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A Novel Model to Measure Supplier Performance in the Supplier Selection Process

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Abstract

Supplier evaluation has become a significant topic over the past decades, as companies have started to become more outsourced oriented. However, previous research on this topic has not paid adequate attention to the limitations associated with availability of accurate and reliable data relating to the performance of potential suppliers. In an attempt to address this issue, this paper proposes a novel supplier evaluation model that can handle imprecise quantitative and qualitative data. Additionally, Decision Maker's opinions regarding both qualitative and quantitative criteria are incorporated into this model so that a more comprehensive and realistic assessment of supplier performance can be achieved. The model combines five separate methods that have specific capabilities to handle multiple limitations in the existing methods: Fuzzy Analytical Hierarchy Process and Fuzzy TOPSIS method are used to analyse qualitative criteria/data; Analytical Hierarchy Process and Axiomatic Design are used to analyse quantitative criteria/data, with a particular focus on handling variability in performance data; and Data Envelopment Analysis is used to integrate the results of the two approaches above so as to comparative assessment of supplier performance. This model is verified using a numerical example.

Key Words: Supplier Selection, Analytical Hierarchy Process, Fuzzy TOPSIS, Axiomatic Design, Data Envelopment Analysis.

1. Introduction

Today's competitive business environment forces companies to continuously optimise their business processes to maintain a strategic advantage in global markets. However, competition increasingly occurs at the level of supply chains rather than at the firm level. Therefore, companies must cooperate and collaborate with their supply chain partners towards enhancing the performance of the overall supply chain. In this regard, supplier selection has an important role to play as the performance of individual suppliers directly affects the performance of the whole supply chain.

There are many aspects of supplier performance that need to be considered in supplier selection and these can be broadly divided into qualitative and quantitative criteria. Both qualitative and quantitative criteria are important measures in selecting suppliers as the effects of factors are often complementary [11]. Despite these complementarities, there seem to have been a strong disparity in the way researchers have used such criteria, especially, between those who have different disciplinary backgrounds. For example, researchers with an operations research background have traditionally focused on quantitative criteria in their solutions while those with business management background have emphasised the significance of qualitative criteria [11]. Such singular-perspective treatment can lead to increasing potential errors in suppler selection decisions. Numerous methods have also been used to measure supplier performance, but they suffer from similar drawbacks. For example, Data Envelopment Analysis (DEA), a widely used method when used on its own, heavily relies on quantitative data. While recognising this limitation, some researchers have used Imprecise Data Envelopment Analysis (IDEA) and Augmented Imprecise Data Envelopment Analysis (AIDEA), using ordinal data while others have combined other methods with DEA to analyse qualitative data, such as Analytical Hierarchy Process (AHP), Fuzzy Analytical Hierarchy Process (FAHP) and Fuzzy TOPSIS method [8][16][22]. However, these studies do not consider imprecise quantitative data comprehensively.

The aim of this paper is to present a comprehensive, yet practically feasible supplier selection model capable of dealing with imprecise qualitative and quantitative data in measuring supplier performance. The proposed model considers Decision Maker's (DM) opinion for both qualitative and quantitative data. The paper will begin by identifying the application, issues and limitations of current methods used for measuring supplier performance in the supplier selection process. It then proposes a model to address these issues followed by a numerical example that illustrates the utility of the model. The paper concludes with a brief discussion about the limitations of the proposed model and directions for future research.

2. Literature Review

Supplier selection is a multi-criteria decision-making problem, as there are many factors affecting the selection of a supplier. These criteria can be divided into two parts; qualitative and quantitative criteria [11]. Considering only one type of criteria in the decision-making process increases the risk of partial treatment supplier performance and may not identify other important aspects that contribute to a successful buyer-supplier relationship. For this reason, a number of researchers have applied Multi Criteria Decision Making (MCDM) methods, such as AHP and Analytical Network Process (ANP) to solve this problem. For example, Barbarosoglu & Yazgac (1997) applied AHP to solve the supplier selection problem in a Turkish Electric company. Akarte et al. (2001) proposed web based AHP to analyse qualitative and quantitative criteria. Bayazit (2006) developed an ANP based model to select suppliers considering both supplier's performance and supplier's capability. Although these methods have been widely applied to solve the supplier selection problem, they rely too heavily on qualitative data and are therefore highly subjective.

