axioms

MDPI

Article

Selection of Business Process Modeling Tool with the Application of Fuzzy DEMATEL and TOPSIS Method

Guangying Jin [1], Guangzhe Jin [2,*] and Haibo Huo [2]

[1] School of Maritime Economics and Management, Dalian Maritime University, Dalian 116026, China
[2] College of Engineering Science and Technology, Shanghai Ocean University, Shanghai 201306, China
* Correspondence: gzjin@shou.edu.cn; Tel.: +86-18840847405

Abstract: The business process modeling tool selection problem has a significant impact on the overall performance of enterprise business process modeling, which will directly affect the development of enterprise information systems. Apart from that, the process to select the business process modeling tool from all alternatives is a Multi-Criteria Decision Making (MCDM) problem. This paper develops a methodology based on the hybrid fuzzy Decision-Making Trial and Evaluation Laboratory (DEMATEL) and Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) method to help companies select the optimal business process modeling tool, where the business process modeling process is more efficient, economic and safe. The proposed method has the following state-of-the-art contributions and features: (1) the latest application of the MCDM methodology to the field of BPM tool selection, (2) addressing the direct and indirect impact between criteria in the selection of BPM tools, and (3) considering the hybrid fuzzy (uncertainty) decision-making issue in the BPM tool selection process. Meanwhile, the mathematical formula in TOPSIS can be regarded as a formula for solving a symmetric problem. The hybrid fuzzy DEMATEL method is used to obtain the weight for the criteria to be considered in the BPM tool selection process, and the TOPSIS method is used to obtain the final business process modeling tool.

Keywords: business process modeling; fuzzy DEMATEL; TOPSIS; MCDM; modeling tool selection

check for updates

Citation: Jin, G.; Jin, G.; Huo, H. Selection of Business Process Modeling Tool with the Application of Fuzzy DEMATEL and TOPSIS Method. *Axioms* **2022**, *11*, 601. https://doi.org/10.3390/axioms11110601

Academic Editors: Darko Božanić and Adis Puška

Received: 11 September 2022
Accepted: 25 October 2022
Published: 28 October 2022

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Business Process Modeling (BPM) is an effective activity of representing business processes for a company and is typically performed by business analysts who provide expertise in the modeling domain [1,2]. For enterprises, BPM is an essential proportion of the quality improvement of Information Systems (IS) [3]. BPM and management are becoming an essential part of today's enterprises [4]. Meanwhile, Business Process Modeling (BPM) tools are considered a great way to connect BPM languages and modeling stakeholders. BPM tools can display the corresponding model to stakeholders, and stakeholders can also operate and control the model through BPM tools. For example, automobile manufacturing modelers can use BPM tools to build automobile manufacturing business process models.

Choosing a proper BPM tool can be seen as an essential problem for a company because poorly chosen BPM tools can have a serious and negative impact on a company's BPM modeling process, which will directly affect the development of enterprise IS. Choosing an effective BPM tool for the company is a complicated process, and different criteria that affect BPM need to be considered [5]. Therefore, the process can be a difficult task for managers in the enterprise to carry out. Meanwhile, the selection of the BPM tool process can be seen as the Multi-Criteria Decision Making (MCDM) issue. The TOPSIS technique is a mainstream MCDM method that can approach the BPM tool selection problem. Additionally, to obtain the optimal BPM tool, the experts must analyze various information and factors in the company that affects BPM tool selection [6,7]. To select the optimal BPM tool, we have to consider different parameters, such as technical parameters

(expressiveness, readability, usability, formability, etc.), economical parameters (application cost, operating cost, etc.), and so on. Meanwhile, there are direct and indirect affecting relationships between these parameters. Additionally, experts will have uncertainty when determining the influence between these parameters, which can be seen as a hybrid fuzzy problem. A fuzzy DEMATEL technique can approach hybrid fuzzy problems and the direct and indirect affecting relationships between the technical parameters.

Although BPM tool choice has a great impact on enterprise IS, there are very few related studies and references on this topic. Therefore, depending on the issues discussed above, the key target of the study is to propose a fuzzy DEMATEL and TOPSIS combination method to support companies in dealing with the BPM tool selection problem.

The main constitutions of this study are shown below:

- Although the MCDM method has been applied in many fields, it has not been applied to the selection of BPM tools. Therefore, the first important constitution of this study is to propose criteria for the selection of BPM tools and an MCDM method for the selection of BPM tools.
- In the BPM tool selection process for a company, there will be direct and indirect interdependence between all the criteria. Therefore, the second important conclusion of this paper is to use DEMATEL analysis to fix the direct and indirect influence problem between criteria in the BPM tool selection process.
- When experts define the affecting rank between BPM tool selection criteria, there is uncertainty here because experts cannot clearly determine the impact of a specific scale value. Therefore, the third objective of this paper is to approach the hybrid fuzzy (uncertainty) decision-making issue.

The rest structure of the paper is shown below. The "Literature Review" section introduces business flow modeling tools and related methods for multicriteria decision-making. The section "Business Process Modeling Tool Selection Methodology" describes the proposed BPM tool selection methodology that integrates fuzzy DEMATEL and TOPSIS. Section "Results" depicts the simulation and experimental results of an example. A detailed discussion and future work will be presented in the "Discussion and Conclusion" section.

2. Literature Review

A business process is a continuous, gradual, and uncontrollable result that a series of intrinsically linked business activities or events produce [2]. It is very important for a company to effectively manage the business process. Apart from that, BPM [8] is one of the essential components of business process management, and BPM can describe the integration and relation of different enterprise activities [3]. The BPM is inseparable from a large number of BPM languages, and there are currently many BPM languages being advocated or practiced [9,10].

In the 1980s, since the first Framework Program of Research and Development (Esprit program), a large number of languages of BPM have appeared in North America and Europe [11]. These include MERISE [12], GRAI [13–15], NIAM [16], CIMOSA [17], IEM [18–20], UML [21], BPMN [22], EPC [23], Petri net [19], IDEFx [24], ARIS [25], 4EM [26], DEMO [27] and so on.

Here, all the business process modeling languages can be divided into the following three categories according to different modeling characterizations [20]:

1. Namely, early or activity-centered languages: NIAM, IDEFx, MERISE, IEM, GRAI, and so on.
2. Business process-centered languages: CIMOSA, ARIS, IEM, BPMN, EPC, Petrinet, and so on.
3. Enterprise knowledge-centered languages: 4EM, DEMO, etc.

In addition, various kinds of BPM tools can support all the BPM languages mentioned above. For example, GDToolkit [28], TimeNet [29], GreatSPN [30], JFern, JPetriNet and PIPE2 can support Petri nets [31]; ADONIS:CE, Bizagi Modeler, Cardanit, BPMN.io &

family, Sparx Enterprise Architect, MagicDraw can support BPMN [32,33]; MO2GO can support IEM [20].

Here, some of the BPM tools are free of charge. For example, for the Petri net supporting tools, JFern, JPetriNet, and PIPE2 are free of charge, and GreatSPN, GDToolkit, and TimeNet are charged; for BPMN supporting tools, ADONIS: CE, Bizagi Modeler, Cardanit and BPMN.io & family are free of charge, and Sparx Enterprise Architect and MagicDraw are charged; for the IEM supporting tool, MO2GO is charged. Although some experts believe that more expensive BPMN tools have more comprehensive features and can handle more difficult business process modeling problems, they can also be more difficult to operate and control, and therefore, employee training can also be more difficult [33]. Meanwhile, some of the BPM languages and corresponding support tools are very easy to learn. For example, the IEM modeling language or MO2GO tool is very simple and straightforward to use, and beginners do not need much training when building a model [34]. Meanwhile, although some of the BPM tools are free of charge or cheap, the learning and expressive efficiency of these tools are not poor.

Therefore, it is very difficult for companies to select an optimal BPM tool, and when project managers select the BPM tools for their company, they must evaluate all candidate BPM tools depending on the different evaluation criteria, such as efficiency criteria, economic criteria, safety criteria, and so on.

Although it is very important for the company to select optimal BPM tools, which will directly affect the development of enterprise IS, there is very limited research and publications in this area. Many researchers and institutions are more focused on the analysis of BPM languages. Khouloud and Sonia proposed an approach for selecting a BPM language based on the requirements of the modeler and considered the different criteria for comparing modeling languages [3]. Vernadat reviewed and summarized important research works and contributions made to BPM over the last four decades, outlining major BPM constructs and their extensions as well as prominent modeling tools and methods [20]. Alotaibi analyzed BPM criteria, methods, and linguistics and divided them into different groups depending on their features [35]. Kožíšek and Vrana summarize the current knowledge of BPM languages, especially for UML, BPMN, and EPC, which are increasingly important in the agri-food industry, and they describe the history of BPM, currently mostly used alternatives [36]. Geiger et al., present an analysis of the current state and evolution of BPM Notation support and implementation [22].

However, these reference studies are related to the selection of BPM language or the review and introduction of different BPM languages, tools, or methods, and there is no specific method for BPM tool selection. Therefore, in this study, we will mainly focus on this issue.

The capability estimation and best choice of BPM tools are related to different levels and various criteria; therefore, the problem of BPM tool selection is the multiple criteria decision-making (MCDM) issue [37,38]. MCDM is a well-known branch of decision-making [39]. It is related to proposing and dealing with multistandard decision-making issues [40]. MCDM supports company BPM experts in quantifying special standards depending on their essentialness in different decision targets [41]. There are many different MCDM methodologies, and several mainstream MCDM methodologies are the Analytic Hierarchy Process (AHP) [42,43], Analytic Network Process (ANP) [44], Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) [45–48], classic MAUT [49], ELECTRE [50] and so on. Here, some methods are more adaptable than others in special decision issues.

The main objective of this research is to select the best BPM tool for companies where many parameters should be considered in decision-making.

These parameters are multidisciplinary (technical parameters, economical parameters, and time parameters), and we apply the TOPSIS method to obtain the final optimal BPM tool. The reasons for choosing the TOPSIS method are as follows [7]:

- The pre- and post-steps of the TOPSIS method are logical and easy to comprehend.

- The calculation steps at a glance.
- The method can use straightforward mathematical criteria descriptions to find optimal candidate options.
- The significance weights are considered in the decision-making process.

Meanwhile, the parameters that we considered in this paper are symmetry parameters. We have to consider not only benefit parameters (efficient parameters) but also cost parameters (economical parameters, time parameters). Therefore, we need to find a decision-making method that can handle positive and negative symmetrical parameters. TOPSIS is a well-known methodology as a symmetrical method used for solving MCMD problems [51,52]. To obtain the best options from all competitors, the TOPSIS methodology uses the key formula of the calculation result of the maximum distance from the Negative-Ideal (N-I) solution and the minimum distance from the Positive-Ideal (P-I) solution [51–54]. Therefore, it can be seen as a symmetric issue approaching the process in mathematical equations.

Apart from that, in the BPM tool selection process for a company, there will also be direct and indirect interdependence between all the criteria, such as the low readability of the BPM tool, which will directly affect and increase the difficulty of tool learning. Therefore, when we define the weight for the BPM tool selection criteria, we must consider direct and indirect interdependence. DEMATEL is an effective methodology to analyze the direct and indirect influence between criteria. There is an algorithm behind the DEMATEL analysis, which is always used to analyze and create the connections of causation between the assessment standards [55,56] or to derive interrelationships among factors [57]. Therefore, we can use DEMATEL analysis to fix the direct and indirect influence problem between criteria.

Additionally, in the DEMATEL analysis, when experts define the affecting rank between BPM tool selection criteria, there is uncertainty here because, in many cases, experts cannot clearly determine the impact of a specific scale value. This uncertain decision issue is the hybrid fuzzy decision-making issue. Many studies have dealt with hybrid fuzzy problems in decision-making. Mardani et al. [58] proposed a hybrid fuzzy AHP decision-making methodology to evaluate healthcare and medical problems. Akram et al. [59] proposed a fuzzy ELECTRE-II method for multicriteria decision-making problems. Celik et al. [60] used interval type-2 fuzzy AHP methods to approach decision-making problems in maritime transportation engineering. A Fuzzy ARAS method is also proposed for recycling facility location problems [61].

Although there are many methods of fuzzy application, there is no application for BPM tool selection. The above fuzzy methods do not consider the direct and indirect relationships between coefficients such as AHP and ELECTRE.

Hence, in this paper, the key objective of this study is to combine the hybrid fuzzy DEMATEL and TOPSIS methods to propose a BPM tool selection method considering the BPM process affecting parameters. This method can help company managers find the optimal BPM tools for their company.

3. Business Process Modeling Tool Selection Methodology

The BPM tool choice process for this research is shown in Figure 1.

First, it is necessary to define the benefit and cost standards that will be applied for the assessment of BPM tool alternatives. Here, we will also determine the corresponding rank value for all the criteria. Afterward, we can use the Fuzzy DEMATEL technique to define the weight for the standards. Then, it is possible to decide the candidate options assessment result according to the TOPSIS method. Finally, we can define the final BPM tool for the company.

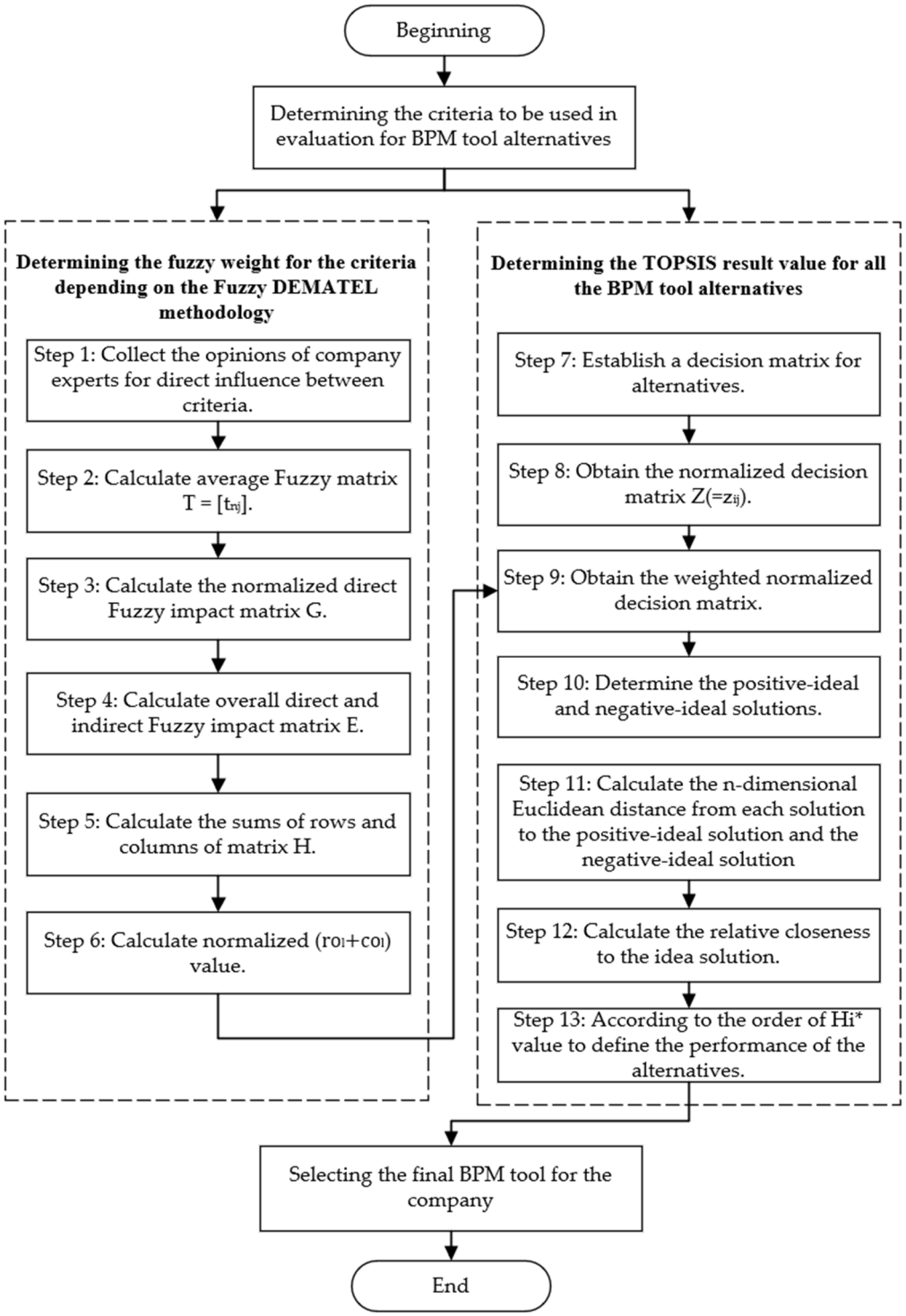

Figure 1. Whole process of the BPM tool selection method.

