Supplier Selection Powered by Industry 4.0 Technologies

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***Abstract*— Supplier selection is an important part of the supply chain due to its high effects on the quality and price of the organization's products or given services. This paper aims to engage industry 4.0 technology in the supplier selection process to reduce the uncertainty of subjective expert judgments by engaging the voice of customers in the criteria evaluation process. For this purpose, a supplier selection methodology has been developed including a decision support system powered by industry 4.0 technologies, to assess the importance of criteria. The proposed methodology is implemented on supplier selection in the dental sector. The evaluation criteria are established through a literature survey and applying the questionnaire to dental experts. The results of the criteria evaluation using the decision support system indicated the most frequent criteria are usability criteria followed by price and esthetics criteria, and the result of the supplier ranking of five potential suppliers using the F-TOPSIS indicated that supplier S4 is the most appropriate supplier.**

***Keywords*— supplier selection, industry 4.0 technologies , questionnaire analysis, MCDM, dental sector.**

I. INTRODUCTION

This In recent years, manufacturing and service industries are experiencing large and quick technological advancements such as industry 4.0 technologies. Santos et al., (2017), described the Industry 4.0 as the smart gathering and application of data in real-time through networking all individual components in order to decrease operational complexity, enhance efficiency and effectiveness, and permanently lower costs. The most popular industry 4.0 technologies in supplier ranking include: big data analytics, cloud computing, internet of things, data mining, artificial intelligence, simulation, and so forth (Mohammed et al., 2022; Birdawod, 2022).

The supplier ranking procedure is crucial for boosting the organization's competitiveness and necessitates the evaluation of many potential alternatives (suppliers) based on various evaluation criteria (Rozados and Tjahjono, 2014). Today's the primary goal of enterprises is to eliminate risks within the supply chain (Massoudi, 2019; Zaidan et al, 2024). Suppliers are often the primary sources of risk to the supply chain resulting in very severe disruptions, as the cost of supplying raw materials is usually the largest component of production costs. Given an appropriate multi-criteria decision-making (MCDM) method for ranking suppliers, the main concern is the uncertainty of expert judgment and inaccessible data, which frequently happens in real-life circumstances. In comparison to traditional data (questionnaire) from expert, there is a vast amount of online data available, which enables decision-makers to eliminate uncertainty, subjectivity, and unpredictability in the decision-making process. Given the digital world's development, organizations have access to many online resources where customers (end users) share their experiences and opinions about various suppliers, products, and services, providing organizations with an ideal opportunity for scraping customer reviews and using this valuable information in decision-making. Rozados et al. (2014) identified 52 sources of big data across the supply chain, and these types of data were divided into three groups: structured, semi-structured, and unstructured. Biedron (2021) & Eleftheria (2018) divided the sources of data in procurement into internal and external sources. Different classification algorithms are used for text classification. Some of the most widespread classifiers are two common deep learning architectures used in NLP are Recurrent Neural Networks (RNN) and Convolutional Neural Network (CNN). In this study, RNN is used for text (customer review) classification. In this study, a decision support module enhanced by industry 4.0 technologies; big data, machine learning and artificial intelligence is developed for criteria evaluation and obtaining the importance of criteria through analyzing the unstructured real-life customers feedbacks. The structure of the paper after the introduction section is as follows: in the second section a review of the literature. The third section includes the proposed methodology. The fourth section includes the numerical illustration and data analysis. The fifth section includes the conclusion of the study.

II. LITERATURE REVIEW

Some researchers tried to involve industry 4.0 technologies in the supplier selection process.

