	Criteria 1	Criteria 2	Criteria 3	Criteria 4	Score	Total Score
S1	0.70	0.18	0.64	1	0.68	32
S2	1.00	0	0.00	0.61	0.58	28
S3	0	0.55	1.00	0	0.21	10
S4	0.3	1.00	0.60	0.83	0.63	30
N. Weight	0.4	0.2	0.1	0.3		

In the ultimate phase, a hybrid score known as 'Hybrid DEA-SMART,' calculated using Equation (3.5), was constructed to determine the ranking of suppliers and identify the best performance. This hybrid score is obtained by multiplying each supplier's efficiency score by the overall score acquired using the Simple Multi Attribute Rating Technique. Table 8 displays the resulting hybrid scores.

Table 8. Evaluation of hybridized score

DMU's	Criteria 1	Criteria 2	Criteria 3	Criteria 4	Hybridized Efficiency Score
S1	0.70	0.18	0.64	1	32
S2	1.00	0	0.00	0.61	28
S3	0	0.55	1.00	0	10
S4	0.3	1.00	0.60	0.83	30

4. Comparison Study

In this section, our aim is to carry out a thorough analysis by comparing different methodologies to determine their effectiveness in solving the specified problem. Our main focus is to assess how well the hybrid DEA-SMART method performs in comparison to the alternative technique, which is the hybrid DEA-AHP method, when applied to the same dataset. The DEA-SMART method combines Data Envelopment Analysis (DEA) with the Simple Multi-Attribute Rating Technique (SMART), while the DEA-AHP method integrates DEA with the Analytic Hierarchy Process (AHP). By adopting a comparative approach, our intention is to highlight the strengths and weaknesses of each method, including their computational complexity and sensitivity to variations in parameters. Ultimately, our objective is to offer valuable insights into the applicability and efficiency of these methodologies in addressing the research problem. Through thorough examination and evaluation, we aim to provide a nuanced understanding of how well the hybrid DEA-SMART method performs in relation to other methodologies, thereby contributing to the advancement of decision-making processes in the context of our study.

4.1 Hybrid DEA-AHP Approach for Suppliers Selection

In the DEA-AHP method proposed by Ramanathan, binary comparison matrices are first created in the AHP method. The output values are taken as all columns of the created comparison matrix, and the Decision Maker Units (DMus) are found as all rows. The created matrix has an equal number of DMus and output values. However, since input values are also required in the implementation of the DEA method, a dummy input with a value of "1" should be added to each column for each DMu (Ramanathan, 2006). The performances of the DMus are calculated using the AHP method. The local weights of the DMus are determined based on the calculated performance values.

STEP 1: If the DMUs are defined as k (k=1,2,…,n), in the first stage, comparison matrices are created for each DMU. If the input variable is denoted as m and the output variable as s, the following model can be applied for comparison.

$$
\begin{aligned}
\mathbf{E}_{k,k'} &= \text{Max} \sum_{r=1}^{p} u_r\, y_{rk} \\
&\text{s.t} \\
&\sum_{i=1}^{z} v_i x_{ik} = 1 \\
&\sum_{r=1}^{p} u_r y_{rk} - \sum_{i=1}^{z} v_i x_{ik} \le 0 \\
&\sum_{r=1}^{p} u_r y_{rk'} - \sum_{i=1}^{z} v_i x_{ik'} \le 0 \\
&u_r \ge 0,\ r=1,\ldots,p \\
&v_i \ge 0,\ i=1,\ldots,z \\
&k \ne k',\ k'=1,\ldots,n
\end{aligned} \tag{4}
$$

where in $\mathbf{e}_{k,k'}$: Efficiency of the **k**th DMC compared to the **k**'th DMC.

After solving the model for each DMU as described above in LINGO program, the values of $\mathbf{e}_{k,k'}$ are determined and placed into matrix E. An example of the resulting E matrix is provided below.

