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Article

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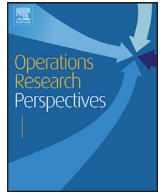
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Supplier selection towards uncertain and unavailable information: An extension of TOPSIS method

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ABSTRACT

Due to intensive competition among business corporations, the selection of supplier becomes more significant for business success. However, supplier selection problems are complex since a large number of criteria need to be considered and, frequently, some criteria cannot be assessed precisely. Moreover, fluctuations of supplier performances as well as unknown information always exist in real-world decisions. This study, therefore, aims to propose a method to facilitate practitioners to logically select a supplier, even when uncertainty and/or unavailability of the assessment information emerge. The TOPSIS method is chosen to be the basis for this development. The rank order centroid (ROC) method is chosen to determine the weights of criteria in order to lessen the degree of subjectivity required from the decision makers as well as uncertainty of the weights assignment. A case of egg supplier selection is given to demonstrate the implementation procedures of the proposed method.

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1. Introduction

In the global competitive market, the performance of suppliers is one of the key factors for business success. It is essential for buying firms to ensure that they receive the best raw materials and services at the right price, time, and quantities, in order to produce world-class quality and profitable products [1–4]. A high performance supplier is able to create value to a purchasing firm and enhance the firm's competitiveness. For example, a company could promote the attractiveness of their product through having its component parts made by a supplier with a strong brand image. A supplier who employs state-of-the-art technology in data interchange and communication could reduce the purchasing cost for buyers and also increase the overall supply chain efficiency [5]. As such, purchasing decisions become more important as the determinant of profitability and sustainability [6].

The usual way that buying firms make decisions on supplier selection is to simultaneously consider the performances of all candidate suppliers against all chosen criteria. The decisions are then made subjectively or intuitively [7]. As stated by Burke and

Miller [8] who conducted in-depth interviews with 60 professionals across various industries in the United States, managers usually made decisions based on their intuition. However, many of them frankly disclosed that they were not intensely confident in those conclusions, and they still needed support from a more logical method. Supplier selection can be viewed as a complex problem concerning not only quantitative criteria but many criteria are also qualitative in nature, implying that the evaluation of suppliers still requires subjective judgements and might not be standardised. Moreover, conflict or argument about the importance of the criteria, or their weights, is also viewed as another common problem in business practices. This is particularly the case when the decision making must rely on group agreement, and the weights are assigned arbitrarily and subjectively [9]. These issues imply the need of a systematic method to support supplier selection. However, when considering a selection method for actual business practices, simplicity is needed as well.

When considering an appropriate mathematical method for selecting a supplier, a major concern which obstructs the employment of many typical methods is a lack of their ability to deal with uncertain and unavailable information which often occurs in real-life situations. When end-product manufacturers or service providers need to select a supplier, they basically evaluate a number of suppliers by asking all potential ones to submit the required information, conducting a site visit, or reviewing historical perfor-

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mance (when ex-suppliers are re-considered) [10,11]. From such processes, it is possible that some sellers do not wish to share all information or spend resources on collecting unavailable information requested by their customers [11]. For example, a number of studies in green supply management reveal that most suppliers feel uncomfortable in providing information relating to environmental issues of their operations [12,13]. A supplier's willingness to share information, as stated by Igarashi et al. [11], depends on the power balance and relationship within the supply chain. This implies that small firms may lack adequate power to ask for a complete collaboration with potential sellers. In addition, for some industries and/or locations, suppliers' and product performances periodically change. Delivery lead time, for instance, may dramatically fluctuate as an influence of the traffic conditions, particularly in urban areas. For the food industry, furthermore, product prices can be affected by national economic and political situation, and the quality can also be affected by climate conditions. As pointed out by Bai et al. [14], supplier instability is the major issue for supplier selection, especially for the foodservice industry. As such, the process of supplier selection needs to take such a dynamic environment into account. Furthermore, many logical methods employed to support supplier selection assume that historical performances of all potential suppliers are precisely known. This might not be true in all real-life situations [6]. In high-tech industries, for example, suppliers' quality levels are often unknown or only partially known to the buyer [15]. Moreover, when new suppliers are considered, it is likely that some aspects of suppliers' performance cannot be directly requested from the new ones, but buyers need to perceive those by experiences such as service quality or flexibility. As a result, for new suppliers, their performances on some criteria might be truly unknown at the date of making decision. As such, many typical methods cannot be employed.

From the issues mentioned above, this research aims to propose a simple method which can support the supplier selection process under situations of having uncertain and incomplete information. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is employed here as a fundamental basis for this purpose. Based on the TOPSIS method, the assessment of one supplier is dependent upon the performances of others. It is therefore a suitable method for comparing all candidate suppliers and selecting the best one. This study extends the ability of the TOPSIS method to be applicable even when the assessment data and/or the weight of criteria are uncertain and/or unavailable. The inclusion of uncertainties in supplier selection process avoids a potential loss of meaningful information, minimises inaccuracies, as well as promotes transparency in the decision making. Furthermore, a solution for the inclusion of qualitative criteria in the supplier selection is also suggested to minimise subjective bias from the assessment. The proposed method facilitates and simplifies purchasing decisions under incomplete conditions, and it can be generalised to any cases of multiple criteria decision making.

In supplier selection problems, two significant issues always exist. One is the selection of criteria to be used, and another is the appropriate method which can facilitate the selection [16]. This paper is therefore organised as follows. Section 2 provides a review of the literature which is divided into two subsections. Section 2.1 focuses on the trends and popularity of criteria for supplier selection. Various terms of the literature-suggested criteria are synthesised so that the list of criteria presented by this study can be fundamental to the development of a specific selection framework for any business sectors. Section 2.2 then presents a review of methods generally used for this purpose. Limitations of those methods are also discussed. The methodology employed for this study is described in Section 3. Section 4 presents the extension of TOPSIS method to enhance its ability to deal with uncertain and unavailable information. A case of egg supplier selection using the pro-

posed method is demonstrated in Section 5. Finally, Section 6 provides the concluding remarks.

2. A literature review of supplier selection

The literature review is divided into two subsections. Section 2.1 is an overview of supplier selection criteria, and the synthesised list of criteria is presented at the end. Section 2.2 then provides a review of selection methods generally used in previous studies.