A hybrid fuzzy (AHP-TOPSIS) model for supplier ranking was given by Ali and Kassam (2022), F-AHP was used to evaluate the importance of criteria, and then the F-TOPSIS method is applied to evaluate the supplier importance. Singh et al. (2018) presented a novel framework based on big data and cloud computing technology for eco-friendly cattle supplier selection by using Fuzzy AHP, DEMATEL, and TOPSIS methods to select the most appropriate supplier. Cavalcante et al. (2019) developed a hybrid technique, combining simulation and machine learning and examine its applications to data-driven decision-making support in resilient supplier selection. Utomo et al. [2019], proposed the idea of utilizing web-based artificial intelligence technology for suppliers' selection in the

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manufacturing industry in industry 4.0 era using a decision support system based online that must be accessible via the web or mobile application. Hasan et al. (2020) developed a decision support system (DSS) based on fuzzy multi-attribute decision making to help the decision maker to incorporate and process such imprecise heterogeneous data in a unified framework to rank a set of resilient suppliers in the logistic 4.0 environment. Furthermore, research papers are still ongoing with industry 4.0 technologies for their relevance.

III. THE PROPOSED METHODOLOGY

The research model with four modules are prepared for supplier selection using integrated F- MCDM and industry 4.0 technologies. The first module considers the problem definition, which involves the studying the needs of the system (organization), and identifying the potential alternatives (suppliers). The remaining modules of the methodology are detailed in the following sections:

3.1 Criteria selection module

The selection of criteria in MCDM problems plays an important role in the supplier selection process, as various criteria are established for different organizations in different fields. In this study, the selection of criteria is done through two steps: a literature survey and a questionnaire method. To determine the appropriate criteria for supplier evaluation, a literature survey is used and the latest books and academic articles on supplier selection criteria are examined, then a questionnaire method is designed and applied to experts to refine the list of criteria for the supplier evaluation process through analyzing customer reviews.

Figure 1 Decision support system steps for criteria evaluation through customer review classification

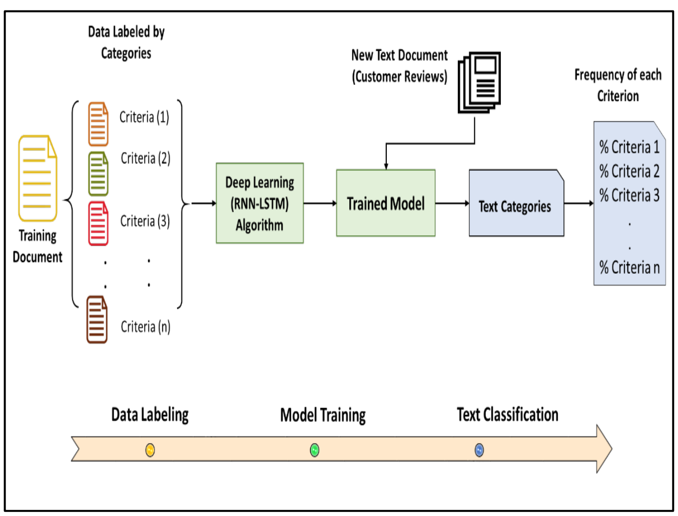

Figure 1 Decision support system steps for criteria evaluation through customer review classification

The review classification results (frequency of each criterion) are normalized to achieve criteria weights (w_e) using the Equation 1, where e = (1, 2 …E) is the number of criteria, and x_e is the frequency of criterion e.

3.2 Criteria evaluation with decision support module

In general, each criterion has different importance or priority depending on the organization policies, the supply situation, and the decision makers and/or experts' judgments. In the normal way, the importance of criteria are achieved by assigning weights to each criterion from the opinion of experts and/or decision-makers through questionnaires. Furthermore, the decision support module is constructed to enter the impact of customer or end-user reviews formed in real-life into a decision of criteria evaluation in place of expert judgments to extract the importance of each criterion. The collected data (customer or end-user reviews) from online sites are cleaned from unusable data and prepared to pass through three stages as illustrated in Figure 1.