Another popular qualitative method used to solve the supplier selection problem is Fuzzy Set Theory (FST). In particular, this method has been utilised to handle uncertainty in the supplier selection process. For example, Chen et al. (2006) proposed a FST model using the concept of TOPSIS to obtain a Fuzzy Positive/Negative Ideal Solution to the problem of supplier selection. Sarkar and Mohapatra (2006) developed a FST model to evaluate the performance and the capability of suppliers. FST, however, is also subjective because it relies on fuzzy numbers, which are not selected based on a commonly agreed basis.

Some authors have integrated FST and AHP to address some of these issues. Kahraman et al. (2003) proposed Fuzzy AHP to select a suitable supplier for a Turkish white goods manufacturing company. Chan and Kumar (2007) also utilised Fuzzy AHP to deal with the supplier selection issue for global supply risks. Even though these studies can be useful in measuring supplier performance, the major drawback is that they do not consider quantitative data.

There are many methods to handle quantitative data in selecting suppliers. One of these methods, is Axiomatic Design. This method is useful to analyse imprecise quantitative data and to obtain decision maker's opinion. You (2011) applied Axiomatic Design to solve supplier selection issue. Another method, which has been widely used to measure supplier performance in the literature of supplier selection, is Data Envelopment Analysis (DEA) (Ho et al., 2010). Liu et al. (2000) proposed DEA to select a preferred supplier with regard to three inputs and two outputs criteria. Talluri & Sarkis (2002) suggested a DEA model to measure performance of eighteen suppliers with regard to four outputs and two inputs. The disadvantage of using DEA for supplier selection is its dependence on quantitative data. This method cannot handle qualitative criteria.

To be able to consider qualitative criteria, some authors have combined other methods with DEA. Ha and Krishnan (2008) proposed AHP-DEA-Neural Network (NN) to address the specific issues as follows. AHP was used to account for to qualitative criteria the scores which were obtained in AHP were transferred into DEA and NN, and these scores and quantitative criteria were analysed in DEA and NN. By comparison, Zeydan et al. (2011) proposed a model, which included Fuzzy AHP, Fuzzy TOPSIS and DEA. Fuzzy AHP and Fuzzy TOPSIS were used to analyse qualitative criteria the scores which were obtained in Fuzzy AHP and Fuzzy TOPSIS were passed to DEA, and these scores and quantitative criteria were analysed in DEA. Although these studies assist in the analysis of qualitative criteria in the measurement of supplier performance, they do not consider imprecise quantitative data. As imprecise data shows variations in real conditions, the analysis of this type of data is necessary to reflect those variations.

Some authors have used a modification of DEA to analyse imprecise quantitative and qualitative data in selecting a supplier. Saen (2007) proposed IDEA to analyse imprecise quantitative and qualitative data in measuring supplier performance. Wu et al. (2007) proposed AIDEA to examine imprecise quantitative and qualitative data to distinguish between an inefficient and efficient supplier. Even though these studies analysed qualitative and imprecise quantitative data, the Decision Maker's opinion was not reflected in the analysis of quantitative data. Thus, these papers did not enable the decision maker to consider more qualitative and imprecise quantitative data.

As such, this paper aims at filling the above gaps as follows:

- The Decision Maker's opinion will be reflected in the imprecise quantitative data, and the Decision Maker will assign a weight to qualitative data used in measuring supplier performance to distinguish between inefficient and efficient suppliers.
- Imprecise qualitative and quantitative data will be examined as two outputs to distinguish between inefficient and efficient suppliers comprehensively. That is, this model enables the Decision Maker to consider more than one qualitative and quantitative criterion for the analysis of qualitative and imprecise quantitative data.

3. Design of Model

To measure supplier performance in the supplier selection process, there is a need to structure supplier selection criteria. Table 1 indicates the supplier selection criteria that will be applied in this study. The criteria are divided into types of data: qualitative and quantitative, and have been compiled from the literature informing this research.

