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

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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

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 [Error! Reference source not found.]. 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 [Error! Reference source not found.,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], Petrinet [19], IDEFx [24Error! Reference source not found.], 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]. Kožišek 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. 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]:

1. The pre- and post-steps of the TOPSIS method are logical and easy to comprehend.
2. The calculation steps at a glance.
3. The method can use straightforward mathematical criteria descriptions to find optimal candidate options.
4. 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 (C₁) | Expressiveness (C₁₁) |
| | Readability (C₁₂) |
| | Usability (C₁₃) |
| | Formality (C₁₄) |
| | Ease of Learning (C₁₅) |
| Economical parameters (C₂) | Application and Installment cost (C₂₁) |
| | Operating cost (C₂₂) |
| | Training cost (C₂₃) |
| Time parameters (C₃) | Application and Installment time (C₃₁) |
| | Operating time (C₃₂) |
| | Training time (C₃₃) |
| Safety parameters (C₄) | Internal safety (C₄₁) |
| | External safety (C₄₂) |

Note. C = Criteria.

In Table 1, we find that there are four types of criteria (Efficiency parameters (C₁), Economical parameters (C₂), Time parameters (C₃), and Safety parameters (C₄)), 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 (C₁)** are related to the factors affecting BPM efficiency. Efficiency parameters include Expressiveness, Readability, Usability, Formality, and Ease of Learning.
   - **Expressiveness (C₁₁):** 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 (C₁₂):** This parameter checks whether the model is simple to comprehend for stakeholders.
   - **Usability (C₁₃):** This parameter checks whether the modeling tool is easy to apply and install.
   - **Formality (C₁₄):** This parameter checks whether the model has ambiguities and inaccuracies in model interpretation.
   - **Ease of Learning (C₁₅):** This parameter checks whether the modeling tool and language are easy for the company modelers to learn.

2. **Economical parameters (C₂)** 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 (C21): The cost of parameter configuration, application, and installation when starting to use the modeling tool in the company.

Operating cost (C22): The rental cost of the modeling tool and the salary of the company modelers.

Training cost (C23): Training costs of modeling tools for company modelers.

3. Time parameters (C3) cluster includes application and installment time, operating time, and training time.

Application and installment time (C31): The time consumption of parameter configuration, application, and installation when starting to use the modeling tool in the company.

Operating time (C32): The time consumed by company modelers operating the modeling tool.

Training time (C33): The time consumed by company modelers to learn the modeling language and tool.

4. Safety parameters (C4) 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 (C41): The safety of BPM tools inside the company, such as the software freezes, disappearance, and error storing modeling data.

External safety (C42): 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.
\[ f_A(y) = \begin{cases} 
  y - d, & (d \leq y \leq e) \\
  e - d, & (y < d) \\
  f - y, & (e \leq y \leq f) \\
  f - e, & (f < y) \\
  0, & (y < d, y > f)
\end{cases} \] (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.

| Direct Influence Degree | Fuzzy Rank Value | Triangular Fuzzy Scale |
|-------------------------|------------------|------------------------|
| No impact               | 0                | 0                      | 0.25                   |
| Low impact              | 1                | 0                      | 0.5                    |
| Medium impact           | 2                | 0.25                   | 0.75                   |
| High impact             | 3                | 0.5                    | 1                      |
| Very high impact        | 4                | 0.75                   | 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 $B_{ij} = (d_{ij}^q, e_{ij}^q, f_{ij}^q)$ 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:**
   - $nf_{ij}^q = (f_{ij}^q - min d_{ij}^q)/(max f_{ij}^q - min d_{ij}^q)$
   - $ne_{ij}^q = (e_{ij}^q - min d_{ij}^q)/(max f_{ij}^q - min d_{ij}^q)$
   - $nd_{ij}^q = (d_{ij}^q - min d_{ij}^q)/(max f_{ij}^q - min d_{ij}^q)$

2. **Calculate right and left normalized numbers:**
   - $rn_{ij}^q = nf_{ij}^q/(1 + nf_{ij}^q - ne_{ij}^q)$
   - $ln_{ij}^q = ne_{ij}^q/(1 + ne_{ij}^q - nd_{ij}^q)$

3. **Calculate total generalized crisp numbers:**
   - $tn_{ij}^q = [ln_{ij}^q(1 - ln_{ij}^q) + rn_{ij}^q × ln_{ij}^q]/(1 - ln_{ij}^q + rn_{ij}^q)$

4. **Calculate crisp numbers:**
   - $p_{ij}^q = min d_{ij}^q + tn_{ij}^q × (max f_{ij}^q - min d_{ij}^q)$

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)).

