Sustainable-resilient supplier evaluation for high-consumption drugs during the COVID-19 pandemic using a data-driven decision-making approach

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Abstract

The recent pandemic of COVID-19 has had severe impacts on healthcare services especially the Food and Drug Administration for providing necessary drugs from appropriate suppliers. In the current study, we aim to develop a data-driven model for sustainable-resilient supplier evaluation. So, we identify the related criteria based on literature and experts and then calculate their weights using Fuzzy-Bests-Worst-Method (FBWM). Afterward, the Fuzzy Inference System (FIS) method is employed to evaluate the performance of the suppliers. Finally, three different classification machine learning models are developed based on the supplier historical data in every criterion and also the FIS output as the target column. This study identifies a suitable list of sustainable and resilient criteria for supplier evaluation. Specifically, 22 criteria are identified and categorized into three-dimension (economic, social, environmental, and resilient). The results show that the case study managers pay more attention to 'Responsiveness' and 'Ability'. The two-stage FIS results indicate that 35 records are evaluated as very poor, 70 ones as poor, 98 ones as moderate, 90 ones as good, and 57 as very good ones. Other companies could use the same model for their supplier selection decision-making to have a better decision for selecting their potential suppliers.

Keywords: Data-driven supplier evaluation, Sustainability, Resilience, FBWM, Two-stage FIS

1. Introduction

During the last decades, researchers have focused on the supply chain management (SCM) problem, since its importance for managers in different companies [1]. The supplier selection problem (SSP) is an important part of the SCM that aims to prioritize potential suppliers to select best ones [2]. In other words, supplier evaluation is a critical activity in the purchasing process in a SCM and impacts the benefits of the organization directly [3]. SSP is a multi-criteria decision making (MCDM) issue that is influenced by many conflicting factors such as price, delivery, service, and quality and it is a combination of different types of uncertainties [4]. An appropriate decision-making model should be able to deal with the ambiguity and uncertainty in individual judgments, and to provide a reasonable ranking of several alternatives by assigning reasonable scores [5]. Choosing the right supplier is a challenging issue and making the wrong decision will

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have many negative consequences for companies [6]. In today's highly competitive world, it is almost impossible to produce lower-cost, higher-quality products without leading suppliers [7].

In recent years, increasing global competition and stakeholders, especially government legislators and social-environmental activists, have required many organizations to be sustainable in their performance [8]. So, the organizations are moving to sustainable supply chains, especially in sensitive industries such as perishable supply chains, to reduce supply chain risks. Choosing a sustainable supplier requires evaluating the supplier's performance based on three dimensions include economic, social, and environmental [9]. Despite the popularity of the topic of sustainable supplier selection, this concept is less focused in SSP. However, the benefits of sustainable supply chains include a significant reduction in waste, tangible cost savings, increased revenue and market share, and the hiring of talented employees [10,11].

Today, the business environment provides the preconditions for the formation of a high level of uncertainty and turbulent supply chain behaviors. Hadizadeh et al., (2018) [12] defined resilience for disaster management caused by natural disasters, which can be measured by considering supply chain resistance and recovery speed. Also, Alikhani et al., (2019) [13] called resilience the ability to prepare for unforeseen risks, manage the potential disruptions immediately to enhance customer satisfaction. For instance, a thunderstorm on the 17th of March, 2000, burned the semi-conductors of Philips company which was both Nokia’s and Ericsson’s major supplier. In that situation, Nokia substituted its supplier immediately but Ericson could not and leaded to its market share decrease [14,15]. Besides natural disasters, there are many situations such as terrorism and pandemics like COVID-19 pandemic these days which companies face and have been experienced unprecedented challenges while could not predict them before in the recent COVID-19 pandemic. Based on Kwon, (2020) [16], Fortune magazine reported that, 94% of the Fortune companies faced their supply chain disruptions during COVID-19 pandemic due to big difference between their supply and demand amount. Besides, the current global pandemic of COVID-19 had severe impacts on Food and Drug Administration (FDA) in order to provide needed medications and drugs. For instance, Serum, Remdesivir, and Favipiravir consumption increased as a result. Unfortunately, severe shortage of medicine, hospital beds, vaccines and serum have been occurred in Iran during COVID-19 outbreak and with the increase of number of infected patients, the conditions of pharmacies became more critical like hospitals and the medicines needed by infected patients are not easily available to people. So, hospitals need to be supplied by drug suppliers while sustainability and resilience aspects are necessary due to the reasons mentioned above [17]. However, it is not reasonable to consider sustainability without the resilience aspects, since resilience impacts on sustainability. However, the presence of disturbances in the supply chain reduces its sustainability goals [18]. Thus, resilience practices in critical situations help to create sustainability in the supply chain. In other words, resilience is a competitive advantage of sustainability for suppliers in the supply chain.

There is usually no single supplier who can best meet all of the selection criteria. In fact, one supplier may be the best at one criterion, while another may be the best at another one. Therefore, to analyze the selection of suppliers, it seems essential to evaluate their efficiency according to the various criteria historical data regarding the performance of suppliers in the past [19]. Since multiple criteria create a large amount of data in the evaluation of suppliers, the machine learning techniques can be useful besides multi-criteria decision-making. Machine learning, which is a type of artificial intelligence (AI) could create predictive insights in a large data set and help the organization to achieve the desired results by modeling different scenarios and performs "what-if" analysis automatically [20, 21].

In this study, we aim to provide a data-driven model for sustainable and resilient supplier evaluation. First, we will define the related criteria and then they will be evaluated by Fuzzy-Best-Worst-Method (FBWM). Then, using the expert rules, the Fuzzy Inference System (FIS), the supplier performance will be evaluated. Finally, three different classification machine learning (ML) models will be developed based on the supplier's historical data for supplier evaluation prediction. The remainder of this research is structured as follows: In Section 2, the literature is reviewed. Methods and materials are provided in Section 3. The computational results are described in Section 4. Section 5 is dedicated to the explanation of data-driven models. Eventually, managerial implications and future studies are given in Section 6.

2. Background and literature review

In this section, different researches in supplier selection problems especially in sustainable, resilient, and sustainable-resilient aspects as three research streams.

2.1. Sustainable supplier selection problem

Various studies have been conducted on supplier sustainability indicators. Among recent researches in this stream, Tirkolaee et al., (2020) [22] first used Fuzzy ANP for ranking criteria and sub-criteria and then fuzzy DEMATEL for relationships identification and finally, Fuzzy TOPSIS to prioritizing suppliers for sustainable reliable supplier selection problem with GAMS/CPLEX solver. Yazdani et al., (2021) [23] focused on sustainable supplier selection using integrated combined compromised solution (CoCoSo) and interval valued fuzzy neutrosophic (IVFN) model for a dairy company as case study. Finally, they ranked the potential suppliers and proposed their approach for other companies. Thanh & Lan, (2022) [24] used different MCDM techniques such as Fuzzy Analytical Hierarchy Process (FAHP) method and the Combined Compromise Solution (CoCoSo) algorithm for sustainable supplier evaluation in a food processing company. They defined several criteria based on three dimensions of sustainability (i.e., economic, social, and environmental).Then, they weighted these criteria and finally, ranked the suppliers based on the criteria defined and weighted before. Chia-Nan et al., (2022) [25] tried to propose a model for sustainable supplier selection in a chemical company in Vietnam based on various MCDM technique using spherical fuzzy numbers. They first defined some criteria and weighted them using spherical fuzzy analytical hierarchy process (SF-AHP) and then ranked the suppliers using combined compromise solution (CoCoSo) method in order to select the most appropriate supplier.