Table 1: Supplier Selection Criteria used in the Model

Criteria	Definition	Authors	Qualitative/Quantitative
Compliance with sectoral price behaviours	Proximity of offering price to sectoral price	[2]	Qualitative
Reputation	Image and Position in Industry	[4] [15] [16] [17] [18]	Qualitative
Communication	The flow of information being adequate and efficient	[4] [5] [7] [15]	Qualitative
Defect Ratio	The ratio of rejected parts in the received order	[22]	Quantitative
Complete Quantity	Percentage of orders received complete	[11]	Quantitative
Commit Delivery	Percentage of orders received on commit date	[11]	Quantitative

4. Proposed Model

4.1. Overview of Model

As already suggested, the model proposed in this study combines qualitative and quantitative data. These two sets of data will be processed and used in the Data Envelopment Analysis. This model is shown in Figure 1, where it can be seen on the right hand side, the quantitative data is processed using the AHP. AHP will be used to compare the quantitative criteria, while Axiomatic Design will be used to analyse imprecise quantitative data of suppliers using the Decision Maker's requirements; therefore, both a comparison of quantitative criteria and an analysis of imprecise quantitative data will be provided. On the left hand side of the model, the qualitative data is shown to be treated using FAHP to compare qualitative criteria, and Fuzzy TOPSIS will analyse qualitative data by using weights from Decision Maker; therefore, both a comparison of qualitative criteria and analysis of qualitative data will be provided. The qualitative and quantitative data for each supplier that is obtained from this process is then placed into Data Envelopment Analysis (DEA). In this Output oriented Data Envelopment Analysis DEA, dummy input will be calculated with these two outputs. This calculation will distinguish between inefficient and efficient suppliers.

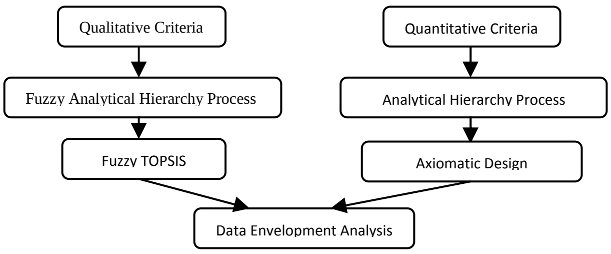

Figure 1: Flow Chart of Model

4.2. Analysis of Qualitative Criteria

FAHP is used to establish priority among qualitative criteria. Steps of this method will be explained as follows [12]:

Let $X = x_1, x_2, ..., x_n$ be an object set, and $U = u_1, u_2, ..., u_n$ be a goal set.

$M_{gi}^1, M_{gi}^2, ..., M_{gi}^m$, $i=1,2,..........,n$, where all the M_{gi}^j (j = 1,2,...,m) all are triangular fuzzy numbers.

The value of the Fuzzy Synthetic Extent with respect to the *ith* object is defined as

$$S_i = \sum_{j=1}^{m} M_{gi}^j \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^j\right]^{-1} = \tilde{W} = \left[\tilde{w}_1, \tilde{w}_2, ..., \tilde{w}_n\right] \quad (1)$$

To obtain $\sum_{j=1}^{m} M_{gi}^{j}$, the fuzzy addition operation of m extent analysis values for a particular matrix is performed such as

$$\sum_{j=1}^{m} M_{gi}^{j} = \left(\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j \right) \quad (2)$$

And to obtain $\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} \right]^{-1}$, the fuzzy addition operation of M_{gi}^{j} (j=1,2…..,m) values is performed such as

$$\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} = \left(\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j \right) \quad (3)$$

And then the inverse of the vector above is computed as,

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} \right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i} \right) \quad (4)$$

At the end of this process, the weights of criteria are obtained. . Fuzzy weights in Table 2 are used in FAHP.

Table 2: Fuzzy Weights

Equal Importance (EI)	(1,1,1)
Preferred Equal Importance (PEI)	(1,2,3)
A Little More Important (ALMI)	(2,3,4)
Preferred A Little More Important (PLMI)	(3,4,5)
Strongly Important (SI)	(4,5,6)
Preferred Strongly Important (PSI)	(5,6,7)
More Strongly Important (MSI)	(6,7,8)
Preferred More Strongly Important (PMSI)	(7,8,9)
Totally Important (TI)	(8,9,9)

After obtaining the weights of each criterion, DM can assign a linguistic rating, as presented in Table 3, to each alternative under the different criteria using Fuzzy TOPSIS. Steps of this method may be explained as follows [22]:

Alternative's ratings can be expressed in matrix form as:

$$\tilde{D} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \text{ (found by Table 2)} \quad (5)$$

$$\tilde{W} = \left[\tilde{w}_1, \tilde{w}_2, \ldots, \tilde{w}_n \right] \text{(Weights found from FAHP)} \quad (6)$$

where x_{ij} is the linguistic variable that can be shown by Triangular Fuzzy Numbers and $x_{ij} = (a_{ij}, b_{ij}, c_{ij})$ is the Fuzzy Assessment Value of each alternative i for each criterion j, which can be utilized to acquire the Positive Fuzzy Performance matrix.