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

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)).

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

where $p_{nm}$ 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):

$$G = \lambda \ast T,$$

where
\[ \lambda = \min \left[ \frac{1}{\max_{1 \leq n \leq J} \sum_{j=1}^{J} t_{nj}} \right] \]  

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 \( \lim_{q \to \infty} G^q \) 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).

  \[ H = \lim_{q \to \infty} (G + G^2 + \ldots + G^q) \]

  \[ = \sum_{q=1}^{\infty} G^q \]  

  where

  \[ \sum_{q=1}^{\infty} G^q = G^1 + G^2 + \ldots + G^q \]

  \[ = G(I + G^1 + G^2 + \ldots + G^{q-1}) \]

  \[ = G(I - G)^{-1}(I - G)(I + G^1 + G^2 + \ldots + G^{q-1}) \]

  \[ = G(I - G)^{-1}(I - G^q) \]

  \[ = G(I - G)^{-1} \]  

- **Step 5:** Calculate the sums of the rows and columns of matrix \( H \).

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

  \[ \text{ro} = [\text{ro}_n] = \left[ \sum_{j=1}^{J} h_{nj} \right] \]  

  \[ \text{co} = [\text{co}_j] = \left[ \sum_{n=1}^{N} h_{nj} \right] \]  

  where \( \text{ro} \) is the sum of the \( n \)th row in matrix \( T \), \( \text{co} \) is the sum of the \( j \)th column in matrix \( T \), and \( [\ ] \) denotes the matrix consisting of the resultant values.

  In Equation (15), the \( \text{ro}_n \) means the total given both direct and indirect fuzzy effects from the criteria \( n \) to the other criteria, and \( \text{co}_j \) means the total received both direct and indirect fuzzy effects from other criteria to criteria \( j \). Therefore, when \( n \) equals \( j \), the value of \((\text{ro}_n + \text{co}_j)\) means the overall impacts both given and received by criteria \( j \), and \((\text{ro}_n + \text{co}_j)\) 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 \((\text{ro}_n + \text{co}_j)\) means the direct and indirect fuzzy effects value of the factors \( j \).

- **Step 6:** Calculate the normalized \((\text{ro}_n + \text{co}_j)\) value.

  \[ \text{NRC}_i = \frac{(\text{ro}_i + \text{co}_i)}{\sum_{j=1}^{J} (\text{ro}_j + \text{co}_j)} \]  

  where \( \sum_{i=1}^{J} \text{NRC}_i = 1 \) and \( \text{NRC}_i \) are normalized \((\text{ro}_i + \text{co}_i)\) 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 \((\text{ro}_n + \text{co}_0)\) 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)).

\[
D = \begin{bmatrix}
A_1 & c_{11} & c_{12} & \cdots & c_{1j} & \cdots & c_{1I} \\
A_2 & c_{21} & c_{22} & \cdots & c_{2j} & \cdots & c_{2I} \\
\vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\
A & c_{I1} & c_{I2} & \cdots & c_{Ij} & \cdots & c_{II} \\
\vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\
A_I & c_{I1} & c_{I2} & \cdots & c_{Ij} & \cdots & c_{II}
\end{bmatrix}
\]  

where \(D\) is the decision matrix, \(A_i\) is alternative to \(i\), \(c_{ij}\) is the \(j\)th standard number corresponding to the \(i\)th alternative (\(A_i\)), \(I\) is the number of alternatives, and \(J\) is the number of criteria.

- Step 8: Get the normalized decision matrix \(Z(=z_{ij})\) (Equation (19)).

\[
z_{ij} = \frac{c_{ij}}{\sqrt{\sum_{i=1}^{I} c_{ij}^2}}
\]  

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

\[
x_{ij} = w_j \cdot z_{ij}
\]

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 \((\text{ro}_n + \text{co}_0)\) value in Section 3.2, and the sum of fuzzy weights is 1 \((\sum_{j=1}^{I} w_j = 1)\).