2.1. Supplier selection criteria

This section provides a review of articles mainly studying criteria for supplier selection. Due to the large number of relevant articles, this review focuses only on previous review articles of supplier selection criteria as well as articles that investigate the criteria through empirical surveys of business practitioners. The aim here is to gather a comprehensive list of criteria which can be a starting point for any sectors to establish their own lists. Studies focusing on a wide cross-section of industries are therefore the target of the review while those based upon a specific industry or business sector are disregarded.

Dickson [17], first of all, is one of the early researchers on supplier selection. He identified 23 criteria based on questionnaires returned from 170 purchasing managers of companies in the United States and Canada. The importance of each criterion was also empirically surveyed. Weber et al. [2] then reviewed 74 relevant articles, published between 1966 to 1990, to provide a broad view of criteria and methods used in supplier selection within the manufacturing sector. Simpson et al. [5] explored whether most companies across a broad area of industries in the United States had a formal process for supplier evaluation, and also identified key criteria by which suppliers were being assessed. The results indicated that almost half of the respondents had no formal method for assessing supplier performance since most companies still employed simple and subjective approaches for supplier selection. Kannan and Tan [18] then employed a questionnaire to examine different attitudes, between American and European companies, towards the importance of each criterion for supplier selection. This study also supports the inclusion of qualitative criteria, such as supplier commitment, in the process of supplier selection due to their significant impact on purchasers' performance, rather than relying merely on quantitative assessment such as product price. Thanaraksakul and Phruksaphanrat [19] reviewed 76 articles addressing supplier selection, since 1966, in order to provide a ranking order of the criteria according to the number of appearances of each criterion. From this, 33 criteria were identified, and they were then classified into five perspectives based on the balanced scorecard model plus the corporate social responsibility perspective. In the following year, 78 related articles published during 2000–2008 were reviewed by Ho et al. [20]. Their objectives were to explore selection methods and criteria prevalently used in academic literature. Deshmukh and Chaudhari [16], similarly, made a review of supplier selection criteria from 49 articles from 1992 to 2007. The results were cross-compared to Dickson [17] and Weber et al. [2] to analyse changes over time of this matter. Abdolshah [10] also presented a summary of supplier selection criteria reported in the academic literature from 1966 to 2012. The number of appearances of each criterion was counted to reflect its importance within the field. Recently, Wetzstein et al. [21] provided a review of 221 articles in supplier selection published during 1990–2015.

According to the previous studies, some interesting points emerge. First of all, product price which fell into the top three most prevalently used criteria in all rankings generated by studies reviewing academic literature [2,10,16,19,20] were generally ranked

lower than that in terms of its importance rated by business practitioners [17,18]. This indicates that price, which usually appears in the list of criteria for purchasing decision, might not be perceived as most important. From the review, product quality and delivery have been among the most common and important criteria for supplier selection for the past few decades.

According to the review, moreover, the list of criteria is likely to be affected by changes of firms' policy and strategy. For example, as pointed out by Weber et al. [2], the emergence of Just-in-time manufacturing in 1966 led to the increasing concern over the criterion 'geographical location'. Also, since the 2000s, the increasing interest of supply chain management, where suppliers are required to quickly respond to short product life cycles as well as fluctuations in the demand quantity and delivery lead times [22], introduces criteria relating to flexibility [10,18,20]. Production facilities and technical capacity were also commonly considered in both academic research and actual practices probably due to their strong association with supplier's flexibility. Suppliers who are able to quickly respond to changes in buyer's requirements always need effective technology and strong resource management. The introduction of supply chain management has also led to the increasing concern of criteria relating to supplier's communication system and information technology. Moreover, according to the increasing requirements of outsourcing design, many buying companies expect suppliers to participate in their new product development and to provide plans for continuous improvement [23]. This has brought up a number of criteria relating to innovation and research and development (R&D) capability [18–20]. Last but not least, criteria relating to environmental protection and social responsibility have been increasingly considered during the past decade due to the emergence of sustainability issues. Since then, supplier selection studies generally incorporate 'green' or 'sustainability' criteria into the evaluation process, as indicated in Govindan et al. [9], Wetzstein et al. [21], Wittstruck and Teuteberg [24], Hsu et al. [25], Kannan et al. [26], Kumar et al. [27], and Sahu et al. [28].

One of the major issues in applying knowledge from reviewing research articles in actual supplier selection is the fact that a large number of criteria have been introduced. In many articles, more than 20 criteria were provided. Other than this, different researchers provided their own categories of criteria according to their own interpretations. After combining a list of criteria from the review of literature [2,5,9–11,16–20,29], 176 different phrases emerge although some of them refer to the same aspect. Not only is there a wide range of words, moreover, criteria used in most studies are also not clearly defined. Most of them are still qualitative and multi-dimensional. The reason of this might be the fact that the articles reviewed here focused on non-specific industries and it is therefore likely that they needed to standardise the list of criteria, using general terms, in order to allow the criteria to be applicable across all business sectors. To simplify this, 176 phrases were synthesised by combining different phrases mentioning the same aspect into a single phrase through the authors' brainstorming, and only 39 different criteria remain as shown in Table 1. For example, 'Production facilities' from Ávila et al. [29]; 'Production facilities and capacity' from Weber et al. [2]; and 'Technology' from Ho et al. [20] have been combined into the phrase 'Production facilities and technology'.

It is suggested here that, in actual implementation, practitioners need to select only the criteria that truly appeal to their management strategies and interests. They also need to identify concrete indicators as well as a particular assessment scale for each chosen indicator. Note that, the scales can be varied among different persons, and some criteria (or indicators) could be assessed through either qualitative or quantitative scales, or both. This, again, depends on the assessor's perspective and each company's focus. An example of the implementation is shown in Section 5 by present-

ing a list of these 39 criteria to a purchasing manager of a restaurant and asking her to choose only the criteria that were consistent with her business focuses. She was also asked to identify the assessment scales for each chosen criterion.