Table 9. The E matrix for the DEA-AHP method

	1	2	3	...	N
1	1	$E_{1,2}$	$E_{1,3}$	...	$E_{1,N}$
2	$E_{2,1}$	1	$E_{2,3}$	...	$E_{2,N}$
3	$E_{3,1}$	$E_{3,2}$	1	...	$E_{3,N}$
...	...	...	...	...	...
N	$E_{N,1}$	$E_{N,2}$	$E_{N,3}$	...	1

STEP 2: After completing the first step, the AHP hierarchy is established, and a pairwise comparison matrix A is formed.

$$\mathbf{a'}_{k,k'} = \frac{E_{k,k'}}{E_{k',k}} \tag{4.1}$$

Table 10. The A matrix for the DEA-AHP method

	1	2	3	...	N
1	1	$a_{1,2}$	$a_{1,3}$	...	$a_{1,N}$
2	$a_{2,1}$	1	$a_{2,3}$	...	$a_{2,N}$
3	$a_{3,1}$	$a_{3,2}$	1	...	$a_{3,N}$
...	...	...	...	...	...
N	$a_{N,1}$	$a_{N,2}$	$a_{N,3}$	...	1

The columns of the created A matrix are individually summed, and each value in the column is divided by the sum of the column values to create the A' matrix.

$$\mathbf{a'}_{k,k'} = \frac{E_{k,k'}}{\sum_{k=0}^{n} E_{k',k}} \tag{4.2}$$

The values in the rows of the created A' matrix are summed, and normalization is applied to obtain the A'' matrix. With the resulting matrix, ranking is conducted to determine the final rankings of the DMUs.

4.2 Application of hybrid DEA-AHP

In this section, we will utilize the hybrid DEA-AHP method on the dataset displayed in Table 3. Our objective is to evaluate its effectiveness in relation to other methodologies. By using the same dataset, we intend to directly compare the hybrid DEA-AHP with the hybrid DEA-SMART approach. This examination will provide significant insights into the performance and suitability of the hybrid DEA-SMART method in addressing the research problem at hand.

Table 11. Collected data according to criteria and DMU's

DMU's	Input Variable		Output Variable	
Suppliers	Price (I_1)	Distance (I_2)	Delivery Time (O_1)	Quality (O_2)
S1	53	39	0.84	0.92
S2	56	35	0.68	0.85
S3	46	47	0.93	0.74
S4	49	57	0.83	0.89

At this stage, where pairwise comparisons will be made, a total of 16 models have been developed for 4 DMUs using equation (4). Here, we showcase two of the developed models: one that compares DMU1 and DMU2, and another that compares DMU2 and DMU1.

$E_{1,2}$ = Max $0.84u_1 + 0.92u_2$
s.t.
$53v_1 + 39v_2 = 1$
$0.84u_1 + 0.92u_2 - 53v_1 - 39v_2 <= 0$
$0.68u_1 + 0.85u_2 - 56v_1 - 35v_2 <= 0$
$U_1 >= 0$
$U_2 >= 0$
$V_1 >= 0$
$V_2 >= 0$

$E_{2,1}$ = Max $0.68u_1 + 0.85u_2$
s.t.
$56v_1 + 35v_2 = 1$
$0.68u_1 + 0.85u_2 - 56v_1 - 35v_2 <= 0$
$0.84u_1 + 0.92u_2 - 53v_1 - 39v_2 <= 0$
$U_1 >= 0$
$U_2 >= 0$
$V_1 >= 0$
$V_2 >= 0$

After solving the 16 models that were written for 4 Decision Making Units (DMUs), we have constructed the matrix E, which is presented in Table 12. This matrix encompasses the values that have emerged from the comparisons made among the 4 DMUs.

Table 12. Matrix E

	DMU 1	DMU 2	DMU 3	DMU 4
DMU 1	1	1	1	1
DMU 2	1	1	1	1
DMU 3	1	1	1	1
DMU 4	1	1	1	1

Subsequently, we have employed the Analytic Hierarchy Process (AHP) to the values in the E matrix in order to derive the A matrix, utilizing equation (4.1).

Table 13. Matrix A

	DMU 1	DMU 2	DMU 3	DMU 4
DMU 1	1	1	1	1
DMU 2	1	1	1	1
DMU 3	1	1	1	1
DMU 4	1	1	1	1

Following this, we have normalized the columns of the A matrix by applying equation (4.2) in order to obtain the A' matrix.

Table 14. Matrix A'

	DMU 1	DMU 2	DMU 3	DMU 4
DMU 1	0.25	0.25	0.25	0.25
DMU 2	0.25	0.25	0.25	0.25
DMU 3	0.25	0.25	0.25	0.25
DMU 4	0.25	0.25	0.25	0.25

The normalization process has then been implemented on the rows of the A' matrix, resulting in the final A" matrix, as dictated by equation (4.3). This ultimate matrix has greatly facilitated the determination of the rankings for the DMUs based on the defined criteria.