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

\[
P-I \text{ solution: } x_i^* = \begin{cases} 
\max_i x_{ij}, & i \in l' \\
\min_i x_{ij}, & i \in l''
\end{cases}
\]  

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

\[
N-I \text{ solution: } x_i^0 = \begin{cases} 
\min_i x_{ij}, & i \in l' \\
\max_i x_{ij}, & i \in l''
\end{cases}
\]  

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)).

\[
\text{Distance to P-I solution: } d_i^* = \sqrt{\sum_{j=1}^{I} (x_{ij} - x_i^*)^2}
\]
Distance to N-I solution: \( d_i^0 = \sqrt{\sum_{j=1}^{I} (x_{ij} - x_i^0)^2} \) (24)

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

\[
H_i^* = \frac{d_i^0}{d_i^0 + d_i^*}
\] (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 Table 1 and Table 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.

| Alternative | Efficiency (C_1) | Economical (C_2) | Time (C_3) | Safety (C_4) |
|-------------|------------------|------------------|------------|-------------|
| 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_i, C_2, C_3 and C_4) and corresponding sub-parameters (C_{i1}, C_{i2}, C_{i3}, C_{i4}, C_{i5}, C_{i6}, C_{i7}, C_{i8}, C_{i9}, C_{i10} and C_{i11}) 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 (C_i) | 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 | 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 $\lambda$ value (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 ($\sigma r$ 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 (C_i) | Efficiency (C_1) | Economical (C_2) | Time (C_3) | Safety (C_4) | $r_{o}$ | $r_{o} + c_{o}$ |
|---------|-----------------|-----------------|-----------|-------------|-------|-------------|
| 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 | 6.535 | 7.184 | 6.194 | 6.375 | – | – |

The $r_{o}$ (highlighted in yellow) means the total given both direct and indirect effects from criteria to the other criteria, and co (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 \( r_0 \) and \( c_0 \) values, when \( n \) equals \( j \), \((r_0 + c_0)\) (highlighted in lime green) value, represents the centrality of criterion j.

Table 16. Total direct influence matrix T between Efficiency (C1) sub-criteria.

| E (C1)     | C11 | C12 | C13 | C14 | C15 | \( r_0 \) | \( r_0 + c_0 \) |
|------------|-----|-----|-----|-----|-----|----------|----------------|
| Expressiveness (C11) | 1.05 | 1.36 | 1.18 | 1.34 | 1.66 | 6.59     | 12.25          |
| Readability (C12)    | 1.14 | 1.16 | 1.07 | 1.38 | 1.54 | 6.29     | 12.81          |
| Usability (C13)      | 1.28 | 1.44 | 1.04 | 1.52 | 1.78 | 7.06     | 12.34          |
| Formality (C14)      | 1.21 | 1.44 | 1.11 | 1.17 | 1.68 | 6.61     | 12.97          |
| Ease of Learning (C15)| 0.98 | 1.12 | 0.88 | 0.95 | 1.08 | 5.01     | 12.75          |
| \( c_0 \)           | 5.66 | 6.52 | 5.28 | 6.36 | 7.74 | —        | —              |

Table 17. Total direct influence matrix T between Economical (C2) sub-criteria.

| E (C2)     | C21 | C22 | C23 | \( r_0 \) | \( r_0 + c_0 \) |
|------------|-----|-----|-----|----------|----------------|
| Application and Installment cost (C21) | 4.73 | 4.89 | 5.2 | 14.82    | 14.82          |
| Operating cost (C22)    | 5.51 | 5.03 | 5.65 | 16.19    | 16.19          |
| Training cost (C23)      | 5.27 | 5.18 | 5.12 | 15.57    | 15.57          |
| \( c_0 \)           | 15.51 | 15.1 | 15.97 | —        | —              |

Table 18. Total direct influence matrix T between Time (C3) sub-criteria.

| E (C3)     | C31 | C32 | C33 | \( r_0 \) | \( r_0 + c_0 \) |
|------------|-----|-----|-----|----------|----------------|
| Application and Installment time (C31) | 0.34 | 3.54 | 4.04 | 7.92     | 7.92           |
| Operating time (C32)    | 0.35 | 3.04 | 3.73 | 7.12     | 7.12           |
| Training time (C33)      | 0.34 | 3.36 | 3.15 | 6.85     | 6.85           |
| \( c_0 \)           | 1.03 | 9.94 | 10.92 | —        | —              |

Table 19. Total direct influence matrix T between Safety (C4) sub-criteria.