2.2. Methods supporting supplier selection

Methods supporting supplier selection were also reviewed in a number of research articles. Weber et al. [2], based on a review of 74 articles, classified methods used for this purpose into three categories, including (i) Linear weighting models, (ii) Mathematical programming (e.g., linear programming or goal programming), and (iii) Statistical/probabilities approaches (e.g., cluster analysis or stochastic economic order quantity model). The most utilised approach was found to be the linear weighting models. According to this approach, a weight is assigned to each criterion in order to reflect its importance or its contribution to the decision. The overall performance of each supplier is then computed by summing up that supplier's performance on each criterion multiplied by its weight. Generally, the supplier with the highest composite score indicates that it has the greatest overall performance, and it should be selected.

Ten years later, de Boer et al. [6] also presented a summary of methods supporting supplier selection process based on a review of academic literature. They have classified the methods into five approaches: (i) Linear weighting models, (ii) Total cost of ownership, (iii) Mathematical programming, (iv) Statistical models, and (v) Artificial intelligence-based models. From their review, again, the linear weighting models seemed to be mostly utilised for the final choice-phase of supplier selection. The advantages and limitations of these five approaches were discussed, and other methods that were able to handle the selection process from a different angle were suggested within their article, such as TOPSIS introduced by Hwang and Yoon [30].

Next, Ho et al. [20] summarised methods used for supplier selection according to a review of related articles from 2000 to 2008. The result revealed that the ranking order based on the frequency of uses were Data envelopment analysis (DEA), Mathematical programming, Analytic hierarchy process (AHP), Case-based reasoning (CBR), Analytic network process (ANP), Fuzzy set theory, Simple multi-attribute rating technique (SMART), and Genetic algorithm (GA), respectively. Other than the employment of individual approaches, this study also found that around 40% of the reviewed articles applied integrated approaches to evaluate or select suppliers. The most common ways were the integration of AHP and fuzzy logic with others. Referring back to Weber et al. [2], DEA and AHP, the top two commonly used methods from Ho et al. [20], can be classified into the mathematical programming and the linear weighting approaches, respectively. Similarly, Deshmukh and Chaudhari [16], who reviewed 49 research articles published during 1992–2007, classified supplier selection methods into four categories: (i) Linear weighting, (ii) Mathematical programming, (iii) Statistical approach, and (iv) others, such as cost-based methods and the integrated AHP with fuzzy logic. Lastly, Chai et al. [31] presented a systematic literature review on articles, published from 2008 to 2012, that applied decision making techniques for supplier selection. According to their review, 26 techniques were found, which can be classified into three approaches: (i) Multi-criteria decision making (MCDM), (ii) Mathematical programming, and (iii) Artificial intelligence-based methods. The means of applying these techniques for supplier selection as well as their limitations were also discussed within the article. Their summary revealed that MCDM methods were mostly employed in solving supplier selection problems. Within the group of MCDM methods, AHP remained the most commonly used methods for this purpose (at almost 25% of the most reviewed articles), following by TOPSIS and ANP

Table 1
Synthesised criteria for supplier selection.

1. Certifications	21. Price
2. Cleaner production	22. Procedural compliance
3. Cultural congruence	23. Process control capability
4. Customer satisfaction and impression	24. Product appearance
5. Delivery performance	25. Product knowledge
6. Domestic political stability	26. Product quality
7. Ease of use	27. Product reliability
8. Environmentally friendly products	28. Product safety
9. Financial status	29. Production capacity
10. Geographical location	30. Production facilities and technology
11. Image and experience of suppliers	31. Quick response to emergency, problem, or special request
12. Information technology and communication systems	32. Safety awareness
13. Innovation and R&D	33. Sale policies
14. Inventory and warehousing	34. Social responsibility
15. Invoicing	35. Serviceability
16. Labour relations record	36. Warranties and claim policies
17. Maintainability	37. Willingness to change their products and services to meet buyer's needs
18. Management and organisation	38. Willingness to participate in buyer's new product development and R&D
19. Packaging quality	39. Willingness to share sensitive information
20. Payment terms	

at 14.6% and 12.2%, respectively. Linear programming and DEA, under the group of Mathematical programming methods, were also applied by many researchers, at 15.4% and 10.6%, respectively. This study also found that the trend of supplier selection research after the year 2008 generally focused on solving uncertainties in the assessment and selection processes rather than formulating the problems under deterministic conditions. Most recent studies applied fuzzy formulations to reflect uncertainties (applications of triangular fuzzy number are the main stream) while interval-valued as well as incomplete and imprecise decision information still received little consideration within the field.

Regarding AHP, the most commonly used method for supplier selection, it is usually applied to serve two particular purposes: weighting criteria and/or selecting the best alternative. AHP showed up a number of advantages in the literature. For instance, it is able to deal with qualitative and multi-dimensional criteria where numerical assessment of those criteria is difficult or impossible. Moreover, it employs the pairwise comparison which has been claimed as logical, and this technique is consistent with when people express their sense of preferences [32,33]. An application of AHP, however, also has a number of arguments. First of all, AHP is highly dependent on subjective judgements, and a large number of judgements for pairwise comparison is required, $n(n-1)/2$ judgements for each particular criterion where n denotes the number of alternatives being compared. Consequently, inconsistent judgements occur particularly when many criteria or alternatives are considered [33–35]. Furthermore, a few technical issues, such as the rank reversal problem [36,37] and the violation of the Pareto optimality axiom [38,39], have been reported with the applications of AHP. Therefore, it needs to be employed with caution for these possible problems.

DEA, one of the popular techniques for supplier selection, employs a linear programming technique to analyse the relative efficiency of a set of suppliers. All criteria are here classified into inputs and outputs. Efficient suppliers, who can provide more outputs by using the same inputs or can provide the same outputs with fewer inputs, would be selected [40]. By using DEA, the best supplier can be identified objectively through numerical analysis. DEA, however, has a number of issues that raise concerns. One generally adopted rule of thumb, firstly, specifies that the number of suppliers should be at least twice as large as the number of criteria in order to guarantee the discrimination power of DEA [41,42]. This point is likely to be impossible in many cases where only a few candidates are considered against a large number of criteria. In addition, an application of DEA holds an assumption

Table 2
The assessment matrix Z of i alternatives and j criteria for the traditional TOPSIS.