3.1. Determining the Criteria to Be Used in Evaluation for BPM Tool Alternatives

The main objective of this method is to select the optimal BPM tool for the company that purchases or applies it so that the BPM tool can be used more efficiently, economically, quickly, and safely. The criteria to be considered in the selection of the BPM tool can be decided by the company experts based on the main objective. After the consideration, four important types of criteria to be used for BPM tool selection are proposed. Meanwhile, each criterion type contains several subcriteria. These standards are often what companies need and what company managers think. All these criteria allow the BPM process to be more

efficient, economical, and time-saving. The four criteria and corresponding sub-criteria are shown in Table 1.

Table 1. The criteria and sub-criteria for BPM tool selection.

Criteria	Sub-Criteria
Efficiency parameters (C_1)	Expressiveness (C_{11}) Readability (C_{12}) Usability (C_{13}) Formality (C_{14}) Ease of Learning (C_{15})
Economical parameters (C_2)	Application and Installment cost (C_{21}) Operating cost (C_{22}) Training cost (C_{23})
Time parameters (C_3)	Application and Installment time (C_{31}) Operating time (C_{32}) Training time (C_{33})
Safety parameters (C_4)	Internal safety (C_{41}) External safety (C_{42})

Note. C = Criteria.

In Table 1, we find that there are four types of criteria (Efficiency parameters (C_1), Economical parameters (C_2), Time parameters (C_3), and Safety parameters(C_4)), and every type of criterion also has different corresponding sub-criteria. A detailed description of all these criteria can be seen as follows:

1. Efficiency parameters (C_1) are related to the factors affecting BPM efficiency. Efficiency parameters include Expressiveness, Readability, Usability, Formality, and Ease of Learning.
    - Expressiveness (C_{11}): This parameter checks whether the modeling tool can express various kinds of organizational environments on the basis of informational, structural, behavioral, and functional perspectives [62].
    - Readability (C_{12}): This parameter checks whether the model is simple to comprehend for stakeholders.
    - Usability (C_{13}): This parameter checks whether the modeling tool is easy to apply and install.
    - Formality (C_{14}): This parameter checks whether the model has ambiguities and inaccuracies in model interpretation.
    - Ease of Learning (C_{15}): This parameter checks whether the modeling tool and language are easy for the company modelers to learn.
2. Economical parameters (C_2) related to the various expenses incurred when using the tool. Economical parameters include application and installment costs, operating costs, and training costs.
    - Application and installment cost (C_{21}): The cost of parameter configuration, application, and installation when starting to use the modeling tool in the company.
    - Operating cost (C_{22}): The rental cost of the modeling tool and the salary of the company modelers.
    - Training cost (C_{23}): Training costs of modeling tools for company modelers.
3. Time parameters (C_3) cluster includes application and installment time, operating time, and training time.
    - Application and installment time (C_{31}): The time consumption of parameter configuration, application, and installation when starting to use the modeling tool in the company.
    - Operating time (C_{32}): The time consumed by company modelers operating the modeling tool.
    - Training time (C_{33}): The time consumed by company modelers to learn the modeling language and tool.

4. Safety parameters (C_4) include all parameters that the BPM tool can affect the safety of the IS of the company. Safety parameters include Internal safety and External safety.
   - Internal safety (C_{41}): The safety of BPM tools inside the company, such as the software freezes, disappearance, and error storing modeling data.
   - External safety (C_{42}): The safety of the BPM tool outside of the company, for example, if the tool is vulnerable to network intrusion and whether the modeling data are easily leaked to the outside through the tool.

Then, we can define the evaluation rank for the sub-criteria. Here, we can use a 1–5 scale rank, as shown in Table 2.

Table 2. Evaluation rank used for ranking BPM tools.

Rank	Explanation
1	Very bad
2	Good
3	Normal
4	Bad
5	Very good

Depending on Table 2, company experts can assess the BPM tool alternatives.

3.2. Determining the Fuzzy Weight for the Criteria

Although DEMATEL is an effective methodology to analyze the direct and indirect influence between criteria, it cannot deal with the problem of misjudgment with certainty, and the influence value between the criteria directly depends on the uncertainty decision result of experts on the actual case number. Therefore, for the purpose of approaching the uncertainty issue, Fuzzy DEMATEL extends DEMATEL.

Therefore, after we define the criteria and corresponding rank to be used in the evaluation of BPM tool alternatives, we can use the Fuzzy DEMATEL technique to determine the fuzzy weight for all the standards. The fuzzy set theory was proposed by Zadeh [63] to approach uncertain issues. Here, there is one variable value that must be known, and the variable is the Triangular Fuzzy Number (TFN). The fuzzy theory uses a fuzzy number to present outcome information that experts cannot determine or quantify in a decision model. Meanwhile, the TFN [63] is always applied to solve fuzzy problems in uncertain environments. TFNs are composed of triples (d, e, f). Here, the "d" and "f" values are the upper and lower limits of the fuzzy numbers, respectively, and "e" is the most likely number. The membership function $f_A(x)$ of TFN is expressed as Equation (1) and Figure 2.

$$f_A(y) = \begin{cases} \frac{y-d}{e-d}, & (d \le y \le e) \\ \frac{f-y}{f-e}, & (e \le y \le f) \\ 0, & (y < d,\ y > f) \end{cases} \quad (1)$$

where $f_A(y)$ value will vary between 0 and 1.

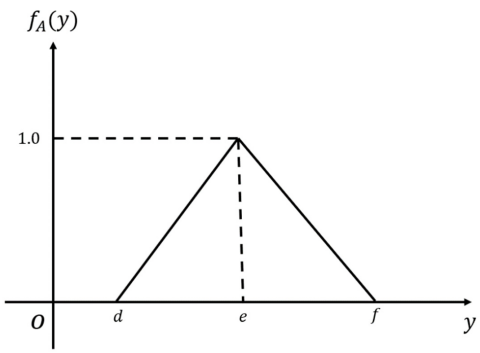

Figure 2. The membership function of the Triangular Fuzzy Number.

After that, we can release the basic process of the Fuzzy DEMATEL method, which can be shown as follows:

- Step 1: Collect the opinions of company experts for direct influence between criteria.

In this step, company experts are asked to define the rank of direct influence between criteria according to pairwise comparison. The fuzzy influence rank value and corresponding description are shown in Table 3. Direct fuzzy influence degree and corresponding triangular fuzzy scale.

Table 3. Direct fuzzy influence degree and corresponding triangular fuzzy scale.

Direct Influence Degree	Fuzzy Rank Value	Triangular Fuzzy Scale		
No impact	0	0	0	0.25
Low impact	1	0	0.25	0.5
Medium impact	2	0.25	0.5	0.75
High impact	3	0.5	0.75	1
Very high impact	4	0.75	1	1

In Table 3, we can find that the direct influence degree ranges from No impact to Very high impact, and the higher the degree, the greater the rank value. Various forms of scales, including sequential, exact, ratio, interval, or perhaps a combination of these, could have been included in this study. However, the sequential scales (linguistic variables) are more appropriate for expressing expert preferences, especially when the number of alternative and qualitative criteria is high. Meanwhile, in this research, the range of the Triangular Fuzzy Scale varies from 0 to 1, and there are 5 direct influence degrees (No impact to Very high impact in Table 3). Therefore, to ensure that there are five Triangular Fuzzy Scales and that the five direct influence degree points are at the center of the triangle (Figure 2), we need to define the Triangular Fuzzy Scale, as in Table 3. Such as Low impact has a triangular fuzzy scale (0, 0.25, 0.5), and the point at 0.25 is exactly at the center of the triangle.

BPM experts can use this degree to define the direct influence degree for every two criteria or sub-criteria, and we can collect opinions of all the experts and release value of TFN for every option. After that we have to defuzzify the TFN and obtain the crisp influence value between criterions. The mainstream and widely acknowledge defuzzification method is the CFCS [64], and the CFCS can obtain the optimal crisp value. If we assume that $B_{ij} = \left(d_{ij}{}^{q}, e_{ij}{}^{q}, f_{ij}{}^{q}\right)$ means the TFN for the criterion i influence criterion j in qth fuzzy survey, the detailed process for defuzzification of CFCS can be seen as following four steps:

(1) Normalization:

$$nf_{ij}{}^{q} = \left(f_{ij}{}^{q} - \min d_{ij}{}^{q}\right) / \left(\max f_{ij}{}^{q} - \min d_{ij}{}^{q}\right) \quad (2)$$

$$ne_{ij}{}^{q} = \left(e_{ij}{}^{q} - \min d_{ij}{}^{q}\right) / \left(\max f_{ij}{}^{q} - \min d_{ij}{}^{q}\right) \quad (3)$$

$$nd_{ij}{}^{q} = \left(d_{ij}{}^{q} - \min d_{ij}{}^{q}\right) / \left(\max f_{ij}{}^{q} - \min d_{ij}{}^{q}\right) \quad (4)$$

(2) Calculate right and left normalized numbers:

$$rn_{ij}{}^{q} = nf_{ij}{}^{q} / \left(1 + nf_{ij}{}^{q} - ne_{ij}{}^{q}\right) \quad (5)$$

$$ln_{ij}{}^{q} = ne_{ij}{}^{q} / \left(1 + ne_{ij}{}^{q} - nd_{ij}{}^{q}\right) \quad (6)$$

(3) Calculate total generalized crisp numbers:

$$tn_{ij}{}^{q} = \left[ln_{ij}{}^{q}\left(1 - ln_{ij}{}^{q}\right) + rn_{ij}{}^{q} \times rn_{ij}{}^{q}\right] / \left(1 - ln_{ij}{}^{q} + rn_{ij}{}^{q}\right) \quad (7)$$

(4) Calculate crisp numbers:

$$p_{ij}{}^{q} = \min d_{ij}{}^{q} + tn_{ij}{}^{q} \times \left(\max f_{ij}{}^{q} - \min d_{ij}{}^{q}\right) \quad (8)$$

After the defuzzification process through Equations (2)–(8), the TFN will be defuzzified to crisp numbers. After that, depending on the crisp numbers, we can create a nonnegative fuzzy matrix D = [p_{mn}] (Equation (9)).

$$D = \begin{bmatrix} 0 & p_{12} & \cdots & p_{1j} & \cdots & p_{1K} \\ p_{21} & 0 & \cdots & p_{2j} & \cdots & p_{2K} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ p_{n1} & p_{n2} & \cdots & 0 & \cdots & p_{nK} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ p_{K1} & p_{K2} & \cdots & p_{Kj} & \cdots & 0 \end{bmatrix} \tag{9}$$

where p_{nj} is the direct fuzzy influence rank to which the expert recognized standard n impacts on standard j, and K is the total number of criteria for BPM tool selection.

- Step 2: Calculate average fuzzy matrix T = [t_{nj}] (Equation (10)).

$$t_{nj} = \frac{1}{TN} \sum_{k=1}^{TN} {p_{nj}}^{k} \tag{10}$$

where p_{mn} is the direct fuzzy influence rank to which the expert recognized standard n impacts on standard j, and TN is the total number of company experts.

- Step 3: Calculate the normalized direct fuzzy impact matrix *G*.

The value in the normalized direct fuzzy influence matrix *G* ranges between [0, 1], and the calculation process of normalization is shown in Equations (11) and (12):

$$G = \lambda * T, \tag{11}$$

where

$$\lambda = \text{Min}\left[\frac{1}{\max\limits_{1 \le n \le J} \sum_{j=1}^{J} t_{nj}}\right] \tag{12}$$

where *G* is the normalized direct fuzzy influence matrix, and J is the total number of factors to the fuzzy influence virtual team member selection.

In Equation (12), depending on Markov chain theory, the normalized direct influence matrix G after it has been multiplied by itself, all the values of the matrix will be close to 0, which is a zero matrix, and it means that $\lim\limits_{o \to \infty} G^{o}$ equals $[0]_{n \times n}$.

- Step 4: Calculate the overall direct and indirect fuzzy impact matrix E.

The calculation process of the overall direct and indirect fuzzy impact matrix E can be seen as Equations (13) and (14).

$$\begin{aligned} H &= \lim_{q \to \infty} \left(G + G^2 + \ldots + G^q \right) \\ &= \sum_{q=1}^{\infty} G^q \end{aligned} \tag{13}$$

where

$$\begin{aligned} \sum_{q=1}^{\infty} G^q &= G^1 + G^2 + \ldots + G^q \\ &= G\left(I + G^1 + G^2 \ldots + G^{q-1} \right) \\ &= G(I-G)^{-1}(I-G)\left(I + G^1 + G^2 \ldots + G^{q-1} \right) \\ &= G(I-G)^{-1}(I-G^q) \\ H &= G(I-G)^{-1} \end{aligned} \tag{14}$$

- Step 5: Calculate the sums of the rows and columns of matrix H.

  The calculation process can be seen as Equations (15) and (16).

$$\mathrm{ro} = [\mathrm{ro_n}] = \left[\sum_{\mathrm{j}=1}^{\mathrm{J}} \mathrm{h_{nj}}\right] \tag{15}$$

$$\mathrm{co} = [\mathrm{co_j}] = \left[\sum_{\mathrm{n}=1}^{\mathrm{J}} \mathrm{h_{nj}}\right] \tag{16}$$

where ro is the sum of the nth row in matrix T, co is the sum of the jth column in matrix T, and [ ] denotes the matrix consisting of the resultant values.

In Equation (15), the $\mathrm{ro_n}$ means the total given both direct and indirect fuzzy effects from the criteria n to the other criteria, and $\mathrm{co_j}$ means the total received both direct and indirect fuzzy effects from other criteria to criteria j. Therefore, when n equals j, the value of $(\mathrm{ro_n} + \mathrm{co_j})$ means the overall impacts both given and received by criteria j, and $(\mathrm{ro_n} + \mathrm{co_j})$ means the centrality of the factors n in all factors. Centrality indicates the position of the factor in the evaluation index system and the magnitude of its effect. Therefore, the value of $(\mathrm{ro_n} + \mathrm{co_j})$ means the direct and indirect fuzzy effects value of the factors j.