2.2. Resilient supplier selection problem

In addition to sustainable supplier selection, recently, many papers focused only on resilient supplier selection. For example, Solgi et al., (2021) [26] conducted a study to select a resilient supplier in the supply chain of complex products and systems with uncertainty. The industry studied in this article was satellite equipment companies. A mathematical model was presented to select the supplier of resilience and assign the order of complex products to them in conditions of uncertainty. Shao et al., (2022) [27] tried to evaluate the suppliers during COVID-19 pandemic and based on disruptions caused by that. So, they developed a multi objective optimization model while could select the best suppliers and then allocate the orders to them. The objectives included in their model were maximizing decentralized procurement, minimizing disruption probability, maximizing sustainability score, maximizing resilience score, and minimizing total cost. They used a novel nRa-NSGA-II algorithm for solving the model. Wang et al., (2022) [28] developed a two-stage supplier selection model while considering uncertainties caused by COVID-19 outbreak for an automotive company in Vietnam. They used spherical fuzzy Analytical Hierarchical Process (SF-AHP) for criteria weighting and grey Complex Proportional Assessment (G-COPRAS) for supplier evaluation. Leong et al., (2022) [29] also proposed a new integrated MCDM model (GRA-BWM-TOPSIS) for resilient supplier selection problem. They first defined several criteria related to resilience such as quality, lead time, cost, flexibility, visibility, responsiveness, and financial stability. They calculated the criteria importance via GRA and the criteria final weights using BWM. Finally, they ranked the potential suppliers using TOPSIS method. Tajmiri & Farhadi, (2022) [30] focused on resilient supplier selection for a steel production company as this company faced some disruptions. They first defined 10 criteria and ranked three suppliers using new MARCOS multi-criterion decision making method while compared the results to TOSIS, VIKOR, COPRAS, and QULAIFLEX methods.

2.3. Sustainable-Resilient supplier selection problem

In this research stream, Kazemitash et al., (2021) [31] have proposed a new method to select a resilient-sustainable supplier. The purpose of this paper is to present a simple model for resilient-sustainable supplier selection. In this model, 114 criteria are selected based on sustainability and resilience criteria and use a simple technique for ranking and selecting suppliers. Fallahpour et al., (2021) [32] developed an integrated decision-making approach in fuzzy environment for selecting a supplier while considering sustainability and resilience in the Malaysian oil industry. They proposed an approach for selecting sustainable and flexible suppliers. First, sustainable criteria based on resilience have been localized to evaluate the supplier performances in the Malaysian oil industry. Accordingly, 30 criteria in the three general categories of stability and flexibility were finalized, evaluated, and analyzed with fuzzy DEMATEL approaches, FBWM, Fuzzy-ANP, and fuzzy inference system (FIS). According to the findings of the proposed model and its implementation in Malaysian palm oil industry, the cost was the most important criterion of general criteria, resource consumption criterion was the most important criterion of sustainability, and finally, the agility was identified as the most important criterion of resilience. Nayeri et al., (2021) [33] have presented a multi-objective stochastic and fuzzy model to design a sustainable, resilient, and responsive supply chain. This study used mixed multi-objective mathematical models to identify a resilient- responsive sustainable supply chain network. The objectives of the proposed model were to minimize the total costs and environmental damage along with maximizing the social impact and the level of responsiveness and flexibility of the supply chain network. Afrasiabi et al., (2022) [34] also proposed an extended hybrid fuzzy MCDM model while focused on sustainable-resilient supplier selection problem. They considered the disruptions caused by COVID-19 pandemic and tried to define the criteria for resilience dimension. So, they used fuzzy best-worst method (FBWM) and then ranked the suppliers using TOPSIS. Their results showed that pollution control, environmental management system, and risk awareness were the most important criteria for supplier selection.

2.4. Research gap

Various studies have been conducted to evaluate suppliers, but the integrated sustainable resilient supplier evaluation rarely had been focused on by researchers. Although some researchers focused on that, the methods used and case studies were different. Furthermore, the contributions of this study could be justified as follow:

- One of the most important issues for hospitals during the corona epidemic, especially at the peak of virus transmission rates among the population, is the high number of hospitalizations. As a result of this increase in hospitalization, the need for medical drugs in hospitals is increasing, which requires the existence of reliable and stable suppliers in this situation who can provide the necessary drugs to hospitals promptly and provide them to hospitals. Based on the literature reviewed, the issue of choosing a supplier of high-dose coronary drugs in peak conditions of hospitalization by people with coronary heart disease is very important, which is addressed in this article as the first research gap and has not been evaluated and selected in other studies.
- AHP as an MCDM technique has been used more than other techniques for determining the importance weights of the criteria in different decision-making problems. AHP requires many pairwise comparisons and it is time-consuming. It also needs tremendous calculation. For instance, Tirkolaee et al (2020) [22] first used the fuzzy AHP method to weight and rank the criteria and sub-criteria, then the fuzzy DEMATEL method to identify the criteria relationships, and finally using fuzzy TOPSIS to prioritize suppliers in choosing a sustainable supplier. So, BWM which is one of the newest MCDM method has been used in this study. Whereas in this study the fuzzy BWM method for weighting criteria and sub-criteria are used in order to deal with uncertainty and vagueness.
- The previous methods used in recent studies were usually unable to suppliers' performance evaluation separately. In other words, when only a new supplier added in decision-making problem, all the comparison processes must be carried out again. Furthermore, FIS as a method is used in this study which does not need recalculation if the number of suppliers are changed Amindoust (2018) [15] has proposed a hybrid model for selecting a sustainable- resilient supplier and a modular fuzzy inference system has been used to weight the criteria and the suppliers have been ranked by DEA method. However, the combination of FBWM method, FIS, and data mining algorithms in the current study. So, the second level of the current study is to provide an integrated FBWM-two-stage FIS model for labeling the suppliers in five different levels.
- Also, data-driven decision-making for selecting a supplier is almost a new challenge for researchers. Most studies have used multi-criteria decision-making

and not data-driven models. For example, Fallahpour et al (2021) [32] presented a hybrid fuzzy framework for selecting a sustainable and resilient supplier. In this study, fuzzy BWM, FANP, and FDEMATEL approaches and their combination with the FIS method have been used to weight the identified criteria and sub-criteria as well as the ranking of suppliers in the Malaysian palm oil industry. But in this study, we try to develop a data-driven model based on machine learning models for sustainable and resilient supplier selection for main drugs used for COVID 19 infected patients. For this aim, first, the criteria and sub-criteria are weighted using FBWM. Then, the supplier performance will be identified by two-stage FIS. Finally, three data-driven classification models are developed to predict the other suppliers in the next periods based on their historical data and performance before.

3. Materials and Methods

In the first step, using reviewing the research literature as well interviews with experts, evaluation criteria and supplier selection in the supply chain of high-consumption drugs in hospitals were identified in the COVID-19 pandemic and finalized by Delphi approach in the panel of experts. The experts of this study include hospital managers, researchers, and experts in the selection and evaluation of drug suppliers who have at least 5 years of experience in drug supply process. The Delphi panel was held in two rounds with 18 experts. So, indicators that weigh more than 6 in the first round enter the second round and in the second round, indicators with a weight of more than 7 are selected as the final indicators. In the second step, the identified criteria were compared through FBWM. So, each criterion will have its weight. Then, through data collected from the case study and the expert rules, the FIS were used for evaluating the supplier performance. In the last step, classification machine learning models are developed which can evaluate the later suppliers. In Figure1 this study proposed framework is depicted.