	Criterion 1	Criterion 2	...	Criterion j
Alternative 1	Z_{11}	Z_{12}	...	Z_{1j}
Alternative 2	Z_{21}	Z_{22}	...	Z_{2j}
...
Alternative i	Z_{i1}	Z_{i2}	...	Z_{ij}

that outputs definitely increase according to the increase of inputs. This assumption may not always be true in practices as well [43]. Moreover, in actual practices, practitioners may be confused with the classification of input and output criteria. As claimed by Ho et al. [20], based on their review, many authors considered 'price' or 'cost' as an input while some authors used it as an output. The quantitative nature of DEA, furthermore, does not provide a solution for the inclusion of qualitative criteria. As such, some authors, such as Saen [44] and Seydel [45], employed rating scales to convert subjective judgements into numerical information. This method, nevertheless, should be employed with caution, particularly for the issues of inconsistency and standardisation in the assessment. Lastly, the principle of DEA might suit the purpose of performance analysis while it might not be a good choice for alternative selection since it is possible that more than one efficient supplier exists, as seen in Bai et al. [14]. Then, practitioners need to find another solution to select the most appropriate one.

To select the most appropriate method, here, TOPSIS becomes the chosen one due to a number of reasons. It is one of the MCDA methods widely used for ranking and/or selecting alternatives. Its logic is simply understandable as it is to select the one having its overall performance at the longest distance from the worst values of the peer group and having the shortest distance from the best performers of each criterion. At the end of the process, the closeness coefficient to the ideal solutions (CC) can be computed for each alternative, which is then used as a composite index to compare and rank alternatives. The procedure to derive the coefficient is described below [46]:

Step 1: Draw the assessment matrix Z of i alternatives and j criteria, as shown in Table 2. Note that assessment data (Z_{ij}) from different criteria has been previously normalised or transformed to a single scale. Here, it is assumed that the transformed scale relies on the benefit criterion which is, the larger the value is, the greater the preference for that criterion.

Step 2: Calculate weighted normalised rating using Eq. (1). Each Z_{ij} is multiplied by W_j , as such matrix Z becomes matrix V .

$$V_{ij} = W_j Z_{ij} \tag{1}$$

where W_j is the relative weight of criterion j , and all W_j are normalised to sum to one.

Step 3: For each criterion, identify positive-ideal and negative-ideal solutions (PIS_j and NIS_j) from Eq. (2) and (3), respectively.

$$PIS_j = \text{Max}(V_{ij}) \tag{2}$$

$$NIS_j = \text{Min}(V_{ij}) \tag{3}$$

Step 4: For each alternative i , calculate the separation measure from the positive-ideal solution (S_{PIS_i}) and that from the negative-ideal solution (S_{NIS_i}), or the distances between alternatives according to the Euclidean distance concept, following Eqs. (4) and (5).

$$S_{PIS_i} = \sqrt{\sum_{j=1}^n (V_{ij} - PIS_j)^2} \tag{4}$$

$$S_{NIS_i} = \sqrt{\sum_{j=1}^n (V_{ij} - NIS_j)^2} \tag{5}$$

Step 5: For each alternative i , calculate the closeness coefficient to the ideal solutions (CC_i) using Eq. (6).

$$CC_i = S_{NIS_i} / (S_{PIS_i} + S_{NIS_i}) \tag{6}$$

Step 6: Select the alternative with the greatest CC_i or rank them according to CC_i .

TOPSIS is claimed as one of the most straightforward methods, and it is also suitable for a large scale problem comprising large numbers of criteria and alternatives. Moreover, it is cognitively comprehensible since the judgment is based on the need for compromise which is in accordance with the normal way people make decisions [47,48]. Nevertheless, its limitations include the inability to deal with qualitative criteria which are difficult to quantify precisely. Also, it cannot be employed in cases having an uncertain score. A number of research articles integrated fuzzy logic into the TOPSIS method in order to solve selection problems with uncertain judgments [4,28,49–51]. The fundamental concept of fuzzy logic is to use linguistic terms, instead of numerical values, to model uncertainties of human judgments [49]. That means, for supplier selection, suppliers' performances and/or criteria weights are assessed through linguistic variables [49]. Some issues, nevertheless, raise concerns for the use of fuzzy logic. First of all, the determination of linguistic variables still needs subjective judgement, and this leads to the question that who is the appropriate decision maker (DM) for this subject. Secondly, the appropriate way to defuzzify the fuzzy numbers is still a question, and the selected alternative sometimes depends on the chosen defuzzification method. Moreover, fuzzy logic only helps DMs to avoid the assignment of crisp numbers by allowing them to make a judgment using linguistic terms. This might be useful for the assessment of qualitative criteria, but it seems to make the problem more complex when quantitative criteria can be simply and straightforwardly assessed towards precise information. For quantitative criteria, generally, there is no need to employ linguistic terms in the assessment. However, most proposed fuzzy methods do not provide a solution for situations where both certain and fuzzy information must be analysed simultaneously. Last but not least, the complexity of fuzzy logic added to the decision algorithm has been criticised as unnecessary, and it tends to make the selection process impractical. As

reviewed by Govindan et al. [9], some studies show that the final decisions emerged from fuzzy AHP are not generally different to those calculated from typical AHP process, and practitioners tend to choose a simple method over a fuzzified one due to its simplicity and transparency. Shafiee et al. [52] also support that a practical method for decision making should be simple but able to provide reliable and realistic results. From these, applications of fuzzy numbers may raise complexity in determining the ultimate conclusion, and the proposed linguistic terms may not be adequately straightforward particularly when some criteria are quantitative or their numerical values can be gathered. For this study, instead of utilising fuzzy logic, uncertainty and incompleteness are modelled through intervals of possible information. This will be further explained in Section 4.

In terms of the criteria weights determination, according to the MCDA literature, a wide range of weighting methods is available. Most of them, however, require a DM to subjectively assign precise scores to reflect degrees of criteria importance, such as AHP, SWING, Point allocation, or Direct rating. These methods have been generally criticised for producing unreliable results since DMs always feel uncomfortable or hesitant in assigning crisp weights, or they lack understanding of such weighting procedures. Consequently, their judgments are highly likely to be vague and perfunctory. Moreover, in group decision making, reaching a consensus regarding the weights of several criteria is difficult particularly when crisp and precise weights are required from them [53–58]. As such, the review from Wetzstein et al. [21] recently shows that most research articles in supplier selection considered just a single DM, while only around 18% of the reviewed articles explicitly presented group decision making in their models.