- Step 6: Calculate the normalized $(\mathrm{ro_n} + \mathrm{co_j})$ value.

$$\mathrm{NRC_l} = \frac{(\mathrm{ro_l} + \mathrm{co_l})}{\sum_{\mathrm{j}=1}^{\mathrm{J}} (\mathrm{ro_j} + \mathrm{co_j})} \tag{17}$$

  where $\sum_{\mathrm{l}=1}^{\mathrm{J}} \mathrm{NRC_l} = 1$ and $\mathrm{NRC_l}$ are normalized $(\mathrm{ro_l} + \mathrm{co_l})$ values.

In Equation (17), we find that this is the easiest approach to reformulate the feature range from 0 to 1, and we can use the normalized $(\mathrm{ro_n} + \mathrm{co_j})$ value (NRC) to define the fuzzy weight for the criteria to influence BPM tool selection.

3.3. Determine the TOPSIS Result Value for All the Candidate BPM Tool Alternatives

After we define the criteria and corresponding weight and rank to be used in the evaluation of BPM tool alternatives, we can use the TOPSIS method to obtain the final BPM tool for the company. The basic process of the TOPSIS method is shown as follows:

- Step 7: Establish a decision matrix for alternatives (Equation (18)).

$$D = \begin{bmatrix} \mathrm{A_1} \\ \mathrm{A_2} \\ \vdots \\ \mathrm{A} \\ \vdots \\ \mathrm{A_I} \end{bmatrix} \begin{bmatrix} \mathrm{C_{11}} & \mathrm{C_{12}} & \cdots & \mathrm{C_{1j}} & \cdots & \mathrm{C_{1J}} \\ \mathrm{C_{21}} & \mathrm{C_{22}} & \cdots & \mathrm{C_{2j}} & \cdots & \mathrm{C_{2J}} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ \mathrm{C_{i1}} & \mathrm{C_{j2}} & \cdots & \mathrm{C_{ij}} & \cdots & \mathrm{C_{iJ}} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ \mathrm{C_{I1}} & \mathrm{C_{I2}} & \cdots & \mathrm{C_{Ij}} & \cdots & \mathrm{C_{IJ}} \end{bmatrix} \tag{18}$$

  where D is the decision matrix, $\mathrm{A_i}$ is alternative to i, $\mathrm{c_{ij}}$ is the jth standard number corresponding to the ith alternative $(\mathrm{A_i})$, I is the number of alternatives, and J is the number of criteria.
- Step 8: Get the normalized decision matrix $\mathrm{Z}(=\mathrm{z_{ij}})$ (Equation (19)).

$$\mathrm{z_{ij}} = \frac{\mathrm{c_{ij}}}{\sqrt{\sum_{\mathrm{i}=1}^{\mathrm{I}} \mathrm{c_{ij}}^2}} \tag{19}$$

- Note. $\mathrm{z_{ij}}$ = Normalized number for jth standard corresponding to ith alternative. I = Sum of candidate options.

- Step 9: Obtain the weighted normalized decision matrix X(=x_{ij}) (Equation (20)).

$$x_{ij} = w_j \cdot z_{ij} \tag{20}$$

The fuzzy weighted normalized decision matrix value is obtained from the multiplication result between the matrix value "z_{ij}" in Equation (19) and the corresponding fuzzy weights. In this research, the fuzzy weight can be defined by the normalized ($ro_n + co_j$) value in Section 3.2, and the sum of fuzzy weights is 1 ($\sum_{j=1}^{n} w_j = 1$).

- Step 10: Decide the P-I and N-I solutions (Equations (21) and (22)).

$$\text{P-I solution}: \; x_j^* = \begin{cases} \max\limits_i x_{ij}, \; i \in l' \\ \min\limits_i x_{ij}, \; i \in l'' \end{cases} \tag{21}$$

where l' is the value set associated with benefit criteria and l'' is the value set associated with cost criteria.

$$\text{N-I solution}: \; x_j^0 = \begin{cases} \min\limits_i x_{ij}, \; i \in l' \\ \max\limits_i x_{ij}, \; i \in l'' \end{cases} \tag{22}$$

where l' and l'' are the number set corresponding to benefit and cost standards, respectively.

- Step 11: Calculate the n-dimensional Euclidean distance from each solution to the P-I solution and the N-I solution (Equations (22) and (23)).

$$\text{Distance to P-I solution}: \; d_i^* = \sqrt{\sum_{j=1}^{J} \left(x_{ij} - x_j^*\right)^2} \tag{23}$$

$$\text{Distance to N-I solution}: \; d_i^0 = \sqrt{\sum_{j=1}^{J} \left(x_{ij} - x_j^0\right)^2} \tag{24}$$

- Step 12: Calculate the relative closeness to the idea solution (Equation (25)).

$$H_i^* = \frac{d_i^0}{(d_i^0 + d_i^*)} \tag{25}$$

where the H_i^* index value lies between 0 and 1.

- Step 13: According to the order of the H_i* number, determine the capability of the alternatives. A higher H_i* number indicates a better alternative capability. Then, we can rank the alternatives depending on the H_i* numbers for the purpose of showing the performance comparison results for all the alternatives.

4. Results

As stated earlier, choosing an effective BPM tool for the company is a complicated process, and different criteria that affect BPM need to be considered. Therefore, choosing an optimal BPM tool will be very difficult for enterprise managers to carry out. Therefore, selecting an optimal BPM tool is very important for the development of the company's IS.

In this example, we consider 8 candidate BPM tools (JFern, JPetriNet, GreatSPN, GDToolkit, TimeNet, ADONIS: CE, Bizagi Modeler and Cardanit). Based on Tables 1 and 2, we can create the rank table (Table 4) for all the sub-parameters to influence BPM tool selection. Here, the project manager can determine the ranking of all sub-parameters through expert surveys.

Table 4. Evaluation rank value for all the business process modelling tool selection sub-criterions in Table 1.

Alternative	Efficiency (C_1)					Economical (C_2)			Time (C_3)			Safety (C_4)	
	C_{12}	C_{12}	C_{13}	C_{14}	C_{15}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}
TL1	2	3	2	3	5	1	2	2	3	3	3	1	1
TL2	3	3	2	3	5	1	2	2	2	2	2	1	1
TL3	4	4	3	2	3	3	4	3	3	1	1	4	5
TL4	4	5	4	3	4	3	2	3	2	3	3	5	5
TL5	4	2	3	4	3	4	3	2	4	4	2	2	2
TL6	3	2	1	2	2	1	1	1	5	5	2	2	1
TL7	4	5	4	3	2	1	3	4	1	2	1	4	5
TL8	5	4	5	3	3	3	4	4	2	2	5	4	5

Note. C = Criteria. TL = Tool.

From Table 4, we can find that there are 8 candidate BPM tools with the different corresponding sub-criteria ranks. After we define all the rank values, we have to define the fuzzy weights of all the four main types of parameters (C_1, C_2, C_3 and C_4) and corresponding sub-parameters (C_{11}, C_{12}, C_{13}, C_{14}, C_{15}, C_{21}, C_{22}, C_{23}, C_{31}, C_{32}, C_{33}, C_{41} and C_{42}) in Table 1.

Therefore, to obtain fuzzy weights for all the criteria, 10 company experts are requested to define the rank of direct fuzzy impact between criteria according to pairwise comparison depending on the direct fuzzy influence level in Table 3. The direct fuzzy influence degrees for 10 company experts can be seen in Tables A1–A5 (Appendix A). Depending on Equation (1), we can release the TFN for the degrees, as shown in Tables A6–A10 (Appendix A). Then, we use Equations (2)–(8) to release the defuzzy crisp values as Tables A11–A15 (Appendix A) for the triangle fuzzy triples.

Then, we can use the crisp values to create the average direct fuzzy influence matrix T (Equation (10)) for the BPM tool selection main criteria and corresponding sub-criterions like Tables 5–9.

Table 5. Average direct fuzzy influence matrix T between BPM tool selection main criterions.

T	C_1 (ADFI)	C_2 (ADFI)	C_3 (ADFI)	C_4 (ADFI)
Efficiency (C_1)	0	0.59	0.545	0.684
Economical (C_2)	0.567	0	0.476	0.613
Time (C_3)	0.566	0.685	0	0.428
Safety (C_4)	0.664	0.755	0.662	0

Note. ADFI = Average Direct Fuzzy Influence value.

Table 6. Average direct fuzzy influence matrix T between Efficiency (C_1) sub-criterions.

T (C_1)	C_{11} (ADFI)	C_{12} (ADFI)	C_{13} (ADFI)	C_{14} (ADFI)	C_{15} (ADFI)
Expressiveness (C_{11})	0	0.493	0.675	0.548	0.786
Readability (C_{12})	0.442	0	0.426	0.929	0.548
Usability (C_{13})	0.497	0.436	0	0.952	0.855
Formality (C_{14})	0.507	0.755	0.414	0	0.866
Ease of Learning (C_{15})	0.602	0.706	0.399	0.076	0

Note. ADFI = Average Direct Fuzzy Influence value.

Table 7. Average direct fuzzy influence matrix T between Economical (C_2) sub-criterions.

T (C_2)	C_{21} (ADFI)	C_{22} (ADFI)	C_{23} (ADFI)
Application and Installment cost (C_{21})	0	0.546	0.687
Operating cost (C_{22})	0.708	0	0.685
Training cost (C_{23})	0.594	0.71	0

Note. ADFI = Average Direct Fuzzy Influence value.

Table 8. Average direct fuzzy influence matrix T between Time (C_3) sub-criterions.

T (C_3)	C_{31} (ADFI)	C_{32} (ADFI)	C_{33} (ADFI)
Application and Installment time (C_{31})	0	0.216	0.628
Operating time (C_{32})	0.036	0	0.73
Training time (C_{33})	0.045	0.667	0

Note. ADFI = Average Direct Fuzzy Influence value.

Table 9. Average direct fuzzy influence matrix T between Safety (C_4) sub-criterions.

T (C_4)	C_{41} (ADFI)	C_{42} (ADFI)
Internal safety (C_{41})	0	0.454
External safety (C_{42})	0.685	0

Note. ADFI = Average Direct Fuzzy Influence value.

In Tables 5–9, all the values are obtained from the average of the direct fuzzy influences, and all these direct influence values are defined by the 10 experts. For example, in Table 5, average direct fuzzy influence rank from C_1 to C_3 is 0.545 which is obtained from the average fuzzy influence value of 10 experts ($\frac{0.73+0.5+0.27+0.27+0.25+0.73+0.5+0.5+0.73+0.97}{10} = 0.545$) (Equation (10)). After that, depending on the Equations (11) and (12), we can calculate the normalized direct influence matrix T (Tables 10–14) for all the criterion and sub-criterions.

Table 10. Normalized direct influence matrix G between BPM tool selection main criteria.

G	Efficiency (C_1)	Economical (C_2)	Time (C_3)	Safety (C_4)
Efficiency (C_1)	0	0.284	0.262	0.329
Economical (C_2)	0.272	0	0.229	0.295
Time (C_3)	0.272	0.329	0	0.206
Safety (C_4)	0.319	0.363	0.318	0

Table 11. Normalized direct influence matrix T between Efficiency (C_1) sub-criteria.

G (C_1)	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
Expressiveness (C_{11})	0	0.18	0.25	0.2	0.29
Readability (C_{12})	0.16	0	0.16	0.34	0.2
Usability (C_{13})	0.18	0.16	0	0.35	0.31
Formality (C_{14})	0.19	0.28	0.15	0	0.32
Ease of Learning (C_{15})	0.22	0.26	0.15	0.03	0

Table 12. Normalized direct influence matrix T between Economical (C_2) sub-criteria.

G (C_2)	C_{21}	C_{22}	C_{23}
Application and Installment cost (C_{21})	0	0.39	0.49
Operating cost (C_{22})	0.51	0	0.49
Training cost (C_{23})	0.43	0.51	0

Table 13. Normalized direct influence matrix T between Time (C_3) sub-criteria.

G (C_3)	C_{31}	C_{32}	C_{33}
Application and Installment time (C_{31})	0	0.26	0.74
Operating time (C_{32})	0.04	0	0.86
Training time (C_{33})	0.05	0.79	0

Table 14. Normalized direct influence matrix T between Safety (C_4) sub-criteria.

G (C_4)	C_{41}	C_{42}
Internal safety (C_{41})	0	0.66
External safety (C_{42})	1	0

In Table 10, for instance, the normalized direct influence value for C_1 to C_3 is 0.262, which is obtained from the multiplication between the direct influence rank from C_1 to C_3 (0.545 in Table 5) and the λ value ($\frac{1}{\max 1 \le n \le 4 \sum_{j=1}^{4} t_{nj}} = \frac{1}{\max\left(\sum_{j=1}^{4} t_{1j}, \sum_{j=1}^{4} t_{2j}, \sum_{j=1}^{4} t_{3j}, \sum_{j=1}^{4} t_{4j}\right)} = \frac{1}{\max(1.819,1.656,1.679,2.081)} = 0.481$) for the average direct influence matrix (Table 5). After that, depending on the Equations (13)–(16), we can obtain the total direct and indirect influence matrix E (Tables 15–19) and the corresponding sum of rows (*or* in Equation (15)) and columns (co in Equation (16)) of the E.

Table 15. Total direct and indirect influence matrix E between BPM tool selection main criteria.

E	Efficiency (C_1)	Economical (C_2)	Time (C_3)	Safety (C_4)	ro_n	$ro_n + co_j$
Efficiency (C_1)	1.484	1.852	1.614	1.696	6.646	13.181
Economical (C_2)	1.592	1.514	1.493	1.573	6.172	13.356
Time (C_3)	1.585	1.756	1.299	1.513	6.153	12.347
Safety (C_4)	1.874	2.062	1.788	1.593	7.317	13.692
co_j	6.535	7.184	6.194	6.375	—	—

The ro_n (highlighted in yellow) means the total given both direct and indirect effects from criteria n to the other criteria, and co_j (highlighted in pink) means the total received both direct and indirect effects from other criterions to criterion j. The overall direct and indirect impact matrix E with corresponding ro_n and co_j values, when n equals j, ($ro_j + co_j$) (highlighted in lime green) value, represents the centrality of criterion j.

Table 16. Total direct influence matrix T between Efficiency (C_1) sub-criteria.

E (C_1)	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	ro_n	$ro_n + co_j$
Expressiveness (C_{11})	1.05	1.36	1.18	1.34	1.66	6.59	12.25
Readability (C_{12})	1.14	1.16	1.07	1.38	1.54	6.29	12.81
Usability (C_{13})	1.28	1.44	1.04	1.52	1.78	7.06	12.34
Formality (C_{14})	1.21	1.44	1.11	1.17	1.68	6.61	12.97
Ease of Learning (C_{15})	0.98	1.12	0.88	0.95	1.08	5.01	12.75
co_j	5.66	6.52	5.28	6.36	7.74	—	—

Table 17. Total direct influence matrix T between Economical (C_2) sub-criteria.

E (C_2)	C_{21}	C_{22}	C_{23}	ro_n	$ro_n + co_j$
Application and Installment cost (C_{21})	4.73	4.89	5.2	14.82	14.82
Operating cost (C_{22})	5.51	5.03	5.65	16.19	16.19
Training cost (C_{23})	5.27	5.18	5.12	15.57	15.57
co_j	15.51	15.1	15.97	—	—

Table 18. Total direct influence matrix T between Time (C_3) sub-criteria.