In the labeling process, after identifying the classifications (set of criteria) by a group of experts, then the examiner sets a number of meanings (reviews) for each criterion to train the classification algorithm. The classification algorithm Long Short Term Memory (LSTM) which is a special type of Recurrent Neural Networks (RNN) is used for text (customer reviews) classification. After training the classification algorithms with a sample of labeled data, the trained algorithm can begin to recognize the same patterns in all new text documents (customer reviews).

$$w_e = \frac{x_e}{\sum_{e=1}^{E} x_e} \qquad (1)$$

The normalized criteria weights achieved from Equation 1, are used in the next module in supplier ranking process using TOPSIS method.

3.3 Alternative (supplier) rankng using fuzzy-TOPSIS

Different MCDM approaches with fuzzy environment are used for supplier ranking problem, such articles (Siddiqui, 2017), (Abdul-Razaq et al., 2019) are used the F-AHP approach, and articles (Yayla and Yildiz, 2012, Massoudi & Birdawod, 2023), (Sevkli et al., 2012) used the F-TOPSIS approach, which is one of efficient and common methods used for this purpose, as it was introduced by (Chen, 2000). Therefore, the F-TOPSIS method was used in this study, with the following steps for supplier ranking:

1. Establish the decision matrix; using the fuzzy linguistic scales. The numerical value of triangular fuzzy numbers is listed in Table 1.

Table 1 Alternative ranking fuzzy linguistic scales using TOPSIS

Symbol	Linguistic Scale	Fuzzy Scale (l, m, u)
VP	Very poor	(0, 0, 2.5)
P	poor	(0, 2.5 , 5)
M	medium	(2.5 , 5, 7.5)

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G	good	(5, 7.5, 10)
VG	Very good	(7.5, 10, 10)

1. The decision matrix $\tilde{X}_{ie}$ of the decision-maker (g) is the fuzzy assessment of alternatives (i) over criteria (e) and is found as follows: where. e = (1, 2 …E) is the number of criteria and
1. i = (1, 2…n) is the No. of alternative.

$$\tilde{X}_{ie} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \dots & \tilde{x}_{1E} \\ \tilde{x}_{21} & \tilde{x}_{22} & \dots & \tilde{x}_{2E} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{N1} & \tilde{x}_{N2} & \dots & \tilde{x}_{NE} \end{bmatrix} \quad (2)$$

2. Evaluate the aggregated value of supplier assessment, if the assessment is made by more than one decision-maker. Assume there are (G) number of decision-makers g = (1, 2 …G), then the aggregated value of the supplier assessment is evaluated by:

$$\tilde{X}_{ie} = \frac{\sum_{g=1}^{G} \tilde{x}_{ie}}{G} \quad (3)$$

3. Normalize the fuzzy decision matrix; in the F-TOPSIS, linear normalization is applied. Let $\tilde{F}$ is aggregated decision matrix with (N) the number of alternatives and (E) the number of criteria. Thus, Equations 5a and 5b, give the normalized fuzzy decision matrix. where (l, m, u) is triangular fuzzy numbers:

$$\tilde{F} = [\tilde{f}_{ie}]_{N\times E} \quad (4)$$

2.
he normalized fuzzy value for (benefit criteria) is as:

$$\tilde{f}_{ie} = \left(\frac{l_{ie}}{u_e^*}, \frac{m_{ie}}{u_e^*}, \frac{u_{ie}}{u_e^*}\right), where\ u_e^* = \max_i u_{ie} \quad (5a)$$

3.
he normalized fuzzy value for (cost criteria) is as:

$$\tilde{f}_{ie} = \left(\frac{l_e^-}{u_{ie}}, \frac{l_e^-}{m_{ie}}, \frac{l_e^-}{l_{ie}}\right), where\ l_e^- = \min_i l_{ie} \quad (5b)$$

4. Evaluate the weighted normalized decision matrix $\tilde{V}$, evaluated by multiplying the weight vector of the criteria by the normalized decision matrix,

$$\tilde{V} = [\tilde{v}_{ie}]_{n\times E} \quad , \quad \tilde{v}_{ie} = \left[w_e \times \tilde{f}_{ie}\right] \quad (6)$$