3.1. Fuzzy Best-Worst Method (FBWM)

The best-worst method was first introduced by Rezaei et al., (2015) [35]. This method is based on pairwise comparisons and using linear programming model. In this method, instead of performing pairwise comparisons for all indicators (criteria and sub-criteria) with each other, which is done in hierarchical analysis, the best and worst indicators are compared to the rest of the indicators, then a maximum problem is formulated to calculate the weight of the different indicators. Finally, using a mathematical model, the weights of each indicator are determined. Also, in this method, a formula for calculating the incompatibility rate is considered to check the validity of the comparisons [36]. Subsequently, Guo & Zhao (2017) [37] presented the fuzzy best-worst method (FBWM) in order to deal with the space of uncertainty. Let $\tilde{a} = (l, m, u)$ denotes a triangular fuzzy number. The Graded Mean Integration Representation (GMIR) (i,e,. $R(\tilde{a})$) is calculated by Equation (1):

$$R(\tilde{a}) = \frac{l + 4m + u}{6} \quad (1)$$

The advantages of this method compared to other multi-criteria decision-making methods are as follow:

- Requires fewer comparative data.
- Requires more stable comparisons, so, more reliable answers are provided.

The steps of the best worst fuzzy method are as follows:

Step 1: Create a system of decision criteria. Assume that the number n of the decision index is $(c_1,c_2,c_3,...,c_n)$.

Step 2: Identify the best (most important, most desirable) as (C_B) and worst (least important and least desirable) as (C_W).

Step 3: Determine fuzzy pairwise comparisons for the best criteria. Using the linguistic terms expressed in Table 1. The vector of $\tilde{A}_B=\left(\tilde{\alpha}_{B1},\tilde{\alpha}_{B2},...\tilde{\alpha}_{Bn}\right)$ is the best criterion compared to other criteria. So, $\tilde{\alpha}_{Bj}$ represents the fuzzy preference of the best index (C_B) over the index (*j*). It is clear that, $\tilde{\alpha}_{BB}=(1,1,1)$.

Step 4: Specify the preference vector of other indicators over the worst indicator as $\tilde{A}_W=\left(\tilde{\alpha}_{1W},\tilde{\alpha}_{2W},...\tilde{\alpha}_{nw}\right)$. In the mentioned vector, $\tilde{\alpha}_{jw}$ is the preference of index (*j*) over the worst index (*w*). It is clear that, $\tilde{\alpha}_{ww}=(1,1,1)$.

Step 5: Find the optimal values of the weights as $\tilde{w}^*_1,\tilde{w}^*_2,...,\tilde{w}^*_n$. Let $\tilde{w}_j=(l^w_j,m^w_j,u^w_j)$, $\tilde{a}_{jw}=(l_{jw},m_{jw},u_{jw})$, $\tilde{a}_{jw}=(l_{jw},m_{jw},u_{jw})$ and $\tilde{\xi}^*=(k^*,k^*,k^*)$. The optimal weights are determined after solving the model of Equation (2).

$$\min \tilde{\xi}^*$$
$$s.t.\begin{cases} \left|\dfrac{(l^w_B,m^w_B,u^w_B)}{(l^w_j,m^w_j,u^w_j)}-(l_{Bj},m_{Bj},u_{Bj})\right|\le(k^*,k^*,k^*)\forall j \\ \left|\dfrac{(l^w_j,m^w_j,u^w_j)}{(l^w_W,m^w_W,u^w_W)}-(l_{jw},m_{jw},u_{jw})\right|\le(k^*,k^*,k^*)\forall j \\ \sum_{j=1}^{n}R(\tilde{w}_j)=1\forall j \\ l^w_j\le m^w_j\le u^w_j\forall j \\ l^w_j\ge 0\forall j \end{cases} \tag{2}$$

$R(\tilde{w}_j)$ is the de-fuzzified value that can be determined from Equation (3).

$$R(\tilde{w}_j) = \frac{l_j^w + 4 \times m_j^w + u_j^w}{6} \quad (3)$$

Step 6: At first, based on the comparison vector of best-to-worst criteria, the Consistency Index (CI) is determined (according to Table 2). Then, the consistency ratio calculated applying the Equation (4). in order to investigate the reliability and compatibility of the outputs. The smaller value for CR (close to zero) is better [37]:

$$CR = \frac{\xi^*}{CI} \quad (4)$$

3.2. Fuzzy Inference System (FIS)

Fuzzy inference systems (FIS) are common in different fields such as engineering and decision-making problems [38]. FIS had been used in 1975 for the first time for a steam engine control using some control rules [39]. Then, in 1978, they were used for a fuzzy controller in an industrial process. Since then, these fuzzy rules have been used widely in different decision-making cases. A fuzzy system contains the components as below:

• A single-phase input generator for converting the numerical values to a fuzzy set.

• A database includes several if-then rules.

• A series of operations for converting inputs to outputs.

• Phasing machine for converting fuzzy output to a crisp value.

Assume that *C* numbers of criteria and *M* numbers of membership functions are available. So, we will have M^C rules. Since the rule numbers may be large, experts could extract the rules rely on just every two inputs. Furthermore, using five initial membership functions below, the fuzzy rules are defined based on Table 3.

- Very Poor: (1,2,3)
- Poor: (2,3,4)
- Moderate: (3,4,5)
- Good: (4,5,6)
- Very Good: (5,6,7)

Using Equation (1), the fuzzy input numbers will be de-fuzzified as the inputs of the FIS. The two-by-two selecting inputs continued when there is no input not used. So, the first stage, each supplier performance ratings are gathered from the experts and the aggregated values are obtained. Following this, the crisp values are provided. The values will be in [1,7] based on the linguistic variables which should be multiplied to criteria importance weights. Considering that the weights are always [0,1], the weighted data will be always related to very poor category. Consequently, the suppliers' performance considered in weak level. To solve this problem, these weights then could be normalized using Equation (5).

$$NWD = \frac{WD}{MPWD} \times 100 \qquad (5)$$

where:

WD: The weighted data of every criterion,

MPWD: The maximum weighted data of every criterion.

The range of NWD is between 0 and 100. Furthermore, the membership functions should be recalculated to be between 0 and 100 as Equation (6).

$$VP = (0,20,40); P = (20,40,60); M = (40,60,80); G = (60,80,100); VG = (80,100,100) \qquad (6)$$

Furthermore, the two-by-two FIS can be developed and each supplier performance level computed.

3.3. Classification machine learning models

- Neural network

Neural network imitates the human brain and is one of the classification models [40]. Neural networks analyze data in their hidden layers to provide an output. This data can be a group of images, sounds, and text that translated and understood by a machine. So that, they can even predict and classify several rows of data [41].

- Decision tree

The decision tree is one of the strongest and most famous classification methods and tools for prediction that, unlike neural networks, produces the law [42]. It explains its prediction in the form of a set of rules, while in neural networks only prediction is expressed and how the network itself remains hidden. In addition, unlike neural networks, the decision tree can use non-numerical data [43]. The decision tree is divided into two types of classification and regression trees, so that if the response variable has a discrete value, it is called a classification tree, and when the tree predicts continuous values, it is called a regression type [44].