E (C_3)	C_{31}	C_{32}	C_{33}	ro_n	$ro_n + co_j$
Application and Installment time (C_{31})	0.34	3.54	4.04	7.92	7.92
Operating time (C_{32})	0.35	3.04	3.73	7.12	7.12
Training time (C_{33})	0.34	3.36	3.15	6.85	6.85
co_j	1.03	9.94	10.92	—	—

Table 19. Total direct influence matrix T between Safety (C_4) sub-criteria.

E (C_4)	C_{41}	C_{42}	ro_n	$ro_n + co_j$
Internal safety (C_{41})	1.94	1.94	3.88	8.76
External safety (C_{42})	2.94	1.94	4.88	8.76
co_j	4.88	3.88	—	—

From the Tables 15–19, we can find the direct and indirect relationships between criteria or sub-criteria. The ro_n (highlighted in yellow) means the total given both direct and indirect effects from criteria n to the other criteria (for example, in Table 15, ro_1 = 1.484 + 1.852 + 1.614 + 1.696 = 6.646), and co_j (highlighted in pink) means the total received both direct and indirect effects from other criteria to criterion j (for example, in Table 15, co1 = 1.484 + 1.592 + 1.585 + 1.874 = 6.535). After, we obtain the overall direct and indirect impact matrix E with corresponding ro_n and co_j values, when n equals j, we can release the (ro_j + co_j) (highlighted in lime green) value, which means the centrality of criterion j, for all the criteria (Tables 15–19).

After that, we can calculate the normalized (ro + co) value for all the criterions and sub-criterions like Table 20.

Table 20. Normalized (ro + co) value (weight) for all the all the business process modelling tool selection criteria and sub-criteria.

Direct Influence Degree	NRC (W)	Sub-Criteria	NRC (W)
Efficiency parameters (C_1)	0.251	Expressiveness (C_{11})	0.194
		Readability (C_{12})	0.203
		Usability (C_{13})	0.196
		Formality (C_{14})	0.205
		Ease of Learning (C_{15})	0.202
Economical parameters (C_2)	0.254	Application and installment cost (C_{21})	0.32
		Operating cost (C_{22})	0.35
		Training cost (C_{23})	0.33
Time parameters (C_3)	0.235	Application and installment time (C_{31})	0.36
		Operating time (C_{32})	0.33
		Training time (C_{33})	0.31
Safety parameters(C_4)	0.26	Internal safety (C_{41})	0.5
		External safety (C_{42})	0.5

Note. NRC = Normalized (ro + co) value. W = Weight.

In Table 20, for example, the NRC value for Efficiency parameters (C_1) is 0.251, which is obtained by dividing ro_1 + co_1 (Efficiency parameters (C_1) in Table 15 by the sum of column ro_n + co_j in Table 15 ($\frac{13.181}{6.646+6.172+6.153+7.317}$ = 0.251). After that, the final weight of sub-parameter is the multiplication of the weights of the four main and corresponding sub-criteria.

After we define the weight for all the criteria and sub-criteria, we can use these weights (Table 20) and Equations (19) and (20), and Table 4 to obtain the weighted normalized values such as Table 21.

Table 21. The weighted normalized value of all the business process modelling tool alternatives in Table 4.

Alternative	Efficiency (C_1)					Economical (C_2)			Time (C_3)			Safety (C_4)	
	C_{11} Max	C_{12} Max	C_{13} Max	C_{14} Max	C_{15} Max	C_{21} Min	C_{22} Min	C_{23} Min	C_{31} Min	C_{32} Min	C_{33} Min	C_{41} Max	C_{42} Max
T1	0.009	0.015	0.011	0.019	0.025	0.012	0.022	0.021	0.03	0.027	0.029	0.014	0.013
T2	0.014	0.015	0.011	0.019	0.025	0.012	0.022	0.021	0.02	0.018	0.019	0.014	0.013
T3	0.018	0.02	0.016	0.012	0.015	0.036	0.045	0.032	0.03	0.009	0.01	0.057	0.063
T4	0.018	0.025	0.021	0.019	0.02	0.036	0.022	0.032	0.02	0.027	0.029	0.057	0.063
T5	0.018	0.01	0.016	0.025	0.015	0.047	0.034	0.021	0.04	0.037	0.019	0.071	0.025
T6	0.014	0.01	0.005	0.012	0.01	0.012	0.011	0.011	0.05	0.046	0.019	0.029	0.013
T7	0.018	0.025	0.021	0.019	0.01	0.012	0.034	0.042	0.01	0.018	0.01	0.029	0.063
T8	0.023	0.02	0.027	0.019	0.015	0.036	0.045	0.042	0.02	0.018	0.048	0.057	0.063

Note. C = Criteria. T = Tool.

In Table 21, the abbreviation max denotes the benefit standard, and abbreviation min denotes the cost standard. The final weighted normalized value for alternative 1 (T1) corresponding to sub-criteria C_{11} is 0.009. The number is obtained by multiplying the final weight of sub-criteria C_{11} (0.251 × 0.194 = 0.049) and the normalized decision matrix value for C_{11} ($0.190 = \frac{2}{\sqrt{\sum_{i=1}^{24} y_{i1}{}^2}}$).

After that, depending on Table 21, Equations (21) and (22), the P-I and N-I solutions are determined. The P-I solution and N-I solution can be seen as Table 22.

Table 22. The P-I and N-I solution of the considered BPM tool alternatives.

Alternative	Efficiency (C_1)					Economical (C_2)			Time (C_3)			Safety (C_4)	
	C_{12} Max	C_{12} Max	C_{13} Max	C_{14} Max	C_{15} Max	C_{21} Min	C_{22} Min	C_{23} Min	C_{31} Min	C_{32} Min	C_{33} Min	C_{41} Max	C_{42} Max
T^+	0.023	0.025	0.027	0.025	0.025	0.012	0.011	0.011	0.01	0.009	0.01	0.071	0.063
T^-	0.009	0.01	0.005	0.012	0.01	0.047	0.045	0.042	0.05	0.046	0.048	0.014	0.013

Note. C = Criteria. T = Tool.

Depending on the data from Tables 21 and 22, Equations (23) and (24), the relative distances of each candidate option from the P-I and N-I solutions can be released. Finally, the relative distance of each candidate option to the P-I solution is released depending on Equation (25). The relative distances of each alternative from the P-I and N-I solutions and the result of the relative distance of each alternative from the P-I solution can be seen as Table 23.

Table 23. TOPSIS result for all 8 candidate Business Process Modelling tools.

Alternative	d_i^*	$d_i{}^0$	C_i^*
T1	0.088	0.06	0.405
T2	0.082	0.071	0.464
T3	0.056	0.09	0.616
T4	0.048	0.086	0.642
T5	0.074	0.073	0.497
T6	0.092	0.067	0.421
T7	0.061	0.092	0.601
T8	0.069	0.083	0.546

Table 23 shows the evaluation result of the considered alternatives obtained by using TOPSIS technology. In Table 23, the C_i* value is obtained by the relative closeness to the ideal solution (Equation (25)). For example, the value for the C_i* value for T1 is 0.405 ($H_i^* = \frac{d_i^0}{(d_i^0+d_i^*)} = \frac{0.06}{(0.06+0.088)} = 0.405$). Meanwhile, in Table 23, di* is the n-dimensional Euclidean distance from each solution in Table 21 to the P-I solution (T^+ Table 22), and d_i^0 is the n-dimensional Euclidean distance from each solution in Table 21 to the N-I solution (T^- Table 22). For example, the d_i^* value for T1 is 0.88 ($\sqrt{\sum_{j=1}^{13}(x_{ij}-x_j^*)^2} = \sqrt{\begin{array}{c}(0.009-0.023)^2+(0.015-0.025)^2+(0.011-0.027)^2+(0.019-0.025)^2+(0.025-0.025)^2+(0.012-0.012)^2+\\(0.022-0.011)^2+(0.021-0.011)^2+(0.003-0.001)^2+(0.027-0.009)^2+(0.029-0.001)^2+(0.014-0.071)^2+\\+(0.013-0.063)^2\end{array}}$ = 0.88). Meanwhile, the d_i^0 value for T1 is 0.06 ($\sqrt{\sum_{j=1}^{13}(x_{ij}-x_j^0)^2} = \sqrt{\begin{array}{c}(0.009-0.009)^2+(0.015-0.01)^2+(0.011-0.05)^2+(0.019-0.012)^2+(0.025-0.001)^2+(0.012-0.047)^2+\\(0.022-0.045)^2+(0.021-0.042)^2+(0.003-0.05)^2+(0.027-0.046)^2+(0.029-0.048)^2+(0.014-0.014)^2+\\+(0.013-0.013)^2\end{array}}$ = 0.06). From the C_i* value in Table 23, it is possible to find that the alternative T4 obtains the highest value (0.642) (highlighted in green). Here, when considering the four types of criteria (BPM efficiency (C_1), various expenses incurred when using the BPM tool (C_2), application, installment, operating and training time (C_3), and security issues affected by BPM tools (C_4)), alternative T4 is the best overall performing BPM tool. Therefore, managers can select BPM tool T4 for the company.

5. Discussion and Conclusions

The business process modeling tool selection problem has a significant influence on the total performance of enterprise business process modeling, which will directly affect the development of the enterprise information system. Some candidate options have to be considered and assessed depending on the affecting parameters (efficiency parameters (C_1), economical parameters (C_2), time parameters (C_3) and safety parameters (C_4)) and corresponding sub-parameters (expressiveness (C_{11}), readability (C_{12}) usability (C_{13}), formality (C_{14}), ease of learning (C_{15}), application and installation cost (C_{21}), operating cost (C_{22}), training cost (C_{23}), application and installation time (C_{31}), operating time (C_{32}), training time (C_{33}), internal safety (C_{41}), and external safety (C_{42})) in a BPM tool choosing issue, causing various ambiguous information. Thus, an optimal assessment method is needed to make effective decisions. Therefore, the BPM tool selection methodology is proposed in this study with the consideration of different BPM tool selection influencing factors.

Apart from that, the process to select the BPM tool from all alternatives is a fuzzy multi-criteria decision-making (MCDM) issue. Thus, we use TOPSIS to obtain the priority of BPM tool alternatives. Here, TOPSIS is applied to determine the priorities of the BPM candidate tools. The proposed method has dramatically improved the usefulness and accuracy of decision-making in the BPM tool choice process. In addition, in the method, we find that the weights of the criteria and sub-criteria in the TOPSIS technique are determined by company expert options through the fuzzy DEMATEL method. After that, the final weight for sub-criteria is the multiplication of the defined two weights, and it is important and may change the ranking of the alternatives. This method can provide a reference for companies purchasing or applying BPM tools when selecting BPM tools so that the BPM tool can be used more efficiently, economically, quickly, and safely. Rather than providing assistance to the business process modeling tool manufacturer (Bonita [65], Camunda [66], etc. Of course, it is also possible for business process modeling tool manufacturers to use this method to evaluate the goodness of their own tools. However, the evaluation should involve the experts from the company interested in purchasing the tool.

Some scholars, such as Zhang and Su, 2019 [67], also proposed the fuzzy DEMATEL and TOPSIS combination method. However, the fuzzy part of this approach is based on a 2-tuple linguistic method and approaches the relationships between the attributes of the

proof participants and determines their weights. The 2-tuple linguistic model is used to aggregate linguistic evaluation information and requires the interpretation of linguistic labels. Even though the model can increase the accuracy in the process of aggregation, it is mainly concerned with semantic ambiguity. However, the fuzzy part studied in this paper is the uncertainty of the decision data (not semantically ambiguous). The Triangular Fuzzy Number not only can be used not only to express the vagueness and uncertainty of decision data but also to represent fuzzy terms in decision data processing. Therefore, the application of triangular fuzzy numbers is more adaptable in our study.

Although the proposed method is developed for the BPM tool selection problem, it is also adaptable for other software tool selections with slight modifications. Such as ERP or office tool selection problems in manufacturing or trading companies. The main part that needs to be modified here is the criteria part. Companies can change the main criteria and sub-criteria (Table 1) according to the characteristics of the software tool they need to choose. For example, the ERP tool selection problem is more about data evaluation and control rather than graphical presentation, so the expressiveness (C_{11}) and formality (C_{14}) criteria can be removed and replaced by the data control or evaluation criteria. Meanwhile, although some criteria do not need to be changed, the contents inside the criteria need to be redefined.

Even though the method is proposed and applied for the BPM tool selection problem, and we can obtain the final BPM tool (T4 in Table 23), there are many study areas for expansion. Studies could help extend the approach by first determining the sub-criteria more rationally and precisely. Second, we find and establish a method of criteria and sub-criteria weight definition in a reasonable way. Meanwhile, as Zhang and Su, 2019 [67] consider the 2-tuple linguistic model in the fuzzy DEMATEL method, it is also very important for our research to consider semantic ambiguity. Therefore, further studies will focus on these study areas.

This study first describes the significance of BPM tool selection for information systems (IS) in companies. After that, the key target is expressed to approach the issue in BPM tool selection. Then, the method is proposed with the application of DEMATEL and the TOPSIS method to approach BPM tool selection with the consideration of different BPM tool evaluation criteria. Finally, depending on the method proposed in this paper, the company can choose the optimal and most suitable BPM tool. This method allows the BPM process in the company to be more economical, efficient, time-saving, and safe.

Author Contributions: Ideas, G.J. (Guangying Jin) and G.J. (GuangZhe Jin); Method, G.J. (Guangying Jin); Writing—Original Draft Preparation, G.J. (Guangying Jin); Writing—Review & Editing, G.J. (Guangying Jin); Supervision, H.H.; Funding Acquisition, G.J. (Guangying Jin). All authors have read and agreed to the published version of the manuscript. **Funding:** The study was supported by

Talent Research Start-up Funding of Dalian Maritime University, authorization code: 02502329.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Degree of direct fuzzy influence between criterions.

E1	C_1 (DFN)	C_2 (DFN)	C_3 (DFN)	C_4 (DFN)	E2	C_1 (DFN)	C_2 (DFN)	C_3 (DFN)	C_4 (DFN)	E3	C_1 (DFN)	C_2 (DFN)	C_3 (DFN)	C_4 (DFN)	E4	C_1 (DFN)	C_2 (DFN)	C_3 (DFN)	C_4 (DFN)	E5	C_1 (DFN)	C_2 (DFN)	C_3 (DFN)	C_4 (DFN)
Efficiency (C_1)	0	2	3	3	C_1	0	2	2	4	C_1	0	3	1	2	C_1	0	3	1	3	C_1	0	1	1	1
Economical (C_2)	3	0	2	2	C_2	2	0	3	1	C_2	3	0	2	3	C_2	1	0	2	2	C_2	2	0	1	2
Time (C_3)	1	2	0	1	C_3	3	4	0	2	C_3	3	3	0	1	C_3	1	1	0	2	C_3	3	1	0	2
Safety (C_4)	1	4	2	0	C_4	1	2	3	0	C_4	3	4	2	0	C_4	1	3	2	0	C_4	2	2	2	0
E6	**C_1 (DFN)**	**C_2 (DFN)**	**C_3 (DFN)**	**C_4 (DFN)**	**E7**	**C_1 (DFN)**	**C_2 (DFN)**	**C_3 (DFN)**	**C_4 (DFN)**	**E8**	**C_1 (DFN)**	**C_2 (DFN)**	**C_3 (DFN)**	**C_4 (DFN)**	**E9**	**C_1 (DFN)**	**C_2 (DFN)**	**C_3 (DFN)**	**C_4 (DFN)**	**E10**	**C_1 (DFN)**	**C_2 (DFN)**	**C_3 (DFN)**	**C_4 (DFN)**
C_1	0	1	3	4	C_1	0	3	2	3	C_1	0	3	2	3	C_1	0	3	3	3	C_1	0	3	4	2
C_2	2	0	4	3	C_2	3	0	1	3	C_2	3	0	1	3	C_2	3	0	1	3	C_2	1	0	2	3
C_3	3	4	0	1	C_3	2	4	0	3	C_3	2	3	0	2	C_3	2	2	0	1	C_3	3	4	0	2
C_4	4	3	3	0	C_4	4	3	4	0	C_4	4	3	4	0	C_4	4	3	3	0	C_4	3	4	2	0

Note. DFI = Direct Fuzzy Influence. C = Criteria. E = Expert.