Table 15. Matrix A"

	DMU 1	DMU 2	DMU 3	DMU 4
DMU 1	0.25	0.25	0.25	0.25
DMU 2	0.25	0.25	0.25	0.25
DMU 3	0.25	0.25	0.25	0.25
DMU 4	0.25	0.25	0.25	0.25

5. Result

During our study, the initial DEA assessment produced an efficiency score of 1.00 for all providers, indicating a uniformly high level of efficiency. However, this uniformity posed a challenge in pinpointing the top-performing supplier based solely on these identical results. Recognizing this limitation, we implemented a distinctive hybrid approach aimed at establishing a ranking system using combined efficiency ratings to differentiate between the providers. As a result of applying this innovative algorithm, the suppliers were ranked as follows: Supplier 1 secured the top position with a hybrid efficiency value of 32, closely trailed by Supplier 4, achieving a score of 30. Supplier 2 claimed the third position, demonstrating a commendable hybrid efficiency score of 28. Lastly, among the efficient providers, Supplier 3 landed in the bottom position with a score of 10. This careful rating not only allows for a more granular evaluation of supplier performance, but it also provides essential insights into the varied degrees of efficiency demonstrated by each provider within the area of our research. Such sophisticated insights might help firms navigate supplier selections in the framework of B2B e-commerce and Industry 4.0. Table 16 presents a complete summary of the relative achievements of suppliers based on their hybridization efficiency scores.

Table 16. Suppliers final ranking

Ranking	DMU's	Hybridized Efficiency Score
1	Supplier 1	32
2	Supplier 4	30
3	Supplier 2	28
4	Supplier 3	10

In our efforts to improve the assessment of supplier efficiency, we utilized the DEA-AHP method to compare the results of two different approaches. However, our analysis showed that the use of DEA-AHP posed similar challenges to the initial DEA assessment. Despite being integrated with DEA, the AHP method did not offer a reliable solution for identifying the top-performing supplier. This limitation highlighted the need for a more sophisticated approach to evaluating suppliers. While the DEA-SMART method provided a fresh perspective, the inclusion of DEA-AHP did not lead to significant enhancements in differentiating between providers based on efficiency scores. This discovery emphasizes the complexity of supplier evaluation and underscores the importance of exploring alternative methodologies to gain comprehensive insights into supplier performance

6. Conclusion

In summary, when we apply hybrid DEA-SMART model, applying Simple Multi Attribute Rating Technique gives weight to each criterion and this results in changing the order of ranking. DEA-SMART supplier selection in B2B e-commerce within the context of Industry 4.0 delivers considerable benefits and boosts corporate productivity and competitiveness. Data Envelopment Analysis (DEA) and the Simple Multi-Attribute Rating Technique (SMART) strengths are combined in this hybrid technique to give a thorough and quantitative evaluation of providers based on several criteria. Businesses may assess supplier effectiveness using the DEA-SMART approach, compare performance, and give priority to suppliers that provide the highest value. It makes data-driven decision-making easier, lessens personal biases, and makes supplier selection procedures more objective. Businesses may take advantage of Industry 4.0 to improve their procurement procedures, optimize supply chain operations, and boost their operational effectiveness by utilizing digital technology and data analytics. Businesses are better equipped to choose and work with the most effective and dependable suppliers in the B2B e-commerce market when they implement the DEA-SMART approach for supplier selection. Consequently, there is an increase in customer happiness, timely delivery, cost optimization, and product quality. The technique also aids in the supply chain's entire digital transformation, which is in line with Industry 4.0's objectives and tenets. The DEA-SMART approach offers a useful framework for firms to adapt and succeed in the rapidly evolving electronic marketplace as B2B e-commerce and Industry 4.0 technologies develop. Organizations may arrive at knowledgeable supplier selection decisions that have an advantageous effect on their operational efficiency, competitiveness, and overall success in the B2B e-commerce landscape of Industry 4.0 by utilizing the strength of quantitative analysis and integrating it with the thorough evaluation of numerous attributes. This methodology provides a trustworthy outcome and may be expanded for similar businesses. Using knowledge-driven approaches like fuzzy logic, the model may be expanded, and a decision support system may be created.

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