- Support vector machine (SVM)

Support vector machine is one of machine learning methods that was introduced based on statistical learning in the 90's by Vapnik [45]. SVM method tries to create a hyperplane for two floors with a maximum distance of each floor to the hyperplane and a point data closest to the hyperplane is used to measure this distance. Hence, these point data are called support vectors. Support vector machines with are used for classification and regression prediction problems [46].

4. Computational results

4.1. Case study

To implement our model, a case study of a hospital in Iran. In the past two years, this hospital provides care services for COVID-19 patients. This hospital receives its desired drugs during the corona epidemic through seven suppliers. Several existing antiviral drugs, used as treatments for the severe acute respiratory syndrome (SARS), the Middle East respiratory syndrome (MERS), human immunodeficiency virus (HIV), and malaria, are being investigated as COVID-19 treatments. So, some treatments that had been used in the clinical treatment include Remdesivir, Lopinavir/ ritonavir, Chloroquine, and Glucocorticoid. The suppliers are located in different places relative to the hospital and each of them has different approaches in the type of financial interaction with the hospital, speed of response, attention to the environment and social issues. The aim of the studied hospital is to evaluate potential suppliers in order to select them in ordering the medicine they need while both sustainability and resilience dimensions are considered. In general, the studied hospital and the seven suppliers of the drugs are shown in Figure 2.

4.2. Criteria selection

After reviewing the theoretical foundations and interviewing experts, 37 criteria related to three dimensions of sustainability (i.e., economic, social, and environmental) and resilience dimension were selected and entered the panel of experts with the Delphi approach. Due to the type of organization's activity, logistics issues in the supply chain and the difficulty of timely delivery of products, management of relationships with supply chain components, and such issues, resilience indicators were selected in the evaluation of suppliers. Among these criteria, the suppliers' resilience to have different scenarios in response to the desired needs, the criteria of having excess production capacity to meet the high needs of medicine at the peak of the corona epidemic, the delivery criterion to deliver medicines to the hospital on time, the distribution criterion to have sufficient infrastructure in the accurate and quality distribution of medicines to hospitals was selected in the resilience category. Also, since macroeconomic issues have affected the whole organizations, the presence of indicators such as product costs and financial capabilities in response to the needs of hospitals in the evaluation of suppliers is of particular importance, which is included in the category of economic indicators of sustainability dimensions [47]. Also, paying attention to contracts and cooperation with human resources, timely payment of salaries to workers is also very important so that workers and employees can perform their activities with sufficient motivation at this time. For this reason, social indicators of sustainability dimensions have also been given basic attention in this study. Another important component in the evaluation of suppliers, which has received major attention in recent years, is attention to environmental criteria. The use of appropriate packaging, the use of pollution control equipment and being environmentally friendly are among the important indicators in the evaluation of suppliers who were included in the environmental category of sustainability dimensions. Table 4 shows the weight of the criteria in the first and second round of the expert panel.

It can be seen that economic criteria have decreased from 5 to 3, social criteria have decreased from 11 to 7 criteria, from 9 environmental criteria only 3 of them remained, and resilience criteria decreased from 12 to 9 which are indicated in Figure 3.

4.3. Computing the Importance Weights of the Criteria using FBWM

According to Fuzzy Best-Worst-Method, first, three dimensions of sustainability and resilience are compared, then the indicators of each category are evaluated. The data of paired comparisons are gathered in Appendices in Table A.1 to A.6. Finally, all indicators are weighted and prioritized. The findings of this section are summarized in Table 5.

Based on results, the most important category is the resilience. It was expected that in COVID-19 outbreak this dimension become more crucial than others. Although Fallahpour & Olugu, et al (2017) [1] concluded that social dimension was the most dimension. The most important criterion which has the most final weight is responsiveness. It seemed that during the corona pandemic, due to the increase of patients and the sensitivity of the speed of providing services to patients, the supplier's responsiveness is a critical criterion and it is given the first priority for drug supply [48]. Also, the second important criterion is the supplier's ability to supply. Obviously, a supplier from whom we expect a high responsiveness level must also have the ability to supply. Accordingly, after these two criteria, delivery criterion has been prioritized as the third criterion. In fact, a supplier who is both responsive and able for drug supply, must also deliver on time. Although this on-time delivery is always important, it will be more important than ever during the Corona pandemic for hospitals. Agility and quality criteria were ranked next. It can be said that agility can be very important due to fluctuations and changes in commonly used drugs. On the other hand, quality, which is always an important criterion in supplying any product, especially medicine, which deals with people's lives and health. Comparing other researches, Fallahpour et al., (2021) [32] concluded that cost, resource consumption, and agility were the most important criteria while we concluded although there are important indicators but not more important than responsiveness and delivery especially in pandemic era. In addition, based on Afrasiabi et al., (2022) [34] results, pollution control, environmental management system, and risk awareness had the most importance weight which two of them are related to environmental dimension and only the last related to resilience. Our study result is different from other researches due to our focus on COVID-19 pandemic period while others did not.

4.4. Suppliers evaluation using the weighted two-stage FIS

As mentioned, two stages exist in the developed weighted FIS as depicted in Figure 4. Firstly, data of all 15 suppliers of the case study hospital with based on each criterion were gathered. This dataset includes 350 rows which are every time that a supplier supplied different drugs for the hospital drugstore. Then, each column is divided into five levels as mentioned in Section 3.3 as performance ratings. The aggregated crisp values and the global weights multiplied in order to calculating the WD. Then, the WD normalized which is NWD. By computing NWD, the first stage of FIS was completed.

In the second stage of FIS, NWD values are as inputs and by performing the two-by-two approach, using the FIS the final performance level for each supplier calculated in five different levels (VP, P, M, G, and VG). Results indicate that 35 suppliers were evaluated as very poor, 70 poor suppliers, 98 moderate ones, 90 good suppliers, and 57 very good ones. This weighted two-stage FIS was run in "Jupyter environment" via python language.

5. Data-driven supplier evaluation model

The FIS output in the previous step is considered as the target column for each supplier as their performance score in five levels. Other criteria are also considered as independent features. So, we try to develop three different classification models for prediction. Three models were developed include decision tree, support vector machine, and neural network. For each classification model, 'GridSearch' is used in order to evaluate different combination of hyperparameters used in each model. Different parameters and the best ones with the most accuracy is summarized in Table 6.

To measure the performance of the multiclass classifier, the class-wise true positives (TPi), true negatives (TNi), false positives (FPi), and false negatives (FNi) are computed. These parameters are used to assess the Accuracy, Precision, Recall, and F1- score of the model. The formulas for computing these measures in multiclass classification are derived as Equation (7-10):

$$Accuracy = \frac{TP_i}{\sum_{i=1}^{l} TP_i + FP_i + TN_i + FN_i} \qquad (7)$$

$$\text{Precision} = \frac{\sum_{i=1}^{l} TP_i}{\sum_{i=1}^{l} TP_i + FN_i} \qquad (8)$$

$$\text{Recall} = \frac{\sum_{i=1}^{l} TP_i}{\sum_{i=1}^{l} TP_i + FP_i} \qquad (9)$$

$$F1-score = 2 \times \left(\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}\right) \qquad (10)$$

The confusion matrix and the accuracy of each classification models are shown in Figure 5. The accuracy of the neural network has the highest score (0.734) which can be reliable. But, in order to evaluate the models more, the precision, recall, and F1-score of each model are calculated based on the equations mentioned above and the results are shown in Table 7.