Table A2. Degree of direct fuzzy influence between Efficiency (C_1) sub-criterions.

E1	C_{11} (DFN)	C_{12} (DFN)	C_{13} (DFN)	C_{14} (DFN)	C_{15} (DFN)	E2	C_{11} (DFN)	C_{12} (DFN)	C_{13} (DFN)	C_{14} (DFN)	C_{15} (DFN)	E3	C_{11} (DFN)	C_{12} (DFN)	C_{13} (DFN)	C_{14} (DFN)	C_{15} (DFN)	E4	C_{11} (DFN)	C_{12} (DFN)	C_{13} (DFN)	C_{14} (DFN)	C_{15} (DFN)	E5	C_{11} (DFN)	C_{12} (DFN)	C_{13} (DFN)	C_{14} (DFN)	C_{15} (DFN)
EX (C_{11})	0	1	1	1	2	C_{11}	0	2	3	1	3	C_{11}	0	1	2	3	3	C_{11}	0	2	1	2	1	C_{11}	0	0	3	0	2
RE (C_{12})	2	0	2	4	2	C_{12}	1	0	1	3	1	C_{12}	2	0	1	4	2	C_{12}	3	0	2	3	2	C_{12}	2	0	1	4	2
US (C_{13})	1	1	0	3	3	C_{13}	2	2	0	3	3	C_{13}	1	2	0	3	3	C_{13}	3	1	0	4	3	C_{13}	0	2	0	3	3
FO (C_{14})	2	3	2	0	4	C_{14}	1	3	2	0	4	C_{14}	1	2	0	0	3	C_{14}	4	3	2	0	3	C_{14}	2	3	1	0	1
EL (C_{15})	4	1	0	2	0	C_{15}	3	2	2	0	0	C_{15}	3	1	0	3	0	C_{15}	4	1	0	2	0	C_{15}	4	2	2	0	0
E6	**C_{11} (DFN)**	**C_{12} (DFN)**	**C_{13} (DFN)**	**C_{14} (DFN)**	**C_{15} (DFN)**	**E7**	**C_{11} (DFN)**	**C_{12} (DFN)**	**C_{13} (DFN)**	**C_{14} (DFN)**	**C_{15} (DFN)**	**E8**	**C_{11} (DFN)**	**C_{12} (DFN)**	**C_{13} (DFN)**	**C_{14} (DFN)**	**C_{15} (DFN)**	**E9**	**C_{11} (DFN)**	**C_{12} (DFN)**	**C_{13} (DFN)**	**C_{14} (DFN)**	**C_{15} (DFN)**	**E10**	**C_{11} (DFN)**	**C_{12} (DFN)**	**C_{13} (DFN)**	**C_{14} (DFN)**	**C_{15} (DFN)**
C_{11}	0	2	3	2		C_{11}	0	1	3	1	2	C_{11}	0	2	1	3	2	C_{11}	0	1	2	2	2	C_{11}	0	3	2	1	3
C_{12}	2	0	2	4		C_{12}	2	0	1	4	2	C_{12}	2	0	2	4	2	C_{12}	1	0	2	4	3	C_{12}	1	0	3	2	3
C_{13}	1	1	0	3		C_{13}	2	1	0	3	3	C_{13}	1	1	0	3	3	C_{13}	3	3	0	3	3	C_{13}	3	1	0	3	2
C_{14}	2	3	2	0		C_{14}	3	3	1	0	4	C_{14}	1	2	2	0	3	C_{14}	1	3	2	0	3	C_{14}	3	3	2	0	4
C_{15}	3	2	2	1		C_{15}	4	1	0	1	0	C_{15}	3	1	0	1	0	C_{15}	3	1	0	2	0	C_{15}	3	2	0	2	0

Note. E = Expert. DFI = Direct Fuzzy Influence. C = Criteria. EX = Expressiveness. RE = Readability. US = Usability. FO = Formality. EL = Ease of Leaning.

Table A3. Degree of direct fuzzy influence between Economical (C_2) sub-criterions.

E1	C_{21} (DFN)	C_{22} (DFN)	C_{23} (DFN)	E2	C_{21} (DFN)	C_{22} (DFN)	C_{23} (DFN)	E3	C_{21} (DFN)	C_{22} (DFN)	C_{23} (DFN)	E4	C_{21} (DFN)	C_{22} (DFN)	C_{23} (DFN)	E5	C_{21} (DFN)	C_{22} (DFN)	C_{23} (DFN)
Application and Installment cost (C_{21})	0	2	3	C_{21}	0	1	2	C_{21}	0	2	2	C_{21}	0	1	3	C_{21}	0	3	2
Operating cost (C_{22})	4	0	4	C_{22}	3	0	1	C_{22}	2	0	3	C_{22}	2	0	3	C_{22}	3	0	3
Training cost (C_{23})	3	3	0	C_{23}	2	2	0	C_{23}	1	2	0	C_{23}	1	3	0	C_{23}	2	3	0
E6	**C_{21} (DFN)**	**C_{22} (DFN)**	**C_{23} (DFN)**	**E7**	**C_{21} (DFN)**	**C_{22} (DFN)**	**C_{23} (DFN)**	**E8**	**C_{21} (DFN)**	**C_{22} (DFN)**	**C_{23} (DFN)**	**E9**	**C_{21} (DFN)**	**C_{22} (DFN)**	**C_{23} (DFN)**	**E10**	**C_{21} (DFN)**	**C_{22} (DFN)**	**C_{23} (DFN)**
C_{21}	0	1	2	C_{21}	0	3	4	C_{21}	0	3	2	C_{21}	0	3	4	C_{21}	0	3	4
C_{22}	3	0	3	C_{22}	3	0	2	C_{22}	3	0	3	C_{22}	3	0	3	C_{22}	3	0	3
C_{23}	2	4	0	C_{23}	3	2	0	C_{23}	4	4	0	C_{23}	4	2	0	C_{23}	2	4	0

Note. E = Expert. DFI = Direct Fuzzy Influence. C = Criteria.

Table A4. Degree of direct fuzzy influence between Time (C_3) sub-criterions.

E1	**C_{31} (DFN)**	**C_{32} (DFN)**	**C_{33} (DFN)**	**E2**	**C_{31} (DFN)**	**C_{32} (DFN)**	**C_{33} (DFN)**	**E3**	**C_{31} (DFN)**	**C_{32} (DFN)**	**C_{33} (DFN)**	**E4**	**C_{31} (DFN)**	**C_{32} (DFN)**	**C_{33} (DFN)**	**E5**	**C_{31} (DFN)**	**C_{32} (DFN)**	**C_{33} (DFN)**
Application and Installment time(C_{31})	0	1	2	C_{31}	0	0	1	C_{31}	0	1	1	C_{31}	0	1	2	C_{31}	0	0	2
Operating time (C_{32})	0	0	3	C_{32}	0	0	2	C_{32}	0	0	2	C_{32}	0	0	3	C_{32}	0	0	3
Training time (C_{33})	0	2	0	C_{33}	0	3	0	C_{33}	0	1	0	C_{33}	0	2	0	C_{33}	0	2	0
E6	**C_{31} (DFN)**	**C_{32} (DFN)**	**C_{33} (DFN)**	**E7**	**C_{31} (DFN)**	**C_{32} (DFN)**	**C_{33} (DFN)**	**E8**	**C_{31} (DFN)**	**C_{32} (DFN)**	**C_{33} (DFN)**	**E9**	**C_{31} (DFN)**	**C_{32} (DFN)**	**C_{33} (DFN)**	**E10**	**C_{31} (DFN)**	**C_{32} (DFN)**	**C_{33} (DFN)**
C_{31}	0	1	2	C_{31}	0	0	2	C_{31}	0	0	2	C_{31}	0	1	2	C_{31}	0	0	3
C_{32}	0	0	4	C_{32}	0	0	3	C_{32}	0	0	2	C_{32}	0	0	3	C_{32}	0	0	3
C_{33}	0	2	0	C_{33}	0	2	0	C_{33}	0	3	0	C_{33}	0	3	0	C_{33}	0	3	0

Table A5. Degree of direct fuzzy influence between Safety (C_4) sub-criterions.

E1	**C_{41} (DFN)**	**C_{42} (DFN)**	**E2**	**C_{41} (DFN)**	**C_{42} (DFN)**	**E3**	**C_{41} (DFN)**	**C_{42} (DFN)**	**E4**	**C_{41} (DFN)**	**C_{42} (DFN)**	**E5**	**C_{41} (DFN)**	**C_{42} (DFN)**
Internal safety(C_{41})	0	1	C_{41}	0	2	C_{41}	0	1	C_{41}	0	2	C_{41}	0	3
External safety (C_{42})	3	0	C_{42}	2	0	C_{42}	3	0	C_{42}	3	0	C_{42}	3	0
E6	**C_{41} (DFN)**	**C_{42} (DFN)**	**E7**	**C_{41} (DFN)**	**C_{42} (DFN)**	**E8**	**C_{41} (DFN)**	**C_{42} (DFN)**	**E9**	**C_{41} (DFN)**	**C_{42} (DFN)**	**E10**	**C_{41} (DFN)**	**C_{42} (DFN)**
C_{41}	0	2	C_{41}	0	1	C_{41}	0	2	C_{41}	0	2	C_{41}	0	2
C_{42}	2	0	C_{42}	4	0	C_{42}	2	0	C_{42}	3	0	C_{42}	3	0

Note. E = Expert. DFI = Direct Fuzzy Influence. C = Criteria.

Table A6. The corresponding triangle fuzzy numbers in Table A1.

E1	**C_1 (TFN)**	**C_2 (TFN)**	**C_3 (TFN)**	**C_4 (TFN)**	**E2**	**C_1 (TFN)**	**C_2 (TFN)**	**C_3 (TFN)**	**C_4 (TFN)**
Efficiency (C_1)	0	(0.25, 0.5, 0.75)	(0.5, 0.75, 1)	(0.5, 0.75, 1)	C_1	0	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)	(0.75, 1, 1)
Economical (C_2)	(0.5, 0.75, 1)	0	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)	C_2	(0.25, 0.5, 0.75)	0	(0.5, 0.75, 1)	(0, 0.25, 0.5)
Time (C_3)	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)	0	(0, 0.25, 0.5)	C_3	(0.5, 0.75, 1)	(0.75, 1, 1)	0	(0.25, 0.5, 0.75)
Safety (C_4)	(0, 0.25, 0.5)	(0.75, 1, 1)	(0.25, 0.5, 0.75)	0	C_4	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)	(0.5, 0.75, 1)	0
E3	**C_1 (TFN)**	**C_2 (TFN)**	**C_3 (TFN)**	**C_4 (TFN)**	**E4**	**C_1 (TFN)**	**C_2 (TFN)**	**C_3 (TFN)**	**C_4 (TFN)**
C_1	0	(0.5, 0.75, 1)	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)	C_1	0	(0.5, 0.75, 1)	(0, 0.25, 0.5)	(0.5, 0.75, 1)
C_2	(0.5, 0.75, 1)	0	(0.25, 0.5, 0.75)	(0.5, 0.75, 1)	C_2	(0, 0.25, 0.5)	0	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
C_3	(0.5, 0.75, 1)	(0.5, 0.75, 1)	0	(0, 0.25, 0.5)	C_3	(0, 0.25, 0.5)	(0, 0.25, 0.5)	0	(0.25, 0.5, 0.75)
C_4	(0.5, 0.75, 1)	(0.75, 1, 1)	(0.25, 0.5, 0.75)	0	C_4	(0, 0.25, 0.5)	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)	0
E5	**C_1 (TFN)**	**C_2 (TFN)**	**C_3 (TFN)**	**C_4 (TFN)**	**E6**	**E6**	**C_1 (TFN)**	**C_2 (TFN)**	**C_3 (TFN)**
C_1	0	(0, 0.25, 0.5)	(0, 0.25, 0.5)	(0, 0.25, 0.5)	C_1	C_1	0	(0, 0.25, 0.5)	(0.5, 0.75, 1)
C_2	(0.25, 0.5, 0.75)	0	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)	C_2	C_2	(0.25, 0.5, 0.75)	0	(0.75, 1, 1)
C_3	(0.5, 0.75, 1)	(0, 0.25, 0.5)	0	(0.25, 0.5, 0.75)	C_3	C_3	(0.5, 0.75, 1)	(0.75, 1, 1)	0
C_4	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)	0	E6	C_4	(0.75, 1, 1)	(0.5, 0.75, 1)	(0.5, 0.75, 1)
E7	**C_1 (TFN)**	**C_2 (TFN)**	**C_3 (TFN)**	**C_4 (TFN)**	**E8**	**C_1 (TFN)**	**C_2 (TFN)**	**C_3 (TFN)**	**C_4 (TFN)**
C_1	0	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)	(0.5, 0.75, 1)	C_1	0	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)	(0.5, 0.75, 1)
C_2	(0.5, 0.75, 1)	0	(0, 0.25, 0.5)	(0.5, 0.75, 1)	C_2	(0.5, 0.75, 1)	0	(0, 0.25, 0.5)	(0.5, 0.75, 1)
C_3	(0.25, 0.5, 0.75)	(0.75, 1, 1)	0	(0.5, 0.75, 1)	C_3	(0.25, 0.5, 0.75)	(0.5, 0.75, 1)	0	(0.25, 0.5, 0.75)
C_4	(0.75, 1, 1)	(0.5, 0.75, 1)	(0.75, 1, 1)	0	C_4	(0.75, 1, 1)	(0.5, 0.75, 1)	(0.75, 1, 1)	0
E9	**C_1 (TFN)**	**C_2 (TFN)**	**C_3 (TFN)**	**C_4 (TFN)**	**E10**	**C_1 (TFN)**	**C_2 (TFN)**	**C_3 (TFN)**	**C_4 (TFN)**
C_1	0	(0.5, 0.75, 1)	(0.5, 0.75, 1)	(0.5, 0.75, 1)	C_1	0	(0.5, 0.75, 1)	(0.75, 1, 1)	(0.25, 0.5, 0.75)
C_2	(0.5, 0.75, 1)	0	(0, 0.25, 0.5)	(0.5, 0.75, 1)	C_2	(0, 0.25, 0.5)	0	(0.25, 0.5, 0.75)	(0.5, 0.75, 1)
C_3	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)	0	(0, 0.25, 0.5)	C_3	(0.5, 0.75, 1)	(0.75, 1, 1)	0	(0.25, 0.5, 0.75)
C_4	(0.75, 1, 1)	(0.5, 0.75, 1)	(0.5, 0.75, 1)	0	C_4	(0.5, 0.75, 1)	(0.75, 1, 1)	(0.25, 0.5, 0.75)	0

Note. TFN = Triangle Fuzzy Number. C = Criteria.

Table A7. The corresponding triangle fuzzy numbers in Table A2.