To relieve such uncertainties, rank-based weighting methods are suggested. These methods determine the weights based only on a criteria ranking order. As claimed by many academic references [53–58], asking DMs to only rank criteria is much easier, and they normally feel more confident to respond to this request. The weights derived from confidently given information should be more rigorous and reliable. Also, reaching consensus among various DMs on a ranking order is more likely to happen. From the decision literature, many formulas used to convert ordinal numbers into the weights have been proposed, and many comparative studies have found that the Rank Order Centroid (ROC) method outperforms the others, such as the Rank Sum (RS), Rank Exponent (RE), and Rank Reciprocal (RR) methods, in most experimental scenarios and measures, particularly in terms of a choice accuracy [53,54,57–59]. This might be a consequence of the weight distributions generated by ROC. It gives the largest gap, compared to others rank-based methods, between the weights of the most important criterion and the least. According to some studies focusing on decision behaviour, this pattern of weight distribution tends to be mostly consistent with the functions of criteria weights influencing people's choices which are generally steep and non-linear [53,60,61]. ROC is therefore selected for this study. Its equation is shown below.

$$W_j = \frac{1}{J} \sum_{j=1}^J \frac{1}{r_j} \tag{7}$$

where $j=1, 2, \dots, J$ criteria, r_j is the ranking order of criterion j . The most important criterion is ranked first ($r_j=1$), while the least important one has $r_j=J$.

To sum up, TOPSIS is here chosen as a basis for the supplier selection process, in combination with the employment of the ROC weighting method. Uncertainty and unavailability of data are modelled through intervals of possible information. The processes of data collection are described in the next section while the extension of the TOPSIS method is presented in Section 4.

3. Methodology

The study aims to propose a logical method for solving supplier selection problems where uncertain and/or unavailable information are involved. To achieve this, the traditional TOPSIS method is modified. In order to show how the proposed method can be used, a case of egg supplier selection within a large-scale restaurant in Thailand was demonstrated. Before collecting the assessment data for candidate suppliers, the final list of 39 criteria was presented to a purchasing manager of that restaurant, and she was asked to pick only the ones she would use for selecting an egg supplier.

Since several criteria were assessed using different scales and units of measurement, the data needs to be transformed into a single scale before employing the extended TOPSIS to find out the best supplier. The concept of linear utility function was employed for this purpose. Utility reflects the degree of the DM's preference for the value of the criterion being considered, and it is a consequence of his/her attitude toward risk [62]. For each quantitative criterion, the utility of a specific value h , represented by $u(h)$, is estimated from 0 to 100, where $u(h_1) > u(h_2)$ when the value h_1 is preferred to h_2 . According to this, the purchasing manager was asked to determine the best or ideal value of each criterion j as well as the worst value that could be found in real-life situations, and the utilities of 100 and 0 were respectively assigned to those values. To minimise the time of the interview, only the best and the worst values of each criterion were elicited, and the linear utility function was assumed. Then, for each supplier, assessment values $h_{i,j}$ of supplier i towards criterion j could be transformed using Eqs. (8) and (9).

For benefit criteria (the greater is better), the utility is derived by Eq. (8), where $h_{max,j}$ is the best or ideal value of criterion j and $h_{min,j}$ is the worst value.

$$u(h_{i,j}) = \left(\frac{h_{i,j} - h_{min,j}}{h_{max,j} - h_{min,j}} \right) \cdot 100 \tag{8}$$

For cost criteria (the lower is better), the utility is derived by Eq. (9), where $h_{min,j}$ is the best or ideal value of criterion j and $h_{max,j}$ is the worst value.

$$u(h_{i,j}) = \left(\frac{h_{max,j} - h_{i,j}}{h_{max,j} - h_{min,j}} \right) \cdot 100 \tag{9}$$

For qualitative criteria which cannot be assessed directly using a numerical measurement value, the rating scales or the evaluation grades were developed for each criterion. Each grade was attached by a clear definition referring to objective evidence or feasible situations in order to allow the assessor to select the grade which best reflects the actual practices or performances of the supplier being considered. By doing this, the assessment could be standardised and the inconsistency in subjective grading could be minimised, even from different assessors. For each criterion, the grades should be collectively exhaustive or they should cover all feasible cases. Note that, for different criteria, the number of grades can be different depending on how many distinct levels of feasible performances exist which are related to that criterion [63]. The utilities of 100 and 0 were assigned to the best and the worst grades, respectively. Then, the same purchasing manager was asked to assign the utility scores to other in-between grades. This was done since it was likely that the utilities of the definitions created for those in-between grades might not rely on the linear function between the best and the worst grades. The manager was also asked to rank the criteria for selecting an egg supplier. The obtained ranking order was then used to determine the weights for those criteria using the ROC method. After the transformation and weighting processes, the data can be readily input into the proposed TOPSIS model, as shown in the next section.

Table 3

The assessment matrix of i alternatives and j criteria for the extended TOPSIS.

	Criterion 1	Criterion 2	...	Criterion j
Alternative 1	Z_{11Min}	Z_{12Min}	...	Z_{1jMin}
	Z_{11Max}	Z_{12Max}	...	Z_{1jMax}
Alternative 2	Z_{21Min}	Z_{22Min}	...	Z_{2jMin}
	Z_{21Max}	Z_{22Max}	...	Z_{2jMax}
...
Alternative i	Z_{i1Min}	Z_{i2Min}	...	Z_{ijMin}
	Z_{i1Max}	Z_{i2Max}	...	Z_{ijMax}

4. The extension of TOPSIS method

When the performances of some suppliers, against some criteria, cannot be precisely assessed for any reason, two cases typically occur. Firstly, the assessor still has partial knowledge or limited information to determine a range of possible values (for quantitative criteria) or a list of possible grades (for qualitative criteria). For this case, the minimum and the maximum of the utility scores can be identified for the assessment of one supplier against one criterion. The second case is a situation that, for a particular criterion, the assessor completely lacks information about the supplier being assessed. Applied from the evidence theory [64,65], when the information is completely unknown, it is assumed that the right answer could be any value within the whole range of possible answers. According to this, for the assessment of one supplier against one criterion, the minimum and the maximum of the utility scores can be identified towards the range of all feasible values. From this concept, the assessment matrix Z for the traditional TOPSIS (Table 2) is modified to include the minimum and the maximum values of each element, as shown in Table 3. Note that each Z_{ij} is now in the form of the utility score, and $Z_{ijMin} = Z_{ijMax}$ when the assessment is precise and certain.