$$\tilde{R} = \left[\tilde{r}_{ij} \right]_{mxn} \quad (7)$$

where B represents the set of benefit criteria and C represents the set of cost criteria, respectively, and

$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*} \right), j \in B$ and $\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}} \right), j \in C$

for first equation $c_j^* = \max c_{ij}$, if $j \in B$ and for second equation $a_j^- = \min a_{ij}$, if $j \in C$

Thus, the normalized matrix will be obtained after this and the weighted normalized fuzzy decision matrix will be obtained. Fuzzy numbers in this matrix belong to [0,1]. This matrix is as follows:

$\tilde{V} = \left[\tilde{v}_{ij} \right]_{mxn}$, i=1,2,……..,m; j=1,2……..,n

Where $\tilde{v}_{ij} = \tilde{r}_{ij}$ (x) $\tilde{w}_j$ (8)

As mentioned before, fuzzy numbers ($\tilde{v}_{ij}$) in this matrix belongs to [0,1]. Thus, we can define the fuzzy positive-ideal solution (FPIS) and fuzzy negative-ideal solution using the following formula:

$A^* = \left(v_1^*, v_2^*, \ldots, v_n^* \right)$ (FPIS) and

$A^- = \left(v_1^-, v_2^-, \ldots, v_n^- \right)$ (FNIS) where

$\tilde{v}_j^* = (1,1,1)$ and $\tilde{v}_j^- = (0,0,0)$, j= 1,2,…….,n.

The distances (d_i^* and d_i^-) of each alternative A^* from and A^- can now be calculated.

$$d_i^* = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^* \right) \text{ i=1,2,…..,m} \quad (9)$$

$$d_i^- = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^- \right) \text{,i=1,2,……,n} \quad (10)$$

The CC_i (closeness of coefficient) will be defined to determine the rank order of all alternatives once the d_i^* and d_i^- of each alternative are calculated. This step gives the similarities to an ideal solution. The step is CC_i calculated using the equation below:

$$CC_i = \frac{d_i^*}{d_i^* + d_i^-} \quad (11)$$

According to CC_i, the rank order of all alternatives can be determined and the best one from among a set of feasible alternatives obtained. Table 3 shows linguistic variables to use for rating suppliers.

Table 3: Linguistic Variables for Ratings

Very Good (VG)	(9,10,10)
Good (G)	(7,9,10)
Medium Good (MG)	(5,7,9)
Fair (F)	(3,5,7)
Medium Poor (MP)	(1,3,5)
Poor (P)	(0,1,3)
Very Poor (VP)	(0,0,1)

4.3. Analysis of Quantitative Criteria

AHP will be used to determine weightings of criteria. AHP will be calculated by Expert Choice. Steps of this method will be summarised as follows:

- Structuring hierarchy among criteria; that is, criteria are arranged.
- Assigning contribution weights to each criterion, and this will generate a matrix form.
- The total value of each column is obtained, and each column's total value divided by each criterion's value.
- The sum of each row is obtained, and these values are divided by the total number of criteria; thus, the weights of criteria are obtained.
- If Consistency Index is lower than 0.1, AHP is finished.

After obtaining weights from AHP, imprecise quantitative data will be examined in Axiomatic Design (AD). Steps of AD will be shown as follows [21]:

- determining the design range (designer-specified), according to DM's tolerance and objective imprecise value
- determining the system range (supplier's range), according to DM's tolerance and objective imprecise value
- calculating the information content (I_i) for each criterion
- multiplying each information content (I_i) and each criterion weight (w_i, obtained from AHP) as follows:

$$p_i = \left(\frac{commonrange}{systemrange}\right) \tag{12}$$

So, the information content is equal to:

$$I_i = \log_2\left(\frac{systemrange}{commonrange}\right) \tag{13}$$

After analysing qualitative and quantitative criteria, two values will be obtained. The results of FAHP and Fuzzy TOPSIS will provide one value (CC_i) for each supplier and this value is called the "Qualitative Performance Value (QTPV)". The results of AHP and AD will also provide one value (I_{twi}) for each supplier and this value is called the "Quantitative Performance Value (QPV)". In order to make a balance between quantitative and qualitative performance values, we will assign 100 as the highest value for Qualitative Performance Value (as highest value in Fuzzy TOPSIS is the most precious value) and 100 as the smallest value in qualitative performance value (as the smallest value in AD is the most suitable value). Then, the other values will be calculated with respect to those values. QPV and QTPV will be used as output and input(dummy) for the DEA output-oriented BCC model. Output-oriented BCC will be solved by Frontier Analyst 4 software.