E1	**C11 (TFN)**	**C12 (TFN)**	**C13 (TFN)**	**C14 (TFN)**	**C15 (TFN)**	**E2**	**C11 (TFN)**	**C12 (TFN)**	**C13 (TFN)**	**C14 (TFN)**	**C15 (TFN)**
EX (C_{11})	0	(0, 0.25, 0.5)	(0, 0.25, 0.5)	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)	C_{11}	0	(0.25, 0.5, 0.75)	(0.5, 0.75, 1)	(0, 0.25, 0.5)	(0.5, 0.75, 1)
RE (C_{12})	(0.25, 0.5, 0.75)	0	(0.25, 0.5, 0.75)	(0.75, 1, 1)	(0.25, 0.5, 0.75)	C_{12}	(0, 0.25, 0.5)	0	(0, 0.25, 0.5)	(0.5, 0.75, 1)	(0, 0.25, 0.5)
US (C_{13})	(0, 0.25, 0.5)	(0, 0.25, 0.5)	0	(0.5, 0.75, 1)	(0.5, 0.75, 1)	C_{13}	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)	0	(0.5, 0.75, 1)	(0.5, 0.75, 1)
FO (C_{14})	(0.25, 0.5, 0.75)	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)	0	(0.75, 1, 1)	C_{14}	(0, 0.25, 0.5)	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)	0	(0.75, 1, 1)
EL (C_{15})	(0.75, 1, 1)	(0, 0.25, 0.5)	(0, 0, 0.25)	(0.25, 0.5, 0.75)	0	C_{15}	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)	(0, 0, 0.25)	0
E3	**C_{11} (TFN)**	**C_{12} (TFN)**	**C_{13} (TFN)**	**C_{14} (TFN)**	**C_{15} (TFN)**	**E4**	**C_{11} (TFN)**	**C_{12} (TFN)**	**C_{13} (TFN)**	**C_{14} (TFN)**	**C_{15} (TFN)**
C_{11}	0	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)	(0.5, 0.75, 1)	(0.5, 0.75, 1)	C_{11}	0	(0.25, 0.5, 0.75)	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)	(0, 0.25, 0.5)
C_{12}	(0.25, 0.5, 0.75)	0	(0, 0.25, 0.5)	(0.75, 1, 1)	(0.25, 0.5, 0.75)	C_{12}	(0.5, 0.75, 1)	0	(0.25, 0.5, 0.75)	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)
C_{13}	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)	0	(0.5, 0.75, 1)	(0.5, 0.75, 1)	C_{13}	(0.5, 0.75, 1)	(0, 0.25, 0.5)	0	(0.75, 1, 1)	(0.5, 0.75, 1)
C_{14}	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)	(0, 0, 0.25)	0	(0.5, 0.75, 1)	C_{14}	(0.75, 1, 1)	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)	0	(0.5, 0.75, 1)
C_{15}	(0.5, 0.75, 1)	(0, 0.25, 0.5)	(0, 0, 0.25)	(0.5, 0.75, 1)	0	C_{15}	(0.75, 1, 1)	(0, 0.25, 0.5)	(0, 0, 0.25)	(0.25, 0.5, 0.75)	0
E5	**C_{11} (TFN)**	**C_{12} (TFN)**	**C_{13} (TFN)**	**C_{14} (TFN)**	**C_{15} (TFN)**	**E6**	**C_{11} (TFN)**	**C_{12} (TFN)**	**C_{13} (TFN)**	**C_{14} (TFN)**	**C_{15} (TFN)**
C_{11}	0	(0, 0, 0.25)	(0.5, 0.75, 1)	(0, 0, 0.25)	(0.25, 0.5, 0.75)	C_{11}	0	(0.25, 0.5, 0.75)	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)	(0.75, 1, 1)
C_{12}	(0.25, 0.5, 0.75)	0	(0, 0.25, 0.5)	(0.75, 1, 1)	(0.25, 0.5, 0.75)	C_{12}	(0.25, 0.5, 0.75)	0	(0.25, 0.5, 0.75)	(0.75, 1, 1)	(0.5, 0.75, 1)
C_{13}	0	(0.25, 0.5, 0.75)	0	(0.5, 0.75, 1)	(0.5, 0.75, 1)	C_{13}	(0, 0.25, 0.5)	(0, 0.25, 0.5)	0	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)
C_{14}	(0.25, 0.5, 0.75)	(0.5, 0.75, 1)	(0, 0.25, 0.5)	0	(0, 0.25, 0.5)	C_{14}	(0.25, 0.5, 0.75)	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)	0	(0.5, 0.75, 1)
C_{15}	(0.75, 1, 1)	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)	(0, 0, 0.25)	0	C_{15}	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)	(0, 0.25, 0.5)	0
E7	**C_{11} (TFN)**	**C_{12} (TFN)**	**C_{13} (TFN)**	**C_{14} (TFN)**	**C_{15} (TFN)**	**E8**	**C_{11} (TFN)**	**C_{12} (TFN)**	**C_{13} (TFN)**	**C_{14} (TFN)**	**C_{15} (TFN)**
C_{11}	0	(0, 0.25, 0.5)	(0.5, 0.75, 1)	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)	C_{11}	0	(0.25, 0.5, 0.75)	(0, 0.25, 0.5)	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)
C_{12}	(0.25, 0.5, 0.75)	0	(0, 0.25, 0.5)	(0.75, 1, 1)	(0.25, 0.5, 0.75)	C_{12}	(0.25, 0.5, 0.75)	0	(0.25, 0.5, 0.75)	(0.75, 1, 1)	(0.25, 0.5, 0.75)
C_{13}	(0.25, 0.5, 0.75)	(0, 0.25, 0.5)	0	(0.5, 0.75, 1)	(0.5, 0.75, 1)	C_{13}	(0, 0.25, 0.5)	(0, 0.25, 0.5)	0	(0.5, 0.75, 1)	(0.5, 0.75, 1)
C_{14}	(0.5, 0.75, 1)	(0.5, 0.75, 1)	(0, 0.25, 0.5)	0	(0.75, 1, 1)	C_{14}	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)	0	(0.5, 0.75, 1)
C_{15}	(0.75, 1, 1)	(0, 0.25, 0.5)	0	(0, 0.25, 0.5)	0	C_{15}	(0.5, 0.75, 1)	(0, 0.25, 0.5)	(0, 0, 0.25)	(0, 0.25, 0.5)	0
E9	**C_{11} (TFN)**	**C_{12} (TFN)**	**C_{13} (TFN)**	**C_{14} (TFN)**	**C_{15} (TFN)**	**E10**	**C_{11} (TFN)**	**C_{12} (TFN)**	**C_{13} (TFN)**	**C_{14} (TFN)**	**C_{15} (TFN)**
C_{11}	0	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)	C_{11}	0	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)	(0, 0.25, 0.5)	(0.5, 0.75, 1)
C_{12}	(0, 0.25, 0.5)	0	(0.25, 0.5, 0.75)	(0.75, 1, 1)	(0.5, 0.75, 1)	C_{12}	(0, 0.25, 0.5)	0	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)	(0.5, 0.75, 1)
C_{13}	(0.5, 0.75, 1)	(0.5, 0.75, 1)	0	(0.5, 0.75, 1)	(0.5, 0.75, 1)	C_{13}	(0.5, 0.75, 1)	(0, 0.25, 0.5)	0	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)
C_{14}	(0, 0.25, 0.5)	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)	0	(0.5, 0.75, 1)	C_{14}	(0.5, 0.75, 1)	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)	0	(0.75, 1, 1)
C_{15}	(0.5, 0.75, 1)	(0, 0.25, 0.5)	(0, 0, 0.25)	(0.25, 0.5, 0.75)	0	C_{15}	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)	(0, 0, 0.25)	(0.25, 0.5, 0.75)	0

Note. TFN = Triangle Fuzzy Number. C = Criteria.

Table A8. The corresponding triangle fuzzy numbers in Table A3.

E1	**C_{21} (TFN)**	**C_{22} (TFN)**	**C_{23} (TFN)**	**E2**	**C_{21} (TFN)**	**C_{22} (TFN)**	**C_{23} (TFN)**
Application and Installment cost (C_{21})	0	(0.25, 0.5, 0.75)	(0.5, 0.75, 1)	C_{21}	0	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)
Operating cost (C_{22})	(0.75, 1, 1)	0	(0.75, 1, 1)	C_{22}	(0.5, 0.75, 1)	0	(0, 0.25, 0.5)
Training cost (C_{23})	(0.5, 0.75, 1)	(0.5, 0.75, 1)	0	C_{23}	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)	0
E3	**C_{21} (TFN)**	**C_{22}(TFN)**	**C_{23} (TFN)**	**E4**	**C_{21} (TFN)**	**C_{22}(TFN)**	**C_{23} (TFN)**
C_{21}	0	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)	C_{21}	0	(0, 0.25, 0.5)	(0.5, 0.75, 1)
C_{22}	(0.25, 0.5, 0.75)	0	(0.5, 0.75, 1)	C_{22}	(0.25, 0.5, 0.75)	0	(0.5, 0.75, 1)
C_{23}	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)	0	C_{23}	(0, 0.25, 0.5)	(0.5, 0.75, 1)	0
E5	**C_{21} (TFN)**	**C_{22}(TFN)**	**C_{23} (TFN)**	**E6**	**C_{21} (TFN)**	**C_{22}(TFN)**	**C_{23} (TFN)**
C_{21}	0	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)	C_{21}	0	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)
C_{22}	(0.5, 0.75, 1)	0	(0.5, 0.75, 1)	C_{22}	(0.5, 0.75, 1)	0	(0.5, 0.75, 1)
C_{23}	(0.25, 0.5, 0.75)	(0.5, 0.75, 1)	0	C_{23}	(0.25, 0.5, 0.75)	(0.75, 1, 1)	0
E7	**C_{21} (TFN)**	**C_{22}(TFN)**	**C_{23} (TFN)**	**E8**	**C_{21} (TFN)**	**C_{22}(TFN)**	**C_{23} (TFN)**
C_{21}	0	(0.5, 0.75, 1)	(0.75, 1, 1)	C_{21}	0	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)
C_{22}	(0.5, 0.75, 1)	0	(0.25, 0.5, 0.75)	C_{22}	(0.5, 0.75, 1)	0	(0.5, 0.75, 1)
C_{23}	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)	0	C_{23}	(0.75, 1, 1)	(0.75, 1, 1)	0
E9	**C_{21} (TFN)**	**C_{22}(TFN)**	**C_{23} (TFN)**	**E10**	**C_{21} (TFN)**	**C_{22}(TFN)**	**C_{23} (TFN)**
C_{21}	0	(0.5, 0.75, 1)	(0.75, 1, 1)	C_{21}	0	(0.5, 0.75, 1)	(0.75, 1, 1)
C_{22}	(0.5, 0.75, 1)	0	(0.5, 0.75, 1)	C_{22}	(0.5, 0.75, 1)	0	(0.5, 0.75, 1)
C_{23}	(0.75, 1, 1)	(0.25, 0.5, 0.75)	0	C_{23}	(0.25, 0.5, 0.75)	(0.75, 1, 1)	0

Note. TFN = Triangle Fuzzy Number. C = Criteria.

Table A9. The corresponding triangle fuzzy numbers in Table A4.

E1	**C_{31} (TFN)**	**C_{32} (TFN)**	**C_{33} (TFN)**	**E2**	**C_{31} (TFN)**	**C_{32} (TFN)**	**C_{33} (TFN)**
Application and Installment time (C_{31})	0	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)	C_{31}	0	(0, 0, 0.25)	(0, 0.25, 0.5)
Operating time (C_{32})	(0, 0, 0.25)	0	(0.5, 0.75, 1)	C_{32}	(0, 0, 0.25)	0	(0.25, 0.5, 0.75)
Training time (C_{33})	(0, 0, 0.25)	(0.25, 0.5, 0.75)	0	C_{33}	(0, 0, 0.25)	(0.5, 0.75, 1)	0
E3	**C_{31} (TFN)**	**C_{32} (TFN)**	**C_{33} (TFN)**	**E4**	**C_{31} (TFN)**	**C_{32} (TFN)**	**C_{33} (TFN)**
C_{31}	0	(0, 0.25, 0.5)	(0, 0.25, 0.5)	C_{31}	0	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)
C_{32}	(0, 0, 0.25)	0	(0.25, 0.5, 0.75)	C_{32}	(0, 0, 0.25)	0	(0.5, 0.75, 1)
C_{33}	(0, 0, 0.25)	(0, 0.25, 0.5)	0	C_{33}	(0, 0, 0.25)	(0.25, 0.5, 0.75)	0
E5	**C_{31} (TFN)**	**C_{32} (TFN)**	**C_{33} (TFN)**	**E6**	**C_{31} (TFN)**	**C_{32} (TFN)**	**C_{33} (TFN)**
C_{31}	0	(0, 0, 0.25)	(0.25, 0.5, 0.75)	C_{31}	0	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)
C_{32}	(0, 0, 0.25)	0	(0.5, 0.75, 1)	C_{32}	(0, 0, 0.25)	0	(0.75, 1, 1)
C_{33}	(0, 0, 0.25)	(0.25, 0.5, 0.75)	0	C_{33}	(0, 0, 0.25)	(0.25, 0.5, 0.75)	0
E7	**C_{31} (TFN)**	**C_{32} (TFN)**	**C_{33} (TFN)**	**E8**	**C_{31} (TFN)**	**C_{32} (TFN)**	**C_{33} (TFN)**
C_{31}	0	(0, 0, 0.25)	(0.25, 0.5, 0.75)	C_{31}	0	(0, 0, 0.25)	(0.25, 0.5, 0.75)
C_{32}	(0, 0, 0.25)	0	(0.5, 0.75, 1)	C_{32}	(0, 0, 0.25)	0	(0.25, 0.5, 0.75)
C_{33}	(0, 0, 0.25)	(0.25, 0.5, 0.75)	0	C_{33}	(0, 0, 0.25)	(0.5, 0.75, 1)	0
E9	**C_{31} (TFN)**	**C_{32} (TFN)**	**C_{33} (TFN)**	**E10**	**C_{31} (TFN)**	**C_{32} (TFN)**	**C_{33} (TFN)**
C_{31}	0	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)	C_{31}	0	(0, 0, 0.25)	(0.5, 0.75, 1)
C_{32}	(0, 0, 0.25)	0	(0.5, 0.75, 1)	C_{32}	(0, 0, 0.25)	0	(0.5, 0.75, 1)
C_{33}	(0, 0, 0.25)	(0.5, 0.75, 1)	0	C_{33}	(0, 0, 0.25)	(0.5, 0.75, 1)	0

Table A10. The corresponding triangle fuzzy numbers in Table A5.