5. Calculate the fuzzy positive (H^*) and fuzzy negative (H^-) ideal solution:

$$H^* = (\tilde{v}_1^*, \tilde{v}_2^*, \dots, \tilde{v}_E^*), where\ \tilde{v}_e^* = \max_i(\tilde{v}_{ie}) \quad (7a)$$

$$H^- = (v_1^-, v_2^-, \dots, v_E^-), where\ v_e^- = \min_i(\tilde{v}_{ie}) \quad (7b)$$

6. Determine the distance of i^{th} alternative to the fuzzy positive (H^*) and fuzzy negative (H^-) ideal solution, as follows

$$D_i^* = \sum_{e=1}^{E} d(\tilde{v}_{ie}, \tilde{v}_e^*), i = (1,2,\dots,n) \quad (8a)$$

$$D_i^- = \sum_{e=1}^{E} d(\tilde{v}_{ie}, \tilde{v}_e^-), i = (1,2,\dots,n) \quad (8b)$$

Where $d(\tilde{v}_{ie}, \tilde{v}_e^*)$ and $d(\tilde{v}_{ie}, \tilde{v}_e^-)$ are the distance between i^{th} alternative and (H^*) and (H^-) respectively.

7. Determine the closeness coefficient using Equation 9 below, where the alternative with the highest value of (CC_i) is the highest-ranked.

$$CC_i = \frac{D_i^-}{D_i^* + D_i^-} \quad where\ i = 1,2,\dots,n \quad (9)$$

IV. NUMERICAL ILLUSTRATION AND DATA ANALYSIS

The application of study model was implemented in a real case study on a dental clinic for selecting a dental composite-fillings supplier. After a pre-selection process for potential suppliers, five international (first-tier) suppliers were identified and described as (S1, S2, S3, S4, and S5).

4.1 Criteria selection

In this study, the criteria were selected according to a study model, in which a set of evaluation criteria were established through a literature survey by examining academic articles on supplier selection criteria. Then a questionnaire was designed based on the set of criteria and sent to a group of experts to refine the set of criteria and identified the most important criteria. In general, the identified criteria and the description of each criterion are given in Table 2.

Table 2 The evaluation criteria and its description

Symbol	Criteria	Description
C1	Price	the price of the dental composite fillings
C2	Quality	the quality of the dental composite fillings
C3	Accessibility	ease of obtaining the product (product availability) it's availability in local market
C4	Usability	the ease of using the composite filling during filling the tooth by the dentist
C5	Esthetic	the aesthetic appearance or consistency of the color of the composite filling with the color of the tooth

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C6	Durability	the strength of the composite filling

4.2 Criteria evaluation using decision support module

Big data analytics and machine learning have been used to assess the importance of criteria by analyzing real-world customer or end-user feedback by performing the following steps:

4.2.1Data collecting

The Amazon product reviews dataset is used to implement the research methodology of customer reviews analyzing. The dataset of the healthcare products category is used for the study application of (dental fillings). The collected datasets are available publicly in the website (Amazon Review Data) (NI, 2022), developed by (Ni, 2019), where they collected reviews of different categories from the amazon dataset in the form of JSON files.

4.2.2 Data cleaning

The data cleaning process involves removing unimportant data such as (ratings, review time, and so on), as only the review text column was maintained. After the cleaning process, the number of reviews became (1,098,635) reviews of the healthcare and beauty products category. A part of the data (26,978) reviews are used in the labeling process, and the rest (1,071,657) reviews are analyzed to evaluate the importance (frequency) of each criterion.

4.2.3 Data labeling

A part data (customer reviews) were labeled by the examiner using Microsoft Excel (2016) by inserting a label into a list of reviews for each criterion. The total labeled samples are (26,978) reviews, which were distributed into six labels (criteria). The review samples for each label (criterion) and the number of training samples are listed in Table 3.