5. Computational Results

Company X, which is a suit manufacturer, is supplied with fabric from four suppliers. The firm would like to reduce its supply base. For this reason, the company will measure the performance of these suppliers. The company will select efficient suppliers for fabric supply. The Purchase Manager (PM) of company has assigned a value to each supplier and identified the requirements of the company. Firstly, PM will compare criteria to obtain weight of each criterion. Table 4 shows PM's weights for qualitative criteria.

Table 4: PM's weights for Qualitative Criteria

Criteria / Criteria	Compliance with sectoral prices	Reputation	Communication
Compliance with sectoral prices	(1,1,1)	(2,3,4)	(4,5,6)
Reputation	(1/4,1/3,1/2)	(1,1,1)	(2,3,4)
Communication	(1/6,1/5,1/4)	(1/4,1/3,1/2)	(1,1,1)

These weights were calculated in FAHP. Table 5 indicates the results. These results will be added in FTOPSIS.

Table 5: Fuzzy Weights of Qualitative Criteria

Criteria	Fuzzy Weights		
Compliance with sectoral prices	0.384	0.606	0.943
Reputation	0.178	0.291	0.471
Communication	0.078	0.103	0.150

PM assigned a weight for each supplier for each criterion. Table 6 shows weights of suppliers.

Table 6: PM's Weights for Suppliers

Criteria / Suppliers	Compliance with Sectoral Prices	Reputation	Communication
Supplier 1	(7,9,10) (G)	(5,7,9) (MG)	(5,7,9) (MG)
Supplier 2	(9,10,10) (VG)	(7,9,10) (G)	(5,7,9) (MG)
Supplier 3	(7,9,10) (G)	(5,7,9) (MG)	(7,9,10) (G)
Supplier 4	(7,9,10) (G)	(9,10,10) (VG)	(7,9,10) (G)

These weights normalized in Table 7.

Table 7: Normalized Matrix

Criteria / Suppliers	Compliance with Sectoral Prices	Reputation	Communication
Supplier 1	(0.7,0.9,1)	(0.5,0.7,0.9)	(0.5,0.7,0.9)
Supplier 2	(0.9,1,1)	(0.7,0.9,1)	(0.5,0.7,0.9)
Supplier 3	(0.7,0.9,1)	(0.5,0.7,0.9)	(0.7,0.9,1)
Supplier 4	(0.7,0.9,1)	(0.9,1,1)	(0.7,0.9,1)
Criteria Weights	(0.384,0.606,0.943)	(0.178,0.291,0.471)	(0.078,0.103,0.150)

After normalisation of weights, weights of criteria multiplied by suppliers' weights. Table 8 indicates weighted normalized matrix.

Table 8: Weighted Normalized Matrix

Criteria / Suppliers	Compliance with Sectoral Prices	Reputation	Communication
Supplier 1	(0.269,0.545,0.943)	(0.089,0.204,0.424)	(0.039,0.072,0.135)
Supplier 2	(0.346,0.606,0.943)	(0.125,0.262,0.471)	(0.039,0.072,0.135)
Supplier 3	(0.269,0.545,0.943)	(0.089,0.204,0.424)	(0.055,0.093,0.150)
Supplier 4	(0.269,0.222,0.943)	(0.160,0.291,0.471)	(0.055,0.093,0.150)

Closeness of coefficient (CC) values, which were calculated using Eq.11, and score of each supplier are indicated in Table 9.

Table 9: Results for Qualitative Criteria

Suppliers	CC	Scores
Supplier 1	0.3167	92.50
Supplier 2	0.3424	100
Supplier 3	0.3217	93.95
Supplier 4	0.3407	99.50

After obtaining results for qualitative criteria, quantitative criteria compared were using AHP in Expert Choice 13.0. Table 10 indicates weights of quantitative criteria.