E1	**C_{41} (TFN)**	**C_{42} (TFN)**	**E2**	**C_{41} (TFN)**	**C_{42} (TFN)**
Internal safety (C_{41})	0	(0, 0.25, 0.5)	C_{41}	0	(0.25, 0.5, 0.75)
External safety (C_{42})	(0.5, 0.75, 1)	0	C_{42}	(0.25, 0.5, 0.75)	0
E3	**C_{41} (TFN)**	**C_{42} (TFN)**	**E4**	**C_{41} (TFN)**	**C_{42} (TFN)**
C_{41}	0	(0, 0.25, 0.5)	C_{41}	0	(0.25, 0.5, 0.75)
C_{42}	(0.5, 0.75, 1)	0	C_{42}	(0.5, 0.75, 1)	0
E5	**C_{41} (TFN)**	**C_{42} (TFN)**	**E6**	**C_{41} (TFN)**	**C_{42} (TFN)**
C_{41}	0	(0.5, 0.75, 1)	C_{41}	0	(0.25, 0.5, 0.75)
C_{42}	(0.5, 0.75, 1)	0	C_{42}	(0.25, 0.5, 0.75)	0
E7	**C_{41} (TFN)**	**C_{42} (TFN)**	**E8**	**C_{41} (TFN)**	**C_{42} (TFN)**
C_{41}	0	(0, 0.25, 0.5)	C_{41}	0	(0.25, 0.5, 0.75)
C_{42}	(0.75, 1, 1)	0	C_{42}	(0.25, 0.5, 0.75)	0
E9	**C_{41} (TFN)**	**C_{42} (TFN)**	**E10**	**C_{41} (TFN)**	**C_{42} (TFN)**
C_{41}	0	(0.25, 0.5, 0.75)	C_{41}	0	(0.25, 0.5, 0.75)
C_{42}	(0.5, 0.75, 1)	0	C_{42}	(0.5, 0.75, 1)	0

Table A11. The de-fuzzy crisp values for Triangle Fuzzy Numbers in Table A6.

E1	**C_1 (DCV)**	**C_2 (DCV)**	**C_3 (DCV)**	**C_4 (DCV)**	**E2**	**C_1 (DCV)**	**C_2 (DCV)**	**C_3 (DCV)**	**C_4 (DCV)**	**E3**	**C_1 (DCV)**	**C_2 (DCV)**	**C_3 (DCV)**	**C_4 (DCV)**	**E4**	**C_1 (DCV)**	**C_2 (DCV)**	**C_3 (DCV)**	**C_4 (DCV)**	**E5**	**C_1 (DCV)**	**C_2 (DCV)**	**C_3 (DCV)**	**C_4 (DCV)**
Efficiency(C_1)	0.00	0.50	0.73	0.73	C_1	0.00	0.50	0.50	0.97	C_1	0.00	0.73	0.27	0.50	C_1	0.00	0.73	0.27	0.73	C_1	0.00	0.25	0.25	0.25
Economical(C_2)	0.73	0.00	0.50	0.50	C_2	0.50	0.00	0.73	0.27	C_2	0.73	0.00	0.50	0.73	C_2	0.26	0.00	0.49	0.49	C_2	0.49	0.00	0.26	0.49
Time(C_3)	0.26	0.49	0.00	0.26	C_3	0.73	0.97	0.00	0.50	C_3	0.73	0.73	0.00	0.27	C_3	0.26	0.26	0.00	0.49	C_3	0.73	0.27	0.00	0.50
Safety(C_4)	0.27	0.97	0.50	0.00	C_4	0.27	0.50	0.73	0.00	C_4	0.73	0.97	0.50	0.00	C_4	0.27	0.73	0.50	0.00	C_4	0.49	0.49	0.49	0.00
E6	**C_1 (DCV)**	**C_2 (DCV)**	**C_3 (DCV)**	**C_4 (DCV)**	**E7**	**C_1 (DCV)**	**C_2 (DCV)**	**C_3 (DCV)**	**C_4 (DCV)**	**E8**	**C_1 (DCV)**	**C_2 (DCV)**	**C_3 (DCV)**	**C_4 (DCV)**	**E9**	**C_1 (DCV)**	**C_2 (DCV)**	**C_3 (DCV)**	**C_4 (DCV)**	**E10**	**C_1 (DCV)**	**C_2 (DCV)**	**C_3 (DCV)**	**C_4 (DCV)**
C_1	0.00	0.27	0.73	0.97	C_1	0.00	0.73	0.50	0.73	C_1	0.00	0.73	0.50	0.73	C_1	0.00	0.73	0.73	0.73	C_1	0.00	0.73	0.97	0.50
C_2	0.50	0.00	0.97	0.73	C_2	0.73	0.00	0.27	0.73	C_2	0.73	0.00	0.27	0.73	C_2	0.73	0.00	0.27	0.73	C_2	0.27	0.00	0.50	0.73
C_3	0.73	0.97	0.00	0.27	C_3	0.50	0.97	0.00	0.73	C_3	0.50	0.73	0.00	0.50	C_3	0.49	0.49	0.00	0.26	C_3	0.73	0.97	0.00	0.50
C_4	0.97	0.73	0.73	0.00	C_4	0.97	0.73	0.97	0.00	C_4	0.97	0.73	0.97	0.00	C_4	0.97	0.73	0.73	0.00	C_4	0.73	0.97	0.50	0.00

Note. DCV = De-fuzzy Crisp Number. **C =** Criteria.

Table A12. The de-fuzzy crisp values for Triangle Fuzzy Numbers in Table A7.

E1	C_{11} (DVC)	C_{12} (DVC)	C_{13} (DVC)	C_{14} (DVC)	C_{15} (DVC)	E2	C_{11} (DVC)	C_{12} (DVC)	C_{13} (DVC)	C_{14} (DVC)	C_{15} (DVC)	E3	C_{11} (DVC)	C_{12} (DVC)	C_{13} (DVC)	C_{14} (DVC)	C_{15} (DVC)	E4	C_{11} (DVC)	C_{12} (DVC)	C_{13} (DVC)	C_{14} (DVC)	C_{15} (DVC)	E5	C_{11} (DVC)	C_{12} (DVC)	C_{13} (DVC)	C_{14} (DVC)	C_{15} (DVC)
EX (C_{11})	0.00	0.40	0.40	0.40	0.92	C_{11}	0.00	0.60	0.95	0.28	0.95	C_{11}	0.00	0.28	0.60	0.95	0.95	C_{11}	0.00	0.92	0.40	0.92	0.40	C_{11}	0.00	0.05	0.95	0.05	0.60
RE (C_{12})	0.45	0.00	0.45	0.97	0.45	C_{12}	0.28	0.00	0.28	0.95	0.28	C_{12}	0.45	0.00	0.21	0.97	0.45	C_{12}	0.95	0.00	0.60	0.95	0.60	C_{12}	0.45	0.00	0.21	0.97	0.45
US (C_{13})	0.28	0.28	0.00	0.95	0.95	C_{13}	0.60	0.60	0.00	0.95	0.95	C_{13}	0.28	0.60	0.00	0.95	0.95	C_{13}	0.70	0.21	0.00	0.97	0.70	C_{13}	0.05	0.60	0.00	0.95	0.95
FO (C_{14})	0.45	0.70	0.45	0.00	0.97	C_{14}	0.21	0.70	0.45	0.00	0.97	C_{14}	0.28	0.60	0.05	0.00	0.95	C_{14}	0.97	0.70	0.45	0.00	0.70	C_{14}	0.60	0.95	0.28	0.00	0.28
EL (C_{15})	0.54	0.54	0.38	0.08	0.00	C_{15}	0.41	0.95	0.60	0.05	0.00	C_{15}	0.41	0.50	0.05	0.17	0.00	C_{15}	0.97	0.54	0.38	0.08	0.00	C_{15}	0.54	0.64	0.27	0.03	0.00
E6	**C_{11} (DVC)**	**C_{12} (DVC)**	**C_{13} (DVC)**	**C_{14} (DVC)**	**C_{15} (DVC)**	**E7**	**C_{11} (DVC)**	**C_{12} (DVC)**	**C_{13} (DVC)**	**C_{14} (DVC)**	**C_{15} (DVC)**	**E8**	**C_{11} (DVC)**	**C_{12} (DVC)**	**C_{13} (DVC)**	**C_{14} (DVC)**	**C_{15} (DVC)**	**E9**	**C_{11} (DVC)**	**C_{12} (DVC)**	**C_{13} (DVC)**	**C_{14} (DVC)**	**C_{15} (DVC)**	**E10**	**C_{11} (DVC)**	**C_{12} (DVC)**	**C_{13} (DVC)**	**C_{14} (DVC)**	**C_{15} (DVC)**
C_{11}	0.00	0.45	0.70	0.45	0.97	C_{11}	0.00	0.28	0.95	0.28	0.60	C_{11}	0.00	0.60	0.28	0.95	0.60	C_{11}	0.00	0.40	0.92	0.92	0.92	C_{11}	0.00	0.95	0.60	0.28	0.95
C_{12}	0.45	0.00	0.45	0.97	0.70	C_{12}	0.45	0.00	0.21	0.97	0.45	C_{12}	0.45	0.00	0.45	0.97	0.45	C_{12}	0.21	0.00	0.45	0.97	0.70	C_{12}	0.28	0.00	0.95	0.60	0.95
C_{13}	0.28	0.28	0.00	0.95	0.60	C_{13}	0.60	0.28	0.00	0.95	0.95	C_{13}	0.28	0.28	0.00	0.95	0.95	C_{13}	0.95	0.95	0.00	0.95	0.95	C_{13}	0.95	0.28	0.00	0.95	0.60
C_{14}	0.60	0.95	0.60	0.00	0.95	C_{14}	0.70	0.70	0.21	0.00	0.97	C_{14}	0.28	0.60	0.60	0.00	0.95	C_{14}	0.28	0.95	0.60	0.00	0.95	C_{14}	0.70	0.70	0.45	0.00	0.97
C_{15}	0.65	0.95	0.60	0.05	0.00	C_{15}	0.73	0.54	0.21	0.03	0.00	C_{15}	0.41	0.50	0.50	0.05	0.00	C_{15}	0.41	0.95	0.50	0.11	0.00	C_{15}	0.95	0.95	0.50	0.11	0.00

Note. DCV = De-fuzzy Crisp Number. C = Criteria.

Table A13. The de-fuzzy crisp values for Triangle Fuzzy Numbers in Table A8.

E1	C_{21} (DVC)	C_{22} (DVC)	C_{23} (DVC)	E2	C_{21} (DVC)	C_{22} (DVC)	C_{23} (DVC)	E3	C_{21} (DVC)	C_{22} (DVC)	C_{23} (DVC)	E4	C_{21} (DVC)	C_{22} (DVC)	C_{23} (DVC)	E5	C_{21} (DVC)	C_{22} (DVC)	C_{23} (DVC)
Application and Installment cost (C_{21})	0.00	0.50	0.73	C_{21}	0.00	0.27	0.50	C_{21}	0.00	0.50	0.50	C_{21}	0.00	0.27	0.73	C_{21}	0.00	0.73	0.50
Operating cost (C_{22})	0.97	0.00	0.97	C_{22}	0.73	0.00	0.27	C_{22}	0.50	0.00	0.73	C_{22}	0.50	0.00	0.73	C_{22}	0.73	0.00	0.73
Training cost (C_{23})	0.73	0.73	0.00	C_{23}	0.50	0.50	0.00	C_{23}	0.27	0.50	0.00	C_{23}	0.27	0.73	0.00	C_{23}	0.50	0.73	0.00
E6	**C_{21} (DVC)**	**C_{22} (DVC)**	**C_{23} (DVC)**	**E7**	**C_{21} (DVC)**	**C_{22} (DVC)**	**C_{23} (DVC)**	**E8**	**C_{21} (DVC)**	**C_{22} (DVC)**	**C_{23} (DVC)**	**E9**	**C_{21} (DVC)**	**C_{22} (DVC)**	**C_{23} (DVC)**	**E10**	**C_{21} (DVC)**	**C_{22} (DVC)**	**C_{23} (DVC)**
C_{21}	0.00	0.27	0.50	C_{21}	0.00	0.73	0.97	C_{21}	0.00	0.73	0.50	C_{21}	0.00	0.73	0.97	C_{21}	0.00	0.73	0.97
C_{22}	0.73	0.00	0.73	C_{22}	0.73	0.00	0.50	C_{22}	0.73	0.00	0.73	C_{22}	0.73	0.00	0.73	C_{22}	0.73	0.00	0.73
C_{23}	0.50	0.97	0.00	C_{23}	0.73	0.50	0.00	C_{23}	0.97	0.97	0.00	C_{23}	0.97	0.50	0.00	C_{23}	0.50	0.97	0.00

Note. DCV = De-fuzzy Crisp Number. C = Criteria.

Table A14. The de-fuzzy crisp values for Triangle Fuzzy Numbers in Table A9.

E1	C_{31} (DVC)	C_{32} (DVC)	C_{33} (DVC)	E2	C_{31} (DVC)	C_{32} (DVC)	C_{33} (DVC)	E3	C_{31} (DVC)	C_{32} (DVC)	C_{33} (DVC)	E4	C_{31} (DVC)	C_{32} (DVC)	C_{33} (DVC)	E5	C_{31} (DVC)	C_{32} (DVC)	C_{33} (DVC)
Application and Installment time(C_{31})	0.00	0.35	0.65	C_{31}	0.00	0.08	0.50	C_{31}	0.00	0.50	0.50	C_{31}	0.00	0.35	0.65	C_{31}	0.00	0.05	0.65
Operating time (C_{32})	0.03	0.00	0.73	C_{32}	0.05	0.00	0.65	C_{32}	0.05	0.00	0.65	C_{32}	0.03	0.00	0.73	C_{32}	0.03	0.00	0.73
Training time (C_{33})	0.05	0.65	0.00	C_{33}	0.03	0.73	0.00	C_{33}	0.08	0.50	0.00	C_{33}	0.05	0.65	0.00	C_{33}	0.05	0.65	0.00
E6	**C_{31} (DVC)**	**C_{32} (DVC)**	**C_{33} (DVC)**	**E7**	**C_{31} (DVC)**	**C_{32} (DVC)**	**C_{33} (DVC)**	**E8**	**C_{31} (DVC)**	**C_{32} (DVC)**	**C_{33} (DVC)**	**E9**	**C_{31} (DVC)**	**C_{32} (DVC)**	**C_{33} (DVC)**	**E10**	**C_{31} (DVC)**	**C_{32} (DVC)**	**C_{33} (DVC)**
C_{31}	0.00	0.35	0.65	C_{31}	0.00	0.05	0.65	C_{31}	0.00	0.05	0.65	C_{31}	0.00	0.35	0.65	C_{31}	0.00	0.03	0.73
C_{32}	0.03	0.00	0.97	C_{32}	0.03	0.00	0.73	C_{32}	0.05	0.00	0.65	C_{32}	0.03	0.00	0.73	C_{32}	0.03	0.00	0.73
C_{33}	0.05	0.65	0.00	C_{33}	0.05	0.65	0.00	C_{33}	0.03	0.73	0.00	C_{33}	0.03	0.73	0.00	C_{33}	0.03	0.73	0.00

Note. DCV = De-fuzzy Crisp Number. C = Criteria.

Table A15. The de-fuzzy crisp values for Triangle Fuzzy Numbers in Table A10.

E1	**C_{41} (DVC)**	**C_{42} (DVC)**	**E2**	**C_{41} (DVC)**	**C_{42} (DVC)**	**E3**	**C_{41} (DVC)**	**C_{42} (DVC)**	**E4**	**C_{41} (DVC)**	**C_{42} (DVC)**	**E5**	**C_{41} (DVC)**	**C_{42} (DVC)**
Internal safety (C_{41})	0.00	0.27	C_{41}	0.00	0.50	C_{41}	0.00	0.27	C_{41}	0.00	0.50	C_{41}	0.00	0.73
External safety (C_{42})	0.73	0.00	C_{42}	0.50	0.00	C_{42}	0.73	0.00	C_{42}	0.73	0.00	C_{42}	0.73	0.00
E6	**C_{41} (DVC)**	**C_{42} (DVC)**	**E7**	**C_{41} (DVC)**	**C_{42} (DVC)**	**E8**	**C_{41} (DVC)**	**C_{42} (DVC)**	**E9**	**C_{41} (DVC)**	**C_{42} (DVC)**	**E10**	**C_{41} (DVC)**	**C_{42} (DVC)**
C_{41}	0.00	0.50	C_{41}	0.00	0.27	C_{41}	0.00	0.50	C_{41}	0.00	0.50	C_{41}	0.00	0.50
C_{42}	0.50	0.00	C_{42}	0.97	0.00	C_{42}	0.50	0.00	C_{42}	0.73	0.00	C_{42}	0.73	0.00

Note. DCV = De-fuzzy Crisp Number. C = Criteria.