However, the evaluation metrics for all three classification models are compared in different performance levels in Figure 6. Results indicate that neural network precision and F1-score is the highest in all performance levels except the good level. Besides, neural network recall is the highest in all performance levels except the poor level.

6. Conclusion

6.1. Theoretical implications

Selecting the most important supplier with multiple attributes is not easy because of the dimension and hard data gathering. Furthermore, we developed a decision support model for the problem. Three phases in the developed model defined including suitable criteria identification, weighting the criteria using FBWM, running the two-stage FIS, and finally data-driven supplier evaluation machine learning models. A hospital as a case study considered while some data were collected from decision-makers (managers) and the rest of the data were gathered from the database of the hospital to assess suppliers.

The FBWM results showed that the resilience was the most important dimension. It concluded that ‘Ability’ is the most important resilient criterion, and ‘wage’ was the most important sustainability criterion and ‘delivery’ was the most important general dimension. The results revealed that hospital managers focused more on ‘Flexibility’ compared to ‘Quality’ (while the global weight of flexibility is 0.0585 and for the global weight of quality is 0.0233). In addition, ‘ability ‘, ‘agility ‘, and ‘responsiveness ‘are the most important criteria considering the managers’ idea which are all related to resilience aspect. This mentions that for important drugs in the COVID-19 pandemic, resilience is more important than sustainability and general aspects when in the usual period this is not true. After running the two-stage FIS, the results indicate that 35 suppliers were evaluated as very poor, 70 poor suppliers, 98 moderate ones, 90 good suppliers, and 57 very good ones. The best data-driven supplier evaluation model is a neural network with 73% accuracy. It expresses that in nearly 25% of cases the performance level will predict wrong but in other cases which is almost 75% the prediction of performance level is correct. Furthermore, the managers of the hospital can use this model as a decision support tool to evaluate a supplier.

6.2. Managerial implications

This study provides several implications for selecting sustainable resilient suppliers in the important and high-consumption drugs in the COVID-19 pandemic sine the drug supply chain had altered. They are categorized in two perspectives: i) Integration sustainability and resilience criteria for supplier selection and ii) Development of a new hybridized FBWM-two-stage FIS model with classification models of machine learning. This research has generated a suitable list of sustainable resilient criteria for supplier evaluation. Specifically, 23 criteria were determined and they were grouped into three aspects (general, sustainable, and resilient). The global weights of the criteria for manager priorities. In addition, an effective integrated model developed for supplier evaluation concerning the determined criteria. Using this proposed model, managers could evaluate the suppliers that are sustainable and resilient with high accuracy.

There is a lack of studies that have considered the data-driven supplier selection problem. Most of the previous evaluation models for suppliers mostly used multi-criteria decision-making techniques for evaluating the performance of suppliers. Hence, this research has developed a hybridized data-driven FBWM-two-stage FIS model for supplier evaluation and selection for the first time. The importance weights of the criteria were determined via FBWM and each supplier performance level calculated individually via two-stage FIS. Finally, the classification models were developed with the selected criteria and labeled column of the FIS output. In essence, the current model enables could be used for separately fuzzy supplier selection problem.

The proposed model has implemented in a hospital case study in Iran and thus, the findings should not be generalized to other hospitals since the criteria weights and their priorities may be different. Future studied can define other criteria and even other classification models.

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Tables captions

Table1. Linguistic variables transformation

Table 2. The Consistency Index (CI)

Table 3. The fuzzy rule bases

Table 4. The criteria score in Delphi

Table 5. The criteria FBWM weights

Table 6. Parameters of classification models

Table 7. Precision, recall, and f1-score of classification models

Figures captions

Figure 1. The proposed framework of this study

Figure 2. The case study and its supplier location

Figure 3. Supplier criteria and sub-criteria

Figure 4. Two-stage of FIS approach

Figure 5. The classification models result

Figure 6. Precision, recall, and f1-score of classification models

Tables

Table1

Linguistic	MF
Equally important	(1, 1, 1)
Weakly important	(0.667, 1, 1.5)
Fairly important	(1.5, 2, 2.5)
Very important	(2.5, 3, 3.5)
Absolutely important	(3.5, 4, 4.5)

Table 2

	(EI)	(WI)	(FI)	(VI)	(AI)
$\tilde{a}_{BW}$	(1, 1, 1)	(0.667, 1, 1.5)	(1.5, 2, 2.5)	(2.5, 3, 3.5)	(3.5, 4, 4.5)
CI	3.00	3.80	5.29	6.69	8.04

Table 3

Second input	First input				
	VP	**P**	**M**	**G**	**VG**
VP	VP	VP	P	P	M
P	VP	P	P	M	M
M	P	P	M	M	G
G	P	M	M	G	G
VG	M	M	G	G	VG

Table 4

Row	Category	Criterion	Score (Round1)	Score (Round2)
1	Economic	Quality	8.1	7.9
2		Cost	7.2	7.2
3		Turnover	4.2	---
4		Financial power	6.5	6.8

5		Ability	8.1	8.6
6		Workers' contract	7.4	7.3
7		Labor insurance	7.5	7.5
8		Standard working hours	7.1	7.3
9		Overtime payment	6.2	4.9
10		Speed in payment of salaries	7.2	7.2
11	Social	career progression	7.4	7.6
12		Pay attention to religious issues at work	5.2	---
13		Wage	6.9	7.8
14		Disclosure of information to stakeholders	4.8	---
15		gender discrimination	3.1	---
16		Trust	8.4	8.2
17		Resource consumption	6.1	7
18		Eco-friendly	6.7	7.7
19		Pollution control	6.5	7.5
20		Green Certificate	7.1	6.4
21	Environmental	Recycle	6.5	6.1
22		Air pollution	6.1	5.5
23		Water effluent	4.8	---
24		Hazardous waste	6.3	6.2
25		Green R&D	3.5	---
26		Supply	8.3	8.3
27		Delivery	9.1	9.5
28		Flexibility	6.8	7.3
29		Responsibility	6.9	7.5
30		Responsiveness	7.9	7.9
31	Resilience	Participation	6.1	7.1
32		Agility	6.7	8.6
33		Sight	7.1	7.1
34		Risk mitigation	6.5	5.9
35		Surplus inventory	8.5	8.7
36		Risk management culture	7.1	6.9
37		Technological capabilities	5.8	---

Table 5

Row	Category	Weight	Criterion	Internal weight	Final weight	Rank
1	Economical	0.196	Ability	0.441	0.108	**2**
2			Quality	0.352	0.087	**5**
3			Cost	0.207	0.051	**7**
4	Social	0.212	Trust	0.245	0.04	**13**
5			Workers' contract	0.141	0.023	**15**
6			Labor insurance	0.115	0.019	**18**
7			Standard working hours	0.076	0.012	**21**
8			Speed in payment of salaries	0.136	0.022	**16**
9			career progression	0.111	0.018	**19**
10			Wage	0.176	0.029	**14**
11	Environmental	0.191	Resource consumption	0.39	0.055	**6**
12			Eco-friendly	0.314	0.044	**10**
13			Pollution control	0.296	0.042	**11**
14	Resilience	0.401	Responsiveness	0.246	0.111	**1**
15			Participation	0.021	0.009	**22**
16			Agility	0.202	0.091	**4**
17			Sight	0.031	0.014	**20**
18			Surplus inventory	0.047	0.021	**17**
19			Supply	0.111	0.05	**8**
20			Delivery	0.229	0.103	**3**
21			Flexibility	0.091	0.041	**12**
22			Responsibility	0.101	0.046	**9**