Since the input information is uncertain, the output (CC_i) is definitely uncertain. Therefore, instead of obtaining a single CC_i for alternative i , the minimum CC_i and the maximum CC_i are generated (hereafter Min CC_i and Max CC_i). The fact is that alternative i will obtain the lowest CC_i only when all $Z_i (Z_{i1}, Z_{i2}, \dots, Z_{ij})$ are at the lowest level, and all $Z_k (k \neq i)$ are at their greatest level. The same concept is applied to the derivation of Max CC_i , all $Z_i (Z_{i1}, Z_{i2}, \dots, Z_{ij})$ must be at the greatest level while all $Z_k (k \neq i)$ fall at the poorest performances, as shown in Eqs. (10) and (11). After this process, the matrix Z which is a matrix of $(2 \cdot i) \times j$ is converted into a matrix \tilde{Z} which is back to a matrix of $i \times j$. Then the next steps are simply the same as the tradition TOPSIS methods, as shown in Eqs. (12)–(17).

$$\text{If objective function} = \text{Min } CC_i, \tilde{Z}_{kj} = \begin{cases} Z_{kj(\min)}, & k = i \\ Z_{kj(\max)}, & k \neq i \end{cases} \tag{10}$$

$$\text{If objective function} = \text{Max } CC_i, \tilde{Z}_{kj} = \begin{cases} Z_{kj(\max)}, & k = i \\ Z_{kj(\min)}, & k \neq i \end{cases} \tag{11}$$

$$V_{ij} = W_j \tilde{Z}_{ij} \tag{12}$$

$$PIS_j = \text{Max}(V_{ij}) \tag{13}$$

$$NIS_j = \text{Min}(V_{ij}) \tag{14}$$

$$S_{PIS_i} = \sqrt{\sum_{j=1}^n (V_{ij} - PIS_j)^2} \tag{15}$$

Table 4
Example of different sets of criteria ranking order assigned by three DMs.

	Criterion 1	Criterion 2	Criterion 3	Criterion 4	Criterion 5
DM1	1st	3rd	2nd	4th	5th
DM2	2nd	1st	3rd	5th	4th
DM3	1st	2nd	3rd	5th	4th

$$S_{NIS_i} = \sqrt{\sum_{j=1}^n (V_{ij} - NIS_j)^2} \tag{16}$$

$$CC_i = S_{NIS_i} / (S_{PIS_i} + S_{NIS_i}) \tag{17}$$

For each alternative i , Min CC_i and Max CC_i are calculated. Therefore, the total times of calculation is equal to $2 \cdot i$. In order to judge the best alternative, two approaches can be employed. Firstly, the average of Min CC_i and Max CC_i (hereafter Avg CC_i) may be used as a decision index, and the alternative with the highest Avg CC_i is selected. Although Avg CC_i can be used to rank alternatives, it should be remembered that such a ranking may still be inconclusive since this approach always causes a potential loss of meaningful information. Another approach is to select the best alternative based upon the DM's subjective judgment towards his/her risk attitude [62]. For example, if Avg $CC_1 >$ Avg CC_2 but Max $CC_2 >$ Max CC_1 , a DM with the attitude of 'Risk-Seeking' may prefer buying from supplier 2 than 1. On the other hand, if Avg $CC_1 >$ Avg CC_2 but Min $CC_1 <$ Min CC_2 , a DM who is 'Risk-Averse' may avoid selecting supplier 1 due to its potential to show up a very low performance at the date of purchase.

This algorithm can be extended to deal with a case of group decision making where the members cannot reach a consensus in ranking criteria (or the weights), as well as in a case that a single DM feels hesitant in ranking criteria. In respond to this, several sets of criteria weights can be input into the model. For instance, in a case of five criteria, three DMs assign different sets of the ranking orders of those criteria, as shown in Table 4.

According to the ROC method, Eq. (7), the weights for the first-ranked criterion to the least important one are 0.45, 0.26, 0.16, 0.09, and 0.04, respectively. Therefore, sets of possible weights for each criterion are shown below.

$$W_1 = \{0.45, 0.26\}$$

$$W_2 = \{0.45, 0.26, 0.16\}$$

$$W_3 = \{0.26, 0.16\}$$

$$W_4 = \{0.09, 0.04\}$$

$$W_5 = \{0.09, 0.04\}$$

This indicates that, for criterion 1, it should be viewed as either the most important criterion or the second most important one for selecting an alternative. This case might be possible due to an instability in the company's future strategy. Regarding the weights of other criteria, also, the group cannot reach a consensus. However, only a few possible weights for each criterion remain. This decision problem can be quickly solved through the optimisation model where the weights W_j become the decision variables of the two objective functions (Min CC_i and Max CC_i) for each alternative i . To do this, a constraint that the weights must be relative to each other needs to be added, as shown in Eq. (18).

$$\sum_{j=1}^J W_j = 1 \tag{18}$$

In short, the implementation procedure for the extended TOPSIS is summarised as follows:

- (1) Identify the minimum and the maximum values of each alternative i towards j criteria. If the assessment data can be precisely identified, the minimum and the maximum values are equal.
- (2) Transform all assessment values into the utility scores, as explained in Section 3.
- (3) Draw the assessment matrix Z of i alternatives and j criteria, as shown in Table 3. Note that all Z_{ijMin} and Z_{ijMax} are now in the form of the utility scores.
- (4) For cases that the uncertainty of the weights is involved, identify sets of possible weights for each criterion through the ROC method.
- (5) Calculate Min CC_i and Max CC_i for each alternative i based on the optimisation functions shown by Eqs. (10)–(18).
- (6) Select the best alternative based on Avg CC_i and the DM's risk attitude.