References

1. Erasmus, J.; Vanderfeesten, I.; Traganos, K.; Grefen, P. Using business process models for the specification of manufacturing operations. *Comput. Ind.* **2020**, *123*, 103297. [CrossRef]
2. Abhishek, S.; Laurent, T. Functional Programming for Business Process Modeling. *IFAC-PapersOnLine* **2017**, *50*, 10526–10531.
3. Khouloud, G.; Sonia, A.G. An approach for selecting a business process modeling language that best meets the requirements of a modeler. *Procedia Comput. Sci.* **2021**, *181*, 843–851.
4. Kasim, T.; Haracic, M.; Haracic, M. The improvement of business efficiency through business process management. *Econ. Rev. J. Econ. Bus.* **2018**, *16*, 31–43.
5. BPM Expert. *Free & Commercial BPMN 2 Tools for Agile BPM*; PivotPoint Technology Corp.: Fallbrook, CA, USA, 2018.
6. Alaka, H.A.; Oyedele, L.O.; Owolabi, H.A.; Kumar, V.; Ajayi, S.O.; Akinade, O.O.; Bilal, M. Systematic review of bankruptcy prediction models: Towards a framework for tool selection. *Expert Syst. Appl.* **2018**, *94*, 164–184. [CrossRef]
7. Dağdeviren, M.; Yavuz, S.; Kılınç, N. Weapon selection using the AHP and TOPSIS methods under fuzzy environment. *Expert Syst. Appl.* **2009**, *36*, 8143–8151. [CrossRef]
8. Del Giudice, M.; Soto-Acosta, P.; Carayannis, E.; Scuotto, V. Emerging perspectives on business process management (BPM): IT-based processes and ambidextrous organizations, theory and practice. *Bus. Process Manag. J.* **2018**, *24*, 1070–1076. [CrossRef]
9. Utz, W.; Buchmann, R.; Bork, D.; Karagiannis, D. A BPM lifecycle plug-in for modeling methods agility. In Proceedings of the 2020 Americas Conference on Information Systems (AMCIS), Salt Lake City, UT, USA, 10–14 August 2020.
10. Pufahl, L.; Zerbato, F.; Weber, B.; Weber, I. BPMN in healthcare: Challenges and best practices. *Inf. Syst.* **2022**, *107*, 102013. [CrossRef]
11. Vallespir, B.; Ducq, Y. Enterprise modelling: From early languages to models transformation. *Int. J. Prod. Res.* **2018**, *56*, 2878–2896. [CrossRef]
12. Arab, I.; Bourhnane, S.; Kafou, F. Unifying modeling language-merise integration approach for software design. *Int. J. Adv. Comput. Sci. Appl.* **2018**, *9*, 6–12. [CrossRef]
13. El Kihel, Y.; Amrani, A.; Ducq, Y. Linking 4.0 Technologies and performance indicators based on a reference Model for supply chain. In Proceedings of the 13th International Conference on Modeling, Optimization and Simulation, Agadir, Morocco, 12–14 November 2020; pp. 12–14.
14. El Hammoumi, D.Y.A.D. Contribution à la Modélisation de la Supply Chain pour le Pilotage, l'Evaluation de la Performance et l'Intégration des Technologies de l'Industrie 4.0: Application au cas Automobile de PSA Maroc. Ph.D. Thesis, University of Bordeaux, Bordeaux, France, 2021.
15. Zacharewicz, G.; Pirayesh-Neghab, A.; Seregni, M.; Ducq, Y.; Doumeingts, G. Simulation-based enterprise management. In *Guide to Simulation-Based Disciplines*; Springer: Cham, Switzerland, 2017; pp. 261–289.
16. Abrial, J.R. *Data Semantics in Data Base Management*; Koffeman, K., Ed.; North Holland: Amsterdam, The Netherlands, 1974; pp. 1–57.
17. Kosanke, K.; Vernadat, F.; Zelm, M. Means to enable enterprise interoperation: CIMOSA object capability profiles and CIMOSA collaboration view. *Annu. Rev. Control.* **2015**, *39*, 94–101. [CrossRef]
18. Schweizer, H.; Gering, P. Modellierung mit MO 2 GO und Erzeugung eines IEC-konformen Datenoutputs. In *Die Digitalisierung-shürde Lässt sich Meister*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 57–73.
19. Jin, G.; Jäkel, F.W. Execution and evaluation of enterprise models in IEM/MO 2 GO based on Petri net. *Int. J. Adv. Manuf. Technol.* **2018**, *96*, 4517–4537. [CrossRef]
20. Vernadat, F. Enterprise modelling: Research review and outlook. *Comput. Ind.* **2020**, *122*, 103265. [CrossRef]
21. Dakic, D.; Stefanovic, D.; Lolic, T.; Sladojevic, S.; Anderla, A. Production planning business process modelling using UML class diagram. In Proceedings of the 2018 17th International Symposium INFOTEH-JAHORINA (INFOTEH), Jahorina, Bosnia and Herzegovina, 21–23 March 2018; pp. 1–6.
22. Geiger, M.; Harrer, S.; Lenhard, J.; Wirtz, G. BPMN 2.0: The state of support and implementation. *Future Gener. Comput. Syst.* **2018**, *80*, 250–262. [CrossRef]
23. Amjad, A.; Azam, F.; Anwar, M.W.; Butt, W.H.; Rashid, M. Event-driven process chain for modeling and verification of business requirements–a systematic literature review. *IEEE Access* **2018**, *6*, 9027–9048. [CrossRef]
24. Kerbrat, A.; Rivals, I.; Dupuy, P.; Dot, G.; Berg, B.I.; Attali, V.; Schouman, T. Biplanar Low-Dose Radiograph Is Suitable for Cephalometric Analysis in Patients Requiring 3D Evaluation of the Whole Skeleton. *J. Clin. Med.* **2021**, *10*, 5477. [CrossRef] [PubMed]
25. Tbaishat, D. Process architecture development using Riva and ARIS: Comparative study. *Bus. Process Manag. J.* **2018**, *24*, 837–858. [CrossRef]
26. Stirna, J.; Persson, A. An Example of an Enterprise Modeling Method: 4EM. In *Enterprise Modeling*; Springer: Cham, Switzerland, 2018; pp. 51–63.
27. Hunka, F.; van Kervel, S.J. Contract Modeling Utilizing DEMO Co-creation Co-production Model. In Proceedings of the VMBO 2018, Amsterdam, The Netherlands, 26–27 February 2018; pp. 37–45.
28. Binucci, C.; Didimo, W.; Patrignani, M. st-Orientations with Few Transitive Edges. *arXiv* **2022**, arXiv:2208.11414.
29. Zimmermann, A. Modelling and performance evaluation with timenet 4.4. In *International Conference on Quantitative Evaluation of Systems*; Springer: Cham, Switzerland, 2017; pp. 300–303.

30. Amparore, E.G. Stochastic modelling and evaluation using GreatSPN. *ACM SIGMETRICS Perform. Eval. Rev.* **2022**, *49*, 87–91. [CrossRef]
31. TGI Group. Petri Nets World: Online Services for the International Petri Nets Community, University of Hamburg, Germany. 2015. Available online: http://www.informatik.uni-hamburg.de/TGI/PetriNets/index.php (accessed on 10 March 2020).
32. Zbigniew. *Free BPMN Modelling Tools—2020 Edition*; BPM Tips: Warszawa, Poland, 2020.
33. BPM Expert. *How to Select a BPMN Modeling Tool for Business Process Modeling*; PivotPoint Technology Corp.: Fallbrook, CA, USA, 2018.
34. Jäkel, F.W.; Kohl, H. *MO^{2}GO Enterprise Modelling, Analysis and Optimisation*; Fraunhofer-Institute for Production Systems and Design Technology IPK: Berlin, Germany, 1998.
35. Alotaibi, Y. A comprehensive analysis on business process modelling standards, techniques and languages. *Int. J. Comput. Sci. Netw. Secur.* **2020**, *20*, 18–54.
36. Kožíšek, F.; Vrana, I. Business Process Modelling Languages. *AGRIS-Line Pap. Econ. Inform.* **2017**, *9*, 39–49. [CrossRef]
37. Tan, T.; Mills, G.; Papadonikolaki, E.; Liu, Z. Combining multi-criteria decision making (MCDM) methods with building information modelling (BIM): A review. *Autom. Constr.* **2021**, *121*, 103451. [CrossRef]
38. Mufazzal, S.; Muzakkir, S.M. A new multi-criterion decision making (MCDM) method based on proximity indexed value for minimizing rank reversals. *Comput. Ind. Eng.* **2018**, *119*, 427–438. [CrossRef]
39. Rubio-Aliaga, A.; García-Cascales, M.S.; Sánchez-Lozano, J.M.; Molina-Garcia, A. MCDM-based multidimensional approach for selection of optimal groundwater pumping systems: Design and case example. *Renew. Energy* **2021**, *163*, 213–224. [CrossRef]
40. Majumder, M. *Impact of Urbanization on Water Shortage in Face of Climatic Aberrations*; Springer: Cham, Switzerland, 2015.
41. Jin, G.; Sperandio, S.; Girard, P. Selection of design project with the consideration of designers' satisfaction factors and collaboration ability. *Comput. Ind. Eng.* **2019**, *131*, 66–81. [CrossRef]
42. Jin, G.; Sperandio, S.; Girard, P. Management of the design process: Human resource evaluation in factories of the future. *Concurr. Eng.* **2018**, *26*, 313–327. [CrossRef]
43. Ozdemir, Y.S. A Spherical Fuzzy Multi-Criteria Decision-Making Model for Industry 4.0 Performance Measurement. *Axioms* **2022**, *11*, 325. [CrossRef]
44. Kheybari, S.; Rezaie, F.M.; Farazmand, H. Analytic network process: An overview of applications. *Appl. Math. Comput.* **2020**, *367*, 124780. [CrossRef]
45. Bapi, D.; Tanima, S.; Mark, G.; Maria-Teresa, L.; Jose-Luis, V. Post factum analysis in TOPSIS based decision making method. *Expert Syst. Appl.* **2019**, *138*, 112806.
46. Wang, G.; Duan, Y. TOPSIS approach for multi-attribute decision making problems based on n-intuitionistic polygonal fuzzy sets description. *Comput. Ind. Eng.* **2018**, *124*, 573–581. [CrossRef]
47. De Lima Silva, D.F.; de Almeida Filho, A.T. Sorting with TOPSIS through boundary and characteristic profiles. *Comput. Ind. Eng.* **2020**, *141*, 106328. [CrossRef]
48. Jin, G.; Jin, G. Fault-Diagnosis Sensor Selection for Fuel Cell Stack Systems Combining an Analytic Hierarchy Process with the Technique Order Performance Similarity Ideal Solution Method. *Symmetry* **2021**, *13*, 2366. [CrossRef]
49. Dyer, J.S. Multiattribute utility theory (MAUT). In *Multiple Criteria Decision Analysis*; Springer: New York, NY, USA, 2016; pp. 285–314.
50. Figueir, J.R.; Mousseau, V.; Roy, B. ELECTRE methods. In *Multiple Criteria Decision Analysis*; Springer: New York, NY, USA, 2016; pp. 155–185.
51. Agrawal, A.; Seh, A.H.; Baz, A.; Alhakami, H.; Alhakami, W.; Baz, M.; Kumar, R.; Khan, R.A. Software security estimation using the hybrid fuzzy ANP-TOPSIS approach: Design tactics perspective. *Symmetry* **2020**, *12*, 598. [CrossRef]
52. Akram, M.; Smarandache, F. Decision-making with bipolar neutrosophic TOPSIS and bipolar neutrosophic ELECTRE-I. *Axioms* **2018**, *7*, 33. [CrossRef]
53. Naseem, M.H.; Yang, J.; Xiang, Z. Selection of Logistics Service Provider for the E-Commerce Companies in Pakistan based on Integrated GRA-TOPSIS Approach. *Axioms* **2021**, *10*, 208. [CrossRef]
54. Celikbilek, Y.; Tüysüz, F. An in-depth review of theory of the TOPSIS method: An experimental analysis. *J. Manag. Anal.* **2020**, *7*, 281–300. [CrossRef]
55. Yang, Y.P.O.; Shieh, H.M.; Leu, J.D.; Tzeng, G.H. A novel hybrid MCDM model combined with DEMATEL and ANP with applications. *Int. J. Oper. Res.* **2008**, *5*, 160–168.
56. Sun, C.C. A Fuzzy Decision-Making Soft Model for Family Financial Planning in the Post-COVID-19 World. *Axioms* **2022**, *11*, 452. [CrossRef]
57. Sumrit, D.; Anuntavoranich, P. Using DEMATEL method to analyze the causal relations on technological innovation capability evaluation factors in Thai technology-based firms. *Int. Trans. J. Eng. Manag. Appl. Sci. Technol.* **2013**, *4*, 81–103.
58. Mardani, A.; Hooker, R.E.; Ozkul, S.; Yifan, S.; Nilashi, M.; Sabzi, H.Z.; Fei, G.C. Application of decision making and fuzzy sets theory to evaluate the healthcare and medical problems: A review of three decades of research with recent developments. *Expert Syst. Appl.* **2019**, *137*, 202–231. [CrossRef]
59. Akram, M.; Luqman, A.; Kahraman, C. Hesitant Pythagorean fuzzy ELECTRE-II method for multi-criteria decision-making problems. *Appl. Soft Comput.* **2021**, *108*, 107479. [CrossRef]

60. Celik, E.; Akyuz, E. An interval type-2 fuzzy AHP and TOPSIS methods for decision-making problems in maritime transportation engineering: The case of ship loader. *Ocean. Eng.* **2018**, *155*, 371–381. [CrossRef]
61. Karagöz, S.; Deveci, M.; Simic, V.; Aydin, N. Interval type-2 Fuzzy ARAS method for recycling facility location problems. *Appl. Soft Comput.* **2021**, *102*, 107107. [CrossRef]
62. José Luís, P.; Diogo, S. Business Process Modeling Languages: A Comparative Framework. In *New Advances in Information Systems and Technologies*; Springer: Cham, Switzerland, 2016.
63. Zadeh, L.A. Information and control. *Fuzzy Sets* **1965**, *8*, 338–353.
64. Mahmoudi, S.; Jalali, A.; Ahmadi, M.; Abasi, P.; Salari, N. Identifying critical success factors in Heart Failure Self-Care using fuzzy DEMATEL method. *Appl. Soft Comput.* **2019**, *84*, 105729. [CrossRef]
65. Bonita Software. Available online: https://es.bonitasoft.com/ (accessed on 20 May 2021).
66. Camunda. Available online: https://camunda.com/ (accessed on 20 May 2021).
67. Zhang, X.; Su, J. A combined fuzzy DEMATEL and TOPSIS approach for estimating participants in knowledge-intensive crowdsourcing. *Comput. Ind. Eng.* **2019**, *137*, 106085. [CrossRef]