Table 3 Samples of reviews for each category (criteria)

Symbol	4. Reviews Samples	5. Labels 6. (Criteria)	7. No. of Labeled Samples
C1	8. "they worked and great price", "awesome buy for the price!", " I'll give them two stars for the price"	9. Price	10. 12,487
C2	11. "these are good quality", "great quality", "They seem to be of equal quality to the big brands"	12. Quality	13. 2,302
C3	14. "arrived quickly", "fast delivery"," convenient to have available at all times"	15. Accessibility	16. 1,759
C4	17. "perfectly usable", "easy to use and excellent results", "easy to use and carry with you"	18. Usability	19. 10,093
C5	20. "aesthetically pleasing", "aesthetically it looks good and it also feels good", "the color is very nice and everyone always loves aesthetics"	21. Esthetic	22. 143
C6	23. "strong and durable product", "very durable", "great for kids and very durable"	24. Durability	25. 194

4.2.4 Model training

The RNN-LSTM is a proposed method to classify the reviews into selected criteria. MATLAB® software [20] was used for implementing the model. The model includes steps before training: first, the labeled dataset was imported. Next, the split ratio was specified by setting 20% of the data for testing. In a pre-processing step, the data was tokenized. In the processing step, the word embedding layer is included with a dimension of 50, and the input sequence length used is 40. Next, the LSTM layer was included using 80 hidden units. The fully connected layer was formed with the same number of classes (labels). The Softmax layer was applied with the classification layer to convert the values into probabilities. For training options, the mini batch size was used equal to 16. Thus, the training process is presented in Figure 3, with a training accuracy of 98.70%.

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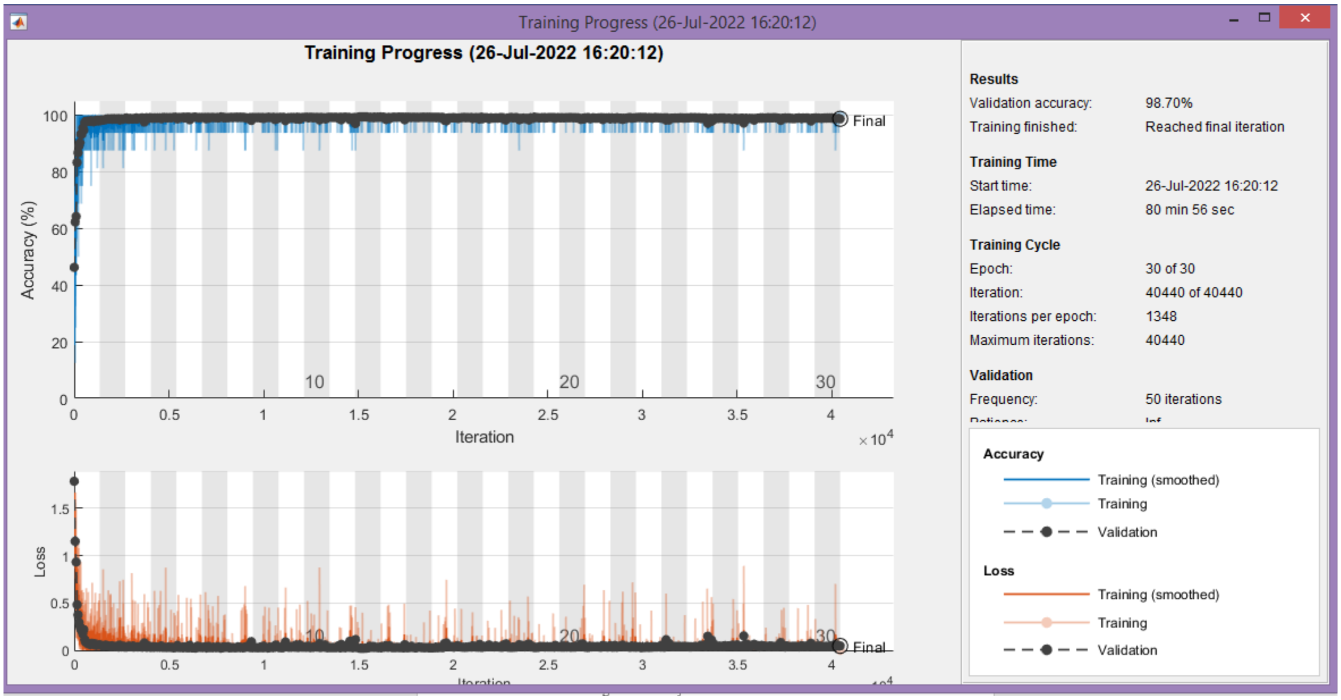
Figure 2 The training process of the LSTM model