| E (C4)     | C41 | C42 | \( r_0 \) | \( r_0 + c_0 \) |
|------------|-----|-----|----------|----------------|
| Internal safety (C41) | 1.94 | 1.94 | 3.88     | 8.76           |
| External safety (C42)  | 2.94 | 1.94 | 4.88     | 8.76           |
| \( c_0 \)           | 4.88 | 3.88 | —        | —              |

From the Tables 15–19, we can find the direct and indirect relationships between criteria or sub-criteria. The \( r_0 \) (highlighted in yellow) means the total given both direct and indirect effects from criteria \( n \) to the other criteria (for example, in Table 15, \( r_0 \) = 1.484 + 1.852 + 1.614 + 1.696 = 6.646), and \( c_0 \) (highlighted in pink) means the total received both direct and indirect effects from other criteria to criterion \( j \) (for example, in Table 15, \( c_0 \) = 1.484 + 1.592 + 1.585 + 1.874 = 6.535). After, we obtain the overall direct and indirect impact matrix E with corresponding \( r_0 \) and \( c_0 \) values, when \( n \) equals \( j \), we can release the \((r_0 + c_0)\) (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 \((r_0 + c_0)\) value for all the criterions and sub-criterions like Table 20.
In Table 20, for example, the NRC value for Efficiency parameters (C₁) is 0.251, which is obtained by dividing $r_{01} + cr_{1}$ (Efficiency parameters (C₁)) in Table 15 by the sum of column $r_{m1} + cr_{0}$ in Table 15 ($\frac{0.646 + 0.172 + 0.153 + 0.317}{13.181} = 0.251$). 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.

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 C₁₁ is 0.009. The number is obtained by multiplying the final weight of sub-criteria C₁₁ (0.251 × 0.194 = 0.049) and the normalized decision matrix value for C₁₁ (0.190 = $\frac{2}{\sqrt{24.4^2 + 31.1^2}}$).

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 (C1) | Economical (C2) | Time (C3) | Safety (C4) |
|-------------|-----------------|-----------------|-----------|-------------|
|             | Max             | Max             | Max       | Max         | Max         | Max         | Max         | Max         | Max         |
| T'          | 0.023           | 0.025           | 0.027     | 0.025       | 0.025       | 0.012       | 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 (\( H_i^* = \frac{d_i^0}{d_i^*+d_i^0} = \frac{0.06}{0.06+0.008} = 0.405 \)). Meanwhile, in Table 23, \( d_i^* \) 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 (\( \sqrt{\sum_{j=1}^{13}(x_{ij} - x_{ij}^*)^2} = \sqrt{(0.009 - 0.023)^2 + (0.015 - 0.025)^2 + (0.011 - 0.027)^2 + (0.019 - 0.025)^2 + (0.025 - 0.025)^2 + (0.012 - 0.012)^2 + (0.022 - 0.011)^2 + (0.021 - 0.011)^2 + (0.003 - 0.001)^2 + (0.027 - 0.009)^2 + (0.029 - 0.001)^2 + (0.014 - 0.071)^2 + (0.013 - 0.063)^2} = 0.88 \)). Meanwhile, the \( d_i^0 \) value for T1 is 0.06 (\( \sqrt{\sum_{j=1}^{13}(x_{ij} - x_{ij}^0)^2} = \sqrt{(0.009 - 0.009)^2 + (0.015 - 0.01)^2 + (0.011 - 0.05)^2 + (0.019 - 0.012)^2 + (0.025 - 0.001)^2 + (0.012 - 0.047)^2 + (0.022 - 0.045)^2 + (0.021 - 0.042)^2 + (0.003 - 0.05)^2 + (0.027 - 0.046)^2 + (0.029 - 0.048)^2 + (0.014 - 0.014)^2 + (0.013 - 0.013)^2} = 0.06 \)). 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 (C1)), various expenses incurred when using the BPM tool (C2), application, installment, operating and training time (C3), and security issues affected by BPM tools (C4)), 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 \( C_{34} \), and external safety \( C_{35} \)) 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.