5. Implementation of the extended TOPSIS to a supplier selection problem

In order to demonstrate the applicability of the proposed method, a case of egg supplier selection was employed. As stated in Section 3, a purchasing manager of a large-scale restaurant in Thailand was asked to select criteria she needed to employ for this particular purpose. The chosen criteria include Product quality, Packaging quality, Product price, Delivery performance, and Serviceability. The assessment scale for each criterion has been determined to suit the characteristics of egg suppliers based on the interview of this manager, as shown in Table 5.

Then, the manager was asked to provide a list of three candidate suppliers with the assessment data of each criterion. Among the three suppliers, she was asked to consider a new one (supplier 1) who has never supplied this restaurant and she has only partial information about it in order to demonstrate how to deal with uncertain and unavailable information. From this, its performances regarding the quality of product and service are completely unknown. For supplier 2 and 3, their performances against some criteria also fluctuate based on historical information. The manager was also asked to rank the importance of the five criteria. The assessment results and the ranking order of the criteria, as well as the criteria weights derived by the ROC method, are shown in Table 6. Next, the assessment data is transformed into the utility scores using the utility function of each criterion which has been provided by the same manager (see Table 7). The transformed utilities are then shown in Table 8.

Following Eqs. (10)–(17), Min CC_i , Max CC_i , and Avg CC_i for each supplier can be derived. The results are shown in Table 9. From the results, based upon the average basis, supplier 2 should be selected since its Avg CC_i is greater than that of the others. The conclusion, however, may vary according to the DM's risk attitude as explained previously. For example, the risk-seeking DM may be eager to try purchasing from supplier 1 since it is possible that its CC reach the greatest score. However, the risk-averse DM may prefer staying in the safe zone by selecting supplier 2. This is to ensure that, although performances of such supplier again all criteria drop to the worst level, the CC is still equal to 0.316 which is not too poor compared to the lowest scores of the others. The level of uncertainty of supplier 2 is also lower than that of the others. This is resulted from the fact that, for supplier 2, only the assessment of one criterion is uncertain while uncertainties from other suppliers are greater than this.

Next, opinions about the ranking orders of criteria from two additional DMs are input to represent a situation of a group decision

Table 5
Examples of assessment scales of the criteria for egg supplier selection.

Criteria	Examples of assessment scales
Product quality	Assessment grades, A–D (A) Good – Quality variables are all greatly beyond minimum requirements specified in a specification document. The supplier can maintain good quality for all product shipments. (B) Moderate – The product just conforms to specifications. Some quality variables only marginally pass the minimum requirements. The supplier can maintain the same quality for all product shipments. (C) Poor – The product just conforms to specifications. Some quality variables only marginally pass the minimum requirements. The supplier cannot maintain the same quality for all product shipments. (D) Very poor – Some quality variables do not conform to specifications (do not pass the minimum requirements). The supplier cannot maintain the same quality for all product shipments.
Packaging quality	Assessment grades, A–C (A) Good – The product package is made from strongly durable material. Its design is able to effectively protect the product from bumping, falling out, as well as being contaminated during the delivery and storage (there has been no evidence of these issues). (B) Moderate – The product package is made from moderately durable material. Its design is not very robust. The products sometimes show evidence of damage caused by bumping, falling out, as well as being contaminated during the delivery and storage. (C) Poor – The product package is made from cheap or non-durable material. Its design is not able to effectively protect the product from bumping, falling out, as well as being contaminated during the delivery and storage. The products always show evidence of damage caused by these issues.
Product price	Product price on the date of purchasing (monetary unit)
Delivery performance	Delivery lead time (the total time from the placement of an order until the delivery is completed) (h)
Serviceability	Assessment grades, A–C (A) Good – The supplier always has a quick response (within one day) after receiving feedback. The corrective action is always reported. (B) Moderate – The supplier often has a slow response (longer than one day) after receiving feedback. The corrective action may be reported. (C) Poor – The supplier never responds after receiving feedback.

Table 6
The assessment matrix of 3 alternatives and 5 criteria (before transformation).

	Product quality (grades A–D)	Packaging quality (grades A–C)	Product price (Thai baht/egg)	Delivery performance (h)	Serviceability (Grades A–C)
Supplier 1	Unknown	B–A	2.55–3.2	1	Unknown
Supplier 2	B	B	2.9	2	B–A
Supplier 3	B–A	C–B	3.2	1–1.5	C
Criteria ranking / ROC weights	1 / 0.45	3 / 0.16	2 / 0.26	4 / 0.09	5 / 0.04

Table 7
Equivalence between assessment data and the utilities.

Criteria	Grades or numerical data	Utility scores
Product quality	A	100
	B	80
	C	0
Packaging quality	A	100
	B	70
	C	0
Product price	2.5 Baht/egg (or lower)	100
	3.9 Baht/egg (or above)	0
Delivery performance	0.5h (or lower)	100
	3.0h (or above)	0
Serviceability	A	100
	B	50
	C	0

Table 9
The closeness coefficient to the ideal solutions (CC_i) of the three candidate suppliers.

Suppliers	Min	Max	Avg CC_i
Supplier 1	0.073	1.000	0.536
	0.316	0.914	
Supplier 2	0.074	0.884	0.479
	0.316	0.914	

making where a consensus cannot be reached (simulated scenario). **Table 10** shows different sets of criteria ranking order assigned by the three DMs.

This problem can be actually solved by manual calculation, but it may require a long period of time. Therefore, using optimisation software such as Lingo, Matlab, or Excel Solver is suggested in order to lessen the calculation time. For this study, Matlab software was employed to find a set of weights giving the maximum and minimum CC_i . To solve these problems, these constraints were added into the algorithms of the extended TOPSIS or Eqs. (10)–

Table 8
The assessment matrix of 3 alternatives and 5 criteria (after transformation).

Suppliers	Utilities	Product quality	Packaging quality	Product price	Delivery performance	Serviceability
Supplier 1	Min	0	70	50	80	0
	Max	100	100	96.42	80	100
Supplier 2	Min	80	70	71.42	40	50
	Max	80	70	71.42	40	100
Supplier 3	Min	80	0	50	60	0
	Max	100	70	50	80	0

Table 10
Different sets of criteria ranking order assigned by three DMs.