4.2.5Data classification

After the RNN-LSTM model had been trained with labeled data. The new customer dataset (1,071,657) reviews were applied to the trained model to classify the new reviews into six categories (criteria). Then, the output of the data classification (the frequency of each criterion) was normalized using Equation 1. In general, the results of classification and criteria normalization are presented in Table 4.

Table 4 Results of dataset classification and normalized criteria weights

Criteria	Frequency of each Criterion	Weights of Criteria
Price (C1)	26. 201,195	0.19
Quality (C2)	27. 52,464	0.05
Accessibility (C3)	28. 74,078	0.07
Usability (C4)	**29. 547,326**	**0.51**
Esthetic (C5)	30. 120,255	0.11
Durability (C6)	31. 76,339	0.07
Total	**32. 1,071,657**	**1**

From Table 4, the highest frequency criterion means the most important criterion from customer's point of view is usability criterion about 0.51 On the other hand the least important criterion is quality criterion of 0.05.

Results of supplier selection using fuzzy-TOPSIS

A questionnaire was designed based on the set of criteria and applied to 12 dentists who are considered experts to assess the suppliers. The experts (dentists) consist of 2 specialist dentists and 10 general dentists. The suppliers were assessed over each criterion through linguistic terms in Table 1. Then the assessment was aggregated using Equation 3.

The F-TOPSIS method was used for supplier ranking, starting with normalizing the aggregated supplier assessments. The benefits and cost criteria were normalized using Equations (5a) and (5b), respectively. Where all criteria are benefiting type except price (C1) is cost type. Then, the weighted normalized decision matrix was evaluated using Equation 6,

The distances D_i^* and D_i^- were calculated using Equations (8a) and (8b) respectively, after calculating the fuzzy positive (H^*) and negative (H^-) ideal solution using Equations (7a) and (7b) respectively. Finally, the closeness coefficients (CC) of the suppliers were determined using Equation 9, then, the results of (CC) is compared, where the supplier with the highest

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value of (CC) is the top-ranked. Table 5 illustrates the final result of closeness coefficient and ranking of suppliers.

Table 5 Closeness coefficient and ranking of each supplier

Suppliers	D_i^*	D_i^-	Closeness Coefficient (CC_i)	Ranking
S1	0.406	0.360	0.470	3
S2	0.432	0.338	0.439	4
S3	0.448	0.323	0.419	5
S4	0.376	0.411	**0.522**	**1**
S5	0.405	0.362	0.472	2

As indicated in Table 5, the top rank of suppliers is supplier S4 with the value of closeness coefficient equal to 0.522

V. CONCLUSION

One of the most crucial factors to consider in decreasing supply chain costs and improving the quality of a company's product or service is supplier selection by choosing the most efficient supplier based on evaluation criteria. This paper developed a methodology for supplier selection enhanced by industry 4.0 technologies. The study methodology is implemented in the dental clinic to select effective suppliers of dental fillings material. The presented study methodology consists of four modules: The customer reviews were analyzed and classified using the deep learning RNN-LSTM algorithm to extract the criteria weights. Lastly, suppliers were ranked in Descending order of the closeness coefficient based on the criteria weights using the F-TOPSIS method,

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