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Appendix A

Table A1. Degree of direct fuzzy influence between criterions.

| E1 | C1 (DFN) | C2 (DFN) | C3 (DFN) | C4 (DFN) | E2 | C1 (DFN) | C2 (DFN) | C3 (DFN) | C4 (DFN) | E3 | C1 (DFN) | C2 (DFN) | C3 (DFN) | C4 (DFN) | E4 | C1 (DFN) | C2 (DFN) | C3 (DFN) | C4 (DFN) | E5 | C1 (DFN) | C2 (DFN) | C3 (DFN) | C4 (DFN) |
|----|----------|----------|----------|----------|----|----------|----------|----------|----------|----|----------|----------|----------|----------|----|----------|----------|----------|----------|----|----------|----------|----------|----------|
| Efficiency (C1) | 0 | 2 | 3 | 3 | C1 | 0 | 2 | 2 | 4 | C1 | 0 | 3 | 1 | 2 | C1 | 0 | 3 | 1 | 3 | C1 | 0 | 1 | 1 | 1 |
| Economical (C2) | 3 | 0 | 2 | 2 | C2 | 2 | 0 | 3 | 1 | C2 | 3 | 0 | 2 | 3 | C2 | 2 | 0 | 2 | 2 | C2 | 2 | 0 | 1 | 2 |
| Time (C3) | 1 | 2 | 0 | 1 | C3 | 3 | 4 | 0 | 2 | C3 | 3 | 3 | 0 | 1 | C3 | 1 | 1 | 0 | 2 | C3 | 3 | 1 | 0 | 2 |
| Safety (C4) | 1 | 4 | 2 | 0 | C4 | 1 | 2 | 3 | 0 | C4 | 3 | 4 | 2 | 0 | C4 | 1 | 3 | 2 | 0 | C4 | 2 | 2 | 2 | 0 |

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

Table A2. Degree of direct fuzzy influence between Efficiency (C1) sub-criterions.

| E1 | C11 (DFN) | C12 (DFN) | C13 (DFN) | C14 (DFN) | E2 | C11 (DFN) | C12 (DFN) | C13 (DFN) | C14 (DFN) | E3 | C11 (DFN) | C12 (DFN) | C13 (DFN) | C14 (DFN) | E4 | C11 (DFN) | C12 (DFN) | C13 (DFN) | C14 (DFN) | E5 | C11 (DFN) | C12 (DFN) | C13 (DFN) | C14 (DFN) |
|----|------------|------------|------------|------------|----|------------|------------|------------|------------|----|------------|------------|------------|------------|----|------------|------------|------------|------------|----|------------|------------|------------|------------|
| EX (C11) | 0 | 1 | 1 | 1 | 2 | C11 | 0 | 2 | 3 | 1 | 3 | C11 | 0 | 1 | 2 | 3 | 3 | C11 | 0 | 2 | 1 | 2 | 1 | C11 | 0 | 0 | 3 | 0 | 2 |
| RE (C12) | 2 | 0 | 2 | 4 | 2 | C12 | 1 | 0 | 1 | 3 | 1 | C12 | 0 | 0 | 1 | 4 | 2 | C12 | 3 | 0 | 2 | 3 | 2 | C12 | 2 | 0 | 1 | 4 | 2 |
| US (C13) | 0 | 0 | 2 | 0 | 3 | C13 | 2 | 0 | 3 | 3 | C13 | 0 | 1 | 2 | 0 | 3 | C13 | 1 | 0 | 4 | 3 | 3 | C13 | 0 | 2 | 0 | 3 | 3 |
| FO (C14) | 2 | 3 | 3 | 2 | 4 | C14 | 1 | 3 | 2 | 0 | 4 | C14 | 0 | 2 | 0 | 0 | 3 | C14 | 4 | 3 | 2 | 0 | 3 | C14 | 2 | 3 | 1 | 0 | 1 |
| EL (C15) | 4 | 1 | 0 | 2 | 0 | C15 | 3 | 2 | 2 | 0 | 0 | C15 | 3 | 1 | 0 | 3 | 0 | C15 | 4 | 1 | 0 | 2 | 0 | C15 | 4 | 2 | 2 | 0 | 0 |