Table 10: Weights of Quantitative Criteria

Criteria	Weights
Defect Ratio	0.584
Complete Quantity	0.232
Commit Delivery	0.184
Consistency Index=0.026	

Table 11 shows PM's opinion regarding quantitative data and imprecise quantitative data for each supplier.

Table 11: PM's opinion and Imprecise Quantitative Data

Alternatives / Criteria	Purchase Manager	Supplier 1	Supplier 2	Supplier 3	Supplier 4
Defect Ratio	%1-5	%4-6	%2-8	%3-6	%2-6
Complete Quantity	%96-100	%95-%97	%94-98	%92-98	%96-99
Complete Delivery	%97-100	%94-99	%95-99	%94-99	%96-98

Imprecise quantitative data analysed in Axiomatic Design (AD) by using PM's opinion. Table 12 indicates results of AD.

Table 12: Results of Analysis of Quantitative Data

Criteria / Suppliers	Defect Ratio	Complete Quantity	Commit Delivery
Supplier 1	1.00	1.00	1.322
Supplier 2	1.00	1.00	1.00
Supplier 3	0.585	1.585	1.322
Supplier 4	0.415	0.00	1.00

Weights obtained in AHP multiplied by results obtained in AD. Table 13 indicates weighted results, total value and scores of each supplier.

Table 13: Overall Score for Quantitative Data

Criteria / Suppliers	Defect Ratio	Complete Quantity	Commit Delivery	Total	Score
Supplier 1	0.584	0.232	0.243	1.059	40.22
Supplier 2	0.584	0.232	0.184	1.00	42.60
Supplier 3	0.342	0.368	0.243	0.953	44.70
Supplier 4	0.242	0.00	0.184	0.426	100.00

Scores of qualitative and quantitative data were examined as two outputs in Output-oriented DEA in which dummy input was used. Output-oriented DEA was calculated by Frontier Analyst 4, which is software for DEA. Table 14 shows efficiency score, inefficient and efficient suppliers.

Table 14: Overall Results

Suppliers	Efficiency Score	Inefficient/Efficient
Supplier 1	92.5	Inefficient
Supplier 2	100	Efficient
Supplier 3	94.0	Inefficient
Supplier 4	100	Efficient

For this result, PM will select Supplier 2 and Supplier 4 for supplying fabric.

6. Conclusion

In the context of today's competitive environment, companies are increasingly focusing on their supply chain performance. Purchasing from suitable suppliers will ensure enhanced supplier-buyer relationships and this enhancement of supplier-buyer relationship in turn will improve supply chain performance. For this reason, selecting appropriate suppliers is an important business activity for practitioners and academicians. There are many methods to select appropriate supplier in literature. Even though most of these methods are useful in evaluating the performance of suppliers, they do not focus on both qualitative and imprecise quantitative data to measure supplier performance. This can lead to decision makers selecting inappropriate suppliers. In this paper, a supplier selection model comprising technique capable of analysing imprecise qualitative and quantitative data was presented and discussed. To take into account the differences between organisations and the circumstances in which each organisation make their supplier selection decisions, qualitative and quantitative criteria were treated separately. Imprecise quantitative data was analysed by using Decision Maker's opinion and qualitative data was analysed using weights from Decision Maker. Two values for each supplier, one qualitative and one quantitative, along with dummy inputs were placed in output-oriented DEA. After this process, preferred suppliers were identified. The proposed model provides a suitable solution for Decision Makers as qualitative and quantitative data are analysed based on the priorities (weightings) assigned by decision makers to each criteria. The model dealt with imprecise quantitative criteria using AHP and Axiomatic Design, thus considering decision maker's opinion regarding quantitative criteria/data. Additionally, Fuzzy AHP and Fuzzy TOPSIS were used to analyse qualitative data and to obtain decision maker's opinion regarding qualitative criteria/data. As such, the approach proposed in this paper addresses the limitations of existing approaches to supplier selection

Even though this model addresses the analysis of qualitative and imprecise quantitative data, it does not consider order allocation from efficient suppliers. Order allocation from suppliers is the last and important part of supplier the selection process and this is significantly affected by variability in demand. Variation of demand also causes purchase costs and inventory costs. For this reason, uncertain demand should be considered in the supplier selection process. Additionally, suppliers may not be able to meet the increased demand from manufacturers due to limitation of their capacity. This can lead to disruptions in manufacturer's production process. Therefore, the capacity of suppliers should also be considered in the supplier selection in future research.

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