Decision makers	Product quality (W_1)	Packaging quality (W_2)	Product price (W_3)	Delivery performance (W_4)	Serviceability (W_5)
DM1	1st	3rd	2nd	4th	5th
DM2	2nd	3rd	1st	4th	5th
DM3	1st	2nd	3rd	5th	4th

Table 11
The closeness coefficient to the ideal solutions (CC_i) of the three candidate suppliers (with the uncertainty of the weights).

Suppliers	Min	Max	CC _i	Sets of weights which meet the required objective function	Avg CC _i
Supplier 1	Min	0.033		Set (4)	0.5165
	Max	1.000		Every set generates the same result	
Supplier 2	Min	0.230		Set (1)	0.596
	Max	0.962		Set (2)	
Supplier 3	Min	0.026		Set (2)	0.4725
	Max	0.919		Set (1)	

(17).

$$W_1 = \{0.45 \text{ or } 0.26\}$$

$$W_2 = \{0.26 \text{ or } 0.16\}$$

$$W_3 = \{0.45 \text{ or } 0.26 \text{ or } 0.16\}$$

$$W_4 = \{0.09 \text{ or } 0.04\}$$

$$W_5 = \{0.09 \text{ or } 0.04\}$$

and

$$\sum_{j=1}^5 W_j = 1$$

From these additional conditions relating to the weights, Matlab can generate six possible sets of the weights for Product quality (W_1), Packaging quality (W_2), Product price (W_3), Delivery performance (W_4), and Serviceability (W_5), as shown below. These sets of weights are consequences of the combined opinions about the ranking of the criteria among DMs. The optimisation results are then shown in Table 11.

- (1) $\{W_1, W_2, W_3, W_4, W_5\} = \{0.45, 0.26, 0.16, 0.09, 0.04\}$
- (2) $\{W_1, W_2, W_3, W_4, W_5\} = \{0.45, 0.26, 0.16, 0.04, 0.09\}$
- (3) $\{W_1, W_2, W_3, W_4, W_5\} = \{0.45, 0.16, 0.26, 0.09, 0.04\}$
- (4) $\{W_1, W_2, W_3, W_4, W_5\} = \{0.45, 0.16, 0.26, 0.04, 0.09\}$
- (5) $\{W_1, W_2, W_3, W_4, W_5\} = \{0.26, 0.16, 0.45, 0.09, 0.04\}$
- (6) $\{W_1, W_2, W_3, W_4, W_5\} = \{0.26, 0.16, 0.45, 0.04, 0.09\}$

The selection of the best supplier can be based on either the average CC_i or the DMs' risk attitudes, as explained previously. Based on the average, supplier 2 is still the best compromise choice. That means the overall performance of this supplier is not sensitive to the changes of weights according to different opinions given by the three DMs. Each of them tends not to argue about the result since their opinions are all taken into account. The intervals of CC_i for the three suppliers are larger than those from the case of fixed weights as a consequence of an additional kind of uncertainty is inserted into the decision problem. However, this conclusion should stress that supplier 2 is preferred to the others only on an average basis. From existing uncertainties, there is a chance that suppliers 1 and 3 can provide better performances on the date of purchase. In order to improve the robustness and reliability of the obtained ranking order, DMs should try to lessen uncertainties and

incompleteness of the assessment [66,67]. Note that, if all assessments are complete, then there is no difference between the Max, Min, and Avg CC_i .

6. Conclusion

In this paper, first of all, a large number of literature-suggested criteria for supplier selection were reviewed and synthesised into 39 different criteria. These could be fundamental for practitioners and subsequent researchers to identify their own set of criteria which suit the characteristics and focuses of their business. As exemplified by this study, a manager in a large-scale restaurant considered that these 39 criteria were not all significant and applicable to her case, and only five criteria were selected. This, however, does not claim for generalisation since the result was gathered from only a single case. It must be emphasised that an applicable and appropriate list of criteria generally differ from industry to industry as well as from firm to firm due to different focuses and strategies. From the list of criteria proposed, also, practitioners need to identify their own assessment methods and the unit of measurement. For qualitative criteria, rating scales or a set of assessment grades may be used. The grades need to be linked to objective evidence or feasible practices in order to ensure standardisation of the assessment.

In terms of the selection method, the traditional TOPSIS method was developed to be able to deal with uncertainties and unavailability of information which typically occurs in real-world decision situations. ROC method was used to determine the weights of criteria since only a criteria ranking order was required from a DM. In this paper, a solution to deal with a disagreement among DMs regarding the weights was also provided. Through this way, different attitudes towards the ranking order of criteria were all taken into account rather than using a combined weights based on the average value. The proposed solution allows selection problems to be modelled using both precise and interval forms of the information. Subjective judgments required from DMs are also minimised. This is not only implementable to supplier selection problems but also capable of handling other selection problems. An example of an egg supplier selection was conducted using the proposed method in order to demonstrate its applicability. The obtained results can be presented in the forms of a ranking order of all candidate suppliers using Avg CC_i , or the intervals of their possible performances (the intervals between their Min and Max CC_i scores). The latter opens for further discussion among a group of DMs, and it is believed that people are more likely to agree with the interval in the results rather than forcing them to believe in a precise outcome. With this solution, DMs are given more information enabling them

to make more subtle decisions and reach intuitive and satisfactory conclusions.

The extended TOPSIS presented here, however, still does not provide a solution for a case where the uncertainty of the data cannot be described in the interval form but it is better described towards the probabilities of occurrence. For example, based on the case of egg supplier selection, the historical information may indicate that supplier 1 has its product quality at grade A for 70% and another 30% falls at grade B. For quantitative assessment, the price may be either 2.5 baht or 3 baht at 40% and 60% chances of occurrence, respectively. These cases could be seen in real-world decisions, and subsequent studies may extend the ability of TOPSIS by considering such issue. Another point is that ROC and other rank-based weighting methods may be useful and recommended only when many criteria are involved. When the decision relies on only a few criteria, it may not be difficult for DMs to precisely assign weighting scores, and the agreement among various DMs on the criteria weights is more possible. Other weighting methods that directly explain the strength of the DM's preference, such as Direct rating, AHP, or SWING, may be employed instead of ROC.

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