| E6 | C11 (DFN) | C12 (DFN) | C13 (DFN) | C14 (DFN) | E7 | C11 (DFN) | C12 (DFN) | C13 (DFN) | C14 (DFN) | E8 | C11 (DFN) | C12 (DFN) | C13 (DFN) | C14 (DFN) | E9 | C11 (DFN) | C12 (DFN) | C13 (DFN) | C14 (DFN) | E10 | C11 (DFN) | C12 (DFN) | C13 (DFN) | C14 (DFN) |
|----|------------|------------|------------|------------|----|------------|------------|------------|------------|----|------------|------------|------------|------------|----|------------|------------|------------|------------|----|------------|------------|------------|------------|
| C11 | 0 | 2 | 3 | 2 | C11 | 0 | 1 | 3 | 1 | 2 | C11 | 0 | 2 | 1 | 3 | 2 | C11 | 0 | 1 | 2 | 2 | 2 | C11 | 0 | 3 | 2 | 1 | 3 |
| C12 | 2 | 0 | 2 | 4 | C12 | 2 | 0 | 1 | 4 | 2 | C12 | 2 | 0 | 2 | 4 | 2 | C12 | 1 | 0 | 2 | 4 | 3 | C12 | 1 | 0 | 3 | 2 | 3 |
| C13 | 1 | 1 | 0 | 3 | C13 | 2 | 1 | 0 | 3 | 3 | C13 | 1 | 1 | 0 | 3 | 3 | C13 | 3 | 3 | 0 | 3 | 3 | C13 | 3 | 1 | 0 | 3 | 2 |
Note. E = Expert. DFI = Direct Fuzzy Influence. C = Criteria. EX = Expressiveness. RE = Readability. US = Usability. FO = Formality. EL = Ease of Learning.

Table A3. Degree of direct fuzzy influence between Economical (C) sub-criteria.

| E1            | C21 (DFN) | C22 (DFN) | C23 (DFN) | E2            | C21 (DFN) | C22 (DFN) | C23 (DFN) | E3            | C21 (DFN) | C22 (DFN) | C23 (DFN) | E4            | C21 (DFN) | C22 (DFN) | C23 (DFN) | E5            | C21 (DFN) | C22 (DFN) | C23 (DFN) |
|---------------|-----------|-----------|-----------|---------------|-----------|-----------|-----------|---------------|-----------|-----------|-----------|---------------|-----------|-----------|-----------|---------------|-----------|-----------|-----------|
| Application and Installment cost (C31) | 0         | 2         | 3         | C21           | 0         | 1         | 2         | C21           | 0         | 2         | 2         | C21           | 0         | 1         | 3         | C21           | 0         | 3         | 2         |
| Operating cost (C32)                         | 4         | 0         | 4         | C22           | 3         | 0         | 1         | C22           | 2         | 0         | 3         | C22           | 2         | 0         | 3         | C22           | 3         | 0         | 3         |
| Training cost (C33)                          | 3         | 3         | 0         | C23           | 2         | 2         | 0         | C23           | 1         | 2         | 0         | C23           | 1         | 3         | 0         | C23           | 2         | 3         | 0         |

Table A4. Degree of direct fuzzy influence between Time (C) sub-criteria.

| E1            | C31 (DFN) | C32 (DFN) | C33 (DFN) | E2            | C31 (DFN) | C32 (DFN) | C33 (DFN) | E3            | C31 (DFN) | C32 (DFN) | C33 (DFN) | E4            | C31 (DFN) | C32 (DFN) | C33 (DFN) | E5            | C31 (DFN) | C32 (DFN) | C33 (DFN) |
|---------------|-----------|-----------|-----------|---------------|-----------|-----------|-----------|---------------|-----------|-----------|-----------|---------------|-----------|-----------|-----------|---------------|-----------|-----------|-----------|
| Application and Installment time (C31)       | 0         | 1         | 2         | C31           | 0         | 0         | 1         | C31           | 0         | 1         | 1         | C31           | 0         | 1         | 2         | C31           | 0         | 0         | 2         |
| Operating time (C32)                          | 0         | 0         | 3         | C32           | 0         | 0         | 2         | C32           | 0         | 0         | 2         | C32           | 0         | 0         | 3         | C32           | 0         | 0         | 3         |
| Training time (C33)                           | 0         | 2         | 0         | C33           | 0         | 2         | 0         | C33           | 0         | 3         | 0         | C33           | 0         | 3         | 0         | C33           | 0         | 3         | 0         |
Table A5. Degree of direct fuzzy influence between Safety (C) sub-criteria.