Table 6

Model	Parameters	Best parameters
Decision Tree Classifier	param = {'estimator__criterion': ['gini', 'entropy'], 'estimator__max_depth':[30,40,50,60,70,80], 'estimator__min_samples_split':[30,40,50,60,70,80], 'estimator__min_samples_leaf': [20,30,40]}	{'criterion': 'gini', 'max_depth': 30, 'min_samples_leaf': 20, 'min_samples_split': 70}
Support Vector Classifier	param ={'estimator__kernel':['linear', 'rbf','sigmoid'], 'estimator__gamma': [0.001,0.01,0.1,1, 10], 'estimator__C': [0.01, 0.1, 1,10,100] }	{'C': 1, 'gamma': 10, 'kernel': 'rbf'}
Neural Network	param = {"estimator__activation":["relu", "logistic","tanh","identity"], "estimator__hidden_layer_sizes":[(10),(20), (20,30)], "estimator__max_iter" : [10, 50, 100, 200],	{'activation': 'relu', 'hidden_layer_sizes': 10, 'learning_rate_init': 0.01, 'max_iter': 50, 'solver': 'sgd'}

	"estimator__solver": ["sgd", "adam","lbfgs"], "estimator__learning_rate_init": [0.01, 0.001, 0.0001, 0.025]}	

Table 7

Model		Precision	Recall	F1-score
Decision Tree Classifier	VP	0.34	0.27	0.31
	P	0.71	0.64	0.68
	M	0.64	0.77	0.70
	G	0.66	0.74	0.70
	VG	0.72	0.59	0.65
Support Vector Classifier	VP	0.40	0.36	0.38
	P	0.76	0.65	0.70
	M	0.66	0.78	0.72
	G	0.69	0.78	0.73
	VG	0.79	0.66	0.72
Neural Network	VP	0.46	0.41	0.43
	P	0.79	0.63	0.70
	M	0.71	0.80	0.75
	G	0.63	0.81	0.71
	VG	0.86	0.74	0.80

Figures

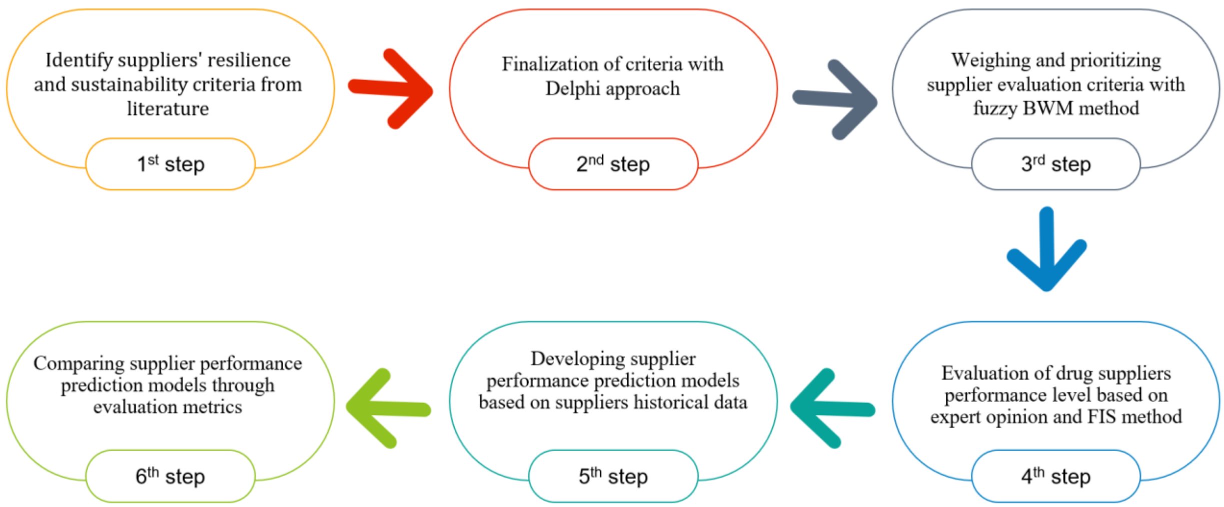

Figure 1

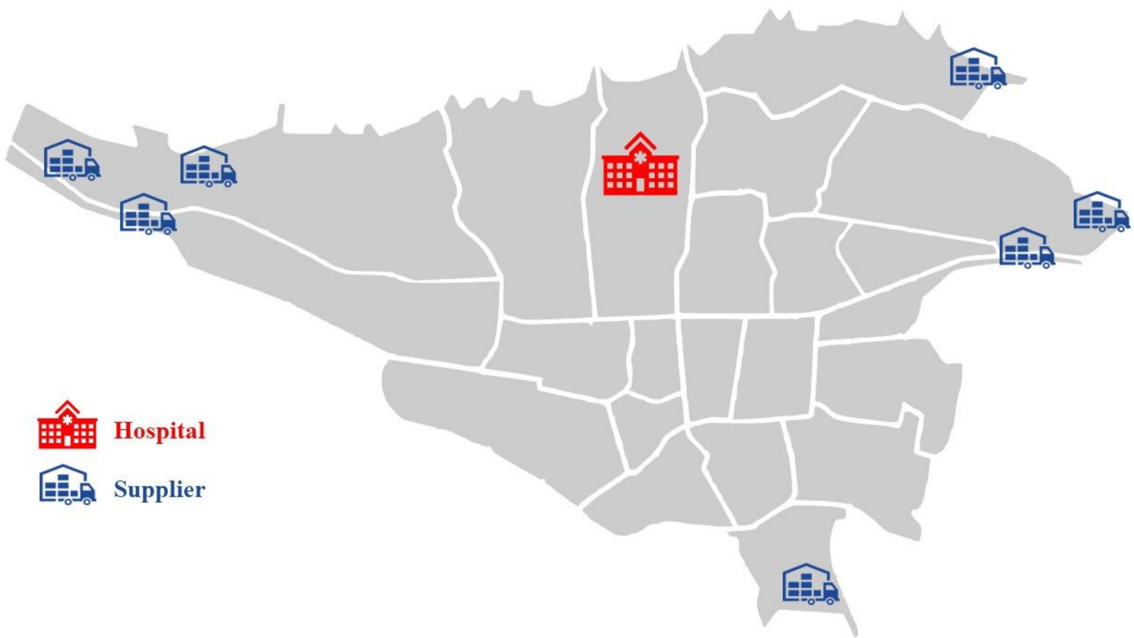

Figure 2

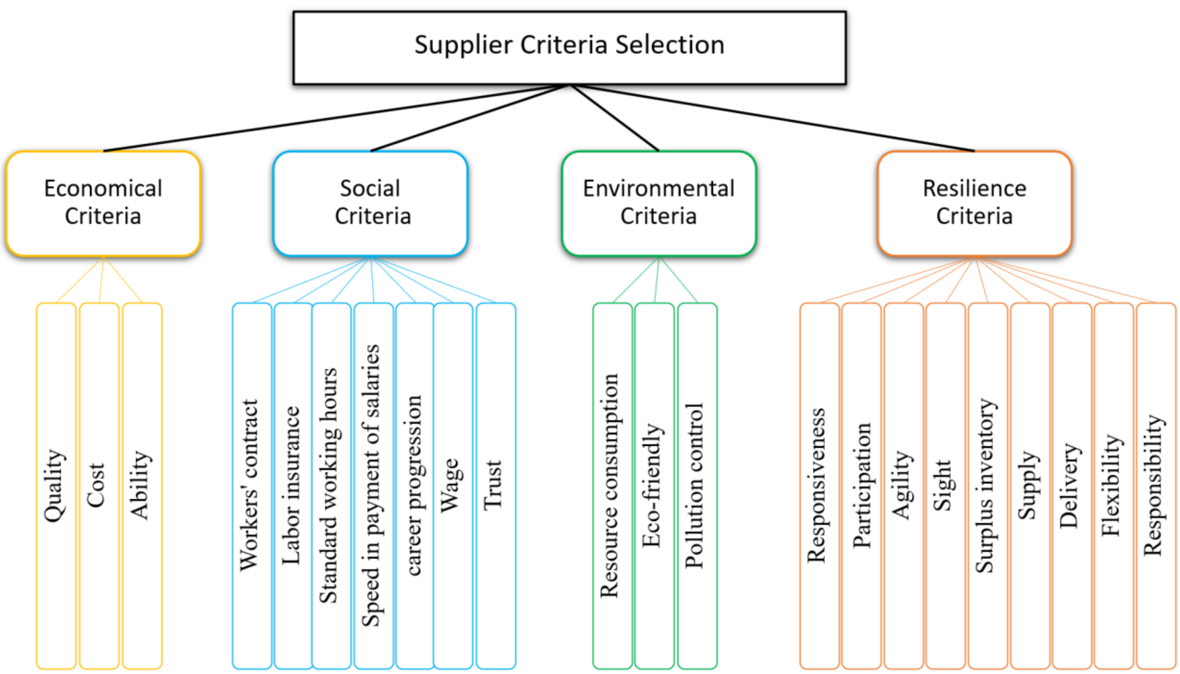

Figure 3

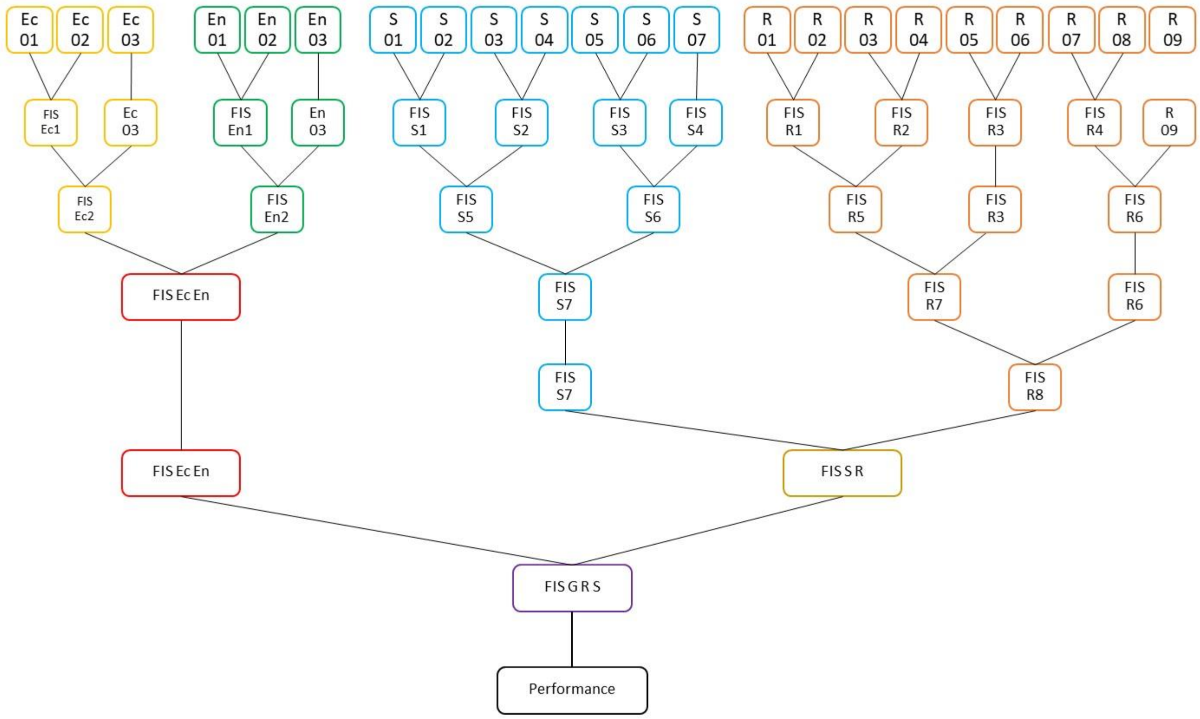

Figure 4

Decision Tree

Actual \ Predicted	VP	P	M	G	VG
VP	12	6	8	4	5
P	15	50	2	2	1
M	9	14	63	6	6
G	4	6	5	59	16
VG	3	2	3	8	41

$$accuracy = \frac{12+50+63+59+41}{350} = 0.642$$

Support Vector Machine

Actual \ Predicted	VP	P	M	G	VG
VP	14	7	7	5	2
P	10	53	3	2	2
M	8	13	65	5	7
G	5	5	6	62	12
VG	2	3	2	5	45

$$accuracy = \frac{14+53+65+62+45}{350} = 0.682$$

Neural Network

Actual \ Predicted	VP	P	M	G	VG
VP	16	10	4	3	2
P	9	55	4	1	1
M	7	12	70	5	4
G	7	9	7	57	10
VG	0	1	3	4	49

$$accuracy = \frac{16+55+70+67+49}{350} = 0.734$$

Figure 5

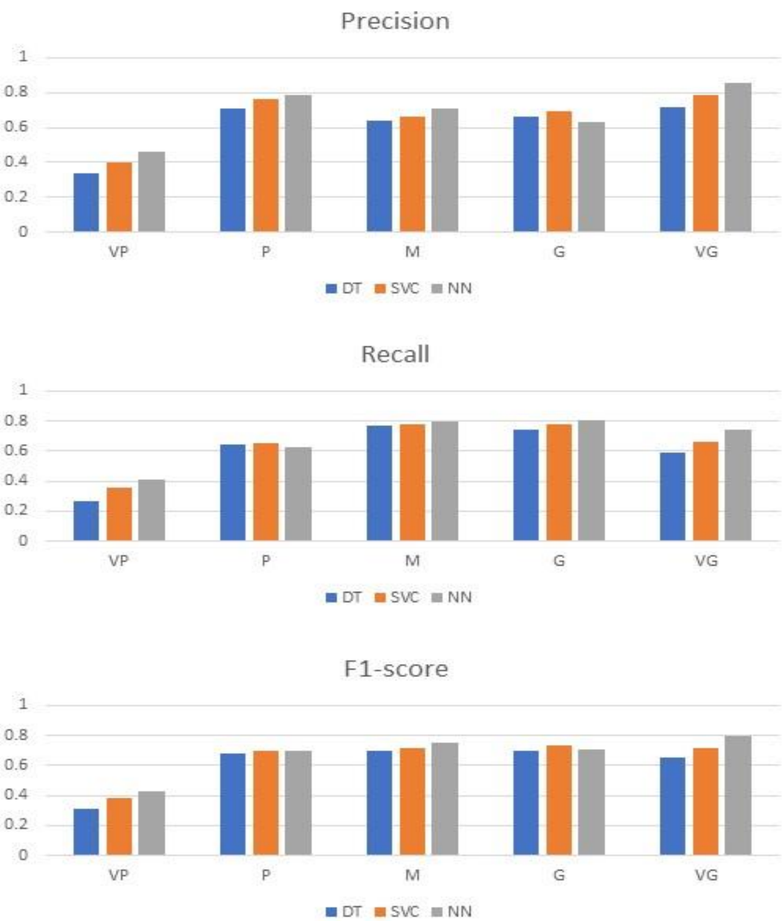
Precision
1
0.8
0.6
0.4
0.2
0
VP
P
M
G
VG
DT
SVC
NN
Recall
1
0.8
0.6
0.4
0.2
0
VP
P
M
G
VG
DT
SVC
NN
F1-score
1
0.8
0.6
0.4
0.2
0
VP
P
M
G
VG
DT
SVC
NN

Figure 6

Appendices

A. Paired comparison matrices

Table A.1. Pair comparison of general Sub-criteria with the best Sub-criteria

Expert		Quality			Cost			Supply			Delivery			Flexibility			Responsibility		
1	Delivery	1	2	2	3	3.5	4	1	1	1	1	1	1	1	1	1	1	1	1
2		3	3.5	4	3	4.5	5	1	1.5	1.5	1	1	1	1	1.5	1.5	1	1	1
3		3	4.5	5	5	5.5	6	1	2	2	1	1	1	1	1.5	1.5	1	1.5	1.5
Average		**2.33**	**3.33**	**3.67**	**3.67**	**4.50**	**5.00**	**1.00**	**1.50**	**1.50**	**1.00**	**1.00**	**1.00**	**1.00**	**1.33**	**1.33**	**1.00**	**1.17**	**1.17**

Table A.2. Pair comparison of general Sub-criteria with the worth Sub-criteria

	Cost			
Expert / **Criteria**	**1**	**2**	**3**	**Average**
Quality	1	1	1	**1.00**
	1	2	2	**1.67**
	1	1.5	1.5	**1.33**
Cost	1	1	1	**1.00**
	1	1	1	**1.00**
	1	1	1	**1.00**
Supply	1	2	2	**1.67**
	1	2	2	**1.67**
	3	3.5	4	**3.50**
Delivery	3	3.5	4	**3.50**
	3	4	4.5	**3.83**
	1	2	2	**1.67**
Flexibility	1	2	2	**1.67**
	3	3.5	4	**3.50**
	3	3.5	4	**3.50**
Responsibility	1	2	2	**1.67**
	3	4.5	5	**4.17**
	1	2	2	**1.67**

Table A.3. Pair comparison of sustainable Sub-criteria with the best Sub-criteria

Expert		Resource consumption			Eco-friendly			Pollution control			Workers' contract			Labor insurance			Standard working hours			Speed in payment of salaries			career progression			Wage		
1	Resource consumption	1	1	1	1	1	1	1	1.5	1.5	1	1	1	1	1.5	1.5	1	2	2	1	1	1	1	2	2	1	1	1
2		1	1	1	1	2	2	1	2	2	1	2	2	1	2	2	3	4	4.5	1	2	2	3	3.5	4	1	1	1
3		1	1	1	1	1.5	1.5	1	1.5	1.5	1	1	1	1	2	2	3	3.5	4	1	2	2	3	3.5	4	1	2	2
Average		**1.00**	**1.00**	**1.00**	**1.00**	**1.50**	**1.50**	**1.00**	**1.67**	**1.67**	**1.00**	**1.33**	**1.33**	**1.00**	**1.83**	**1.83**	**2.33**	**3.17**	**3.50**	**1.00**	**1.67**	**1.67**	**2.33**	**3.00**	**3.33**	**1.00**	**1.33**	**1.33**

Table A.4. Pair comparison of sustainable Sub-criteria with the worth Sub-criteria

Expert / **Criteria**	**1**	**2**	**3**	**Average**
Resource consumption	1	2	2	**1.67**
	3	4.5	5	**4.17**
	3	4	4.5	**3.83**
Eco-friendly	1	1.5	1.5	**1.33**
	3	3.5	4	**3.50**
	1	2	2	**1.67**
Pollution control	1	1.5	1.5	**1.33**
	1	2	2	**1.67**
	1	2	2	**1.67**
Workers' contract	3	3.5	4	**3.50**
	1	2	2	**1.67**
	1	1.5	1.5	**1.33**
Labor insurance	1	1.5	1.5	**1.33**
	1	2	2	**1.67**
	1	2	2	**1.67**
Standard working hours	1	1	1	**1.00**
	1	1	1	**1.00**
	1	1	1	**1.00**
Speed in payment of salaries	3	3.5	4	**3.50**
	1	2	2	**1.67**
	1	2	2	**1.67**
career progression	1	1	1	**1.00**
	1	1.5	1.5	**1.33**
	1	1	1	**1.00**
Wage	1	2	2	**1.67**
	3	3.5	4	**3.50**
	1	1.5	1.5	**1.33**

Table A.5. Pair comparison of resilience Sub-criteria with the best Sub-criteria

Expert		Ability			Responsiveness			Participation			Agility			Sight			Surplus inventory			Trust		
1		1	1	1	1	1	1	1	2	2	1	1	1	1	2	2	1	1.5	1.5	1	1	1
2	**Ability**	1	1	1	1	2	2	3	3.5	4	1	1.5	1.5	3	4.5	5	3	4	4.5	1	2	2
3		1	1	1	1	1.5	1.5	1	2	2	1	1	1	3	4	4.5	3	4	4.5	1	2	2
Average		**1.00**	**1.00**	**1.00**	**1.00**	**1.50**	**1.50**	**1.67**	**2.50**	**2.67**	**1.00**	**1.17**	**1.17**	**2.33**	**3.50**	**3.83**	**2.33**	**3.17**	**3.50**	**1.00**	**1.67**	**1.67**

Table A.6. Pair comparison of resilience Sub-criteria with the worth Sub-criteria

Expert / Criteria	1	2	3	Average
Ability	1	2	2	**1.67**
	3	3.5	4	**3.50**
	5	5.5	6	**5.50**
Responsiveness	1	1.5	1.5	**1.33**
	3	3.5	4	**3.50**
	1	2	2	**1.67**
Participation	1	2	2	**1.67**
	1	2	2	**1.67**
	1	1.5	1.5	**1.33**
Agility	1	2	2	**1.67**
	3	3.5	4	**3.50**
	1	2	2	**1.67**
Sight	1	1	1	**1.00**
	1	1	1	**1.00**
	1	1	1	**1.00**
Surplus inventory	1	2	2	**1.67**
	3	3.5	4	**3.50**
	3	3.5	4	**3.50**
Trust	1	2	2	**1.67**
	3	3.5	4	**3.50**
	1	2	2	**1.67**