| E1          | C4 (DFN) | C5 (DFN) | E2          | C4 (DFN) | C5 (DFN) | E3          | C4 (DFN) | C5 (DFN) | E4          | C4 (DFN) | C5 (DFN) | E5          | C4 (DFN) | C5 (DFN) |
|-------------|----------|----------|-------------|----------|----------|-------------|----------|----------|-------------|----------|----------|-------------|----------|----------|
| Internal safety (C4) | 0        | 1        | C4 (DFN)    | 0        | 2        | C4 (DFN)    | 0        | 1        | C4 (DFN)    | 0        | 2        | C4 (DFN)    | 0        | 3        |
| External safety (C5)  | 3        | 0        | C5 (DFN)    | 2        | 0        | C5 (DFN)    | 3        | 0        | C5 (DFN)    | 0        | 3        | C5 (DFN)    | 0        | 0        |

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

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

| E1          | C1 (TFN) | C2 (TFN) | C3 (TFN) | C4 (TFN) | C5 (TFN) | C6 (TFN) | C7 (TFN) | C8 (TFN) | C9 (TFN) | C10 (TFN) |
|-------------|----------|----------|----------|----------|----------|----------|----------|----------|----------|-----------|
| Efficiency (C1) | 0        | (0.25, 0.5, 0.75) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | C1        | 0        | (0.25, 0.5, 0.75) | (0.25, 0.5, 0.75) | (0.75, 1, 1) |
| Economical (C2) | (0.5, 0.75, 1) | 0        | (0.25, 0.5, 0.75) | (0.25, 0.5, 0.75) | C2        | (0.25, 0.5, 0.75) | 0        | (0.5, 0.75, 1) | (0.25, 0.5)        |
| Time (C3)       | (0.25, 0.5) | (0.25, 0.5) | 0        | (0.25, 0.5) | C3        | (0.5, 0.75, 1) | (0.75, 1, 1) | 0        | (0.25, 0.5, 0.75) |
| Safety (C4)     | (0.25, 0.5) | (0.25, 0.5) | (0.75, 1, 1) | (0.25, 0.5, 0.75) | C4        | (0.25, 0.5) | (0.25, 0.5, 0.75) | (0.5, 0.75, 1) | 0        |
| C1 (TFN)        | 0        | (0.5, 0.75, 1) | (0.25, 0.5, 0.75) | (0.25, 0.5) | C1        | 0        | (0.5, 0.75, 1) | (0.25, 0.5) | (0.5, 0.75, 1) |
| C2 (TFN)        | (0.5, 0.75) | 0        | (0.25, 0.5) | (0.25, 0.5) | C2        | (0.25, 0.5, 0.75) | 0        | (0.25, 0.5, 0.75) | (0.25, 0.5, 0.75) |
| C3 (TFN)        | (0.5, 0.75, 1) | 0        | (0.25, 0.5, 0.75) | (0.25, 0.5, 0.75) | C3        | (0.5, 0.75) | (0.5, 0.75, 1) | (0.75, 1, 1) | 0        |
| C4 (TFN)        | (0.25, 0.5, 0.75) | (0.25, 0.5, 0.75) | (0.25, 0.5, 0.75) | 0        | E6        | C4        | (0.75, 1, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) |
| E5 (DFN)        | 0        | (0.25, 0.5) | (0.25, 0.5) | (0.25, 0.5) | C1        | C1        | 0        | (0.25, 0.5, 0.75) | (0.5, 0.75, 1) |
| C2 (TFN)        | (0.5, 0.75, 1) | 0        | (0.25, 0.5, 0.75) | (0.5, 0.75, 1) | C2        | C2        | (0.5, 0.75, 1) | 0        | (0.75, 1, 1) |
| C3 (TFN)        | (0.25, 0.5, 0.75) | (0.75, 1, 1) | 0        | (0.5, 0.75, 1) | C3        | C3        | (0.5, 0.75, 1) | (0.5, 0.75, 1) | 0        |
| C4 (TFN)        | (0.75, 1, 1) | (0.75, 0.75) | (0.75, 1, 1) | 0        | C4        | C4        | (0.75, 1, 1) | (0.5, 0.75, 1) | (0.75, 1, 1) |

E6

C4 (DFN) | 0        | 2        | C5 (DFN)    | 0        | 2        | C5 (DFN)    | 0        | 2        | C5 (DFN)    | 0        | 2        | C5 (DFN)    | 0        | 2        |

C5 (DFN) | 2        | 0        | C5 (DFN)    | 4        | 0        | C5 (DFN)    | 2        | 0        | C5 (DFN)    | 3        | 0        | C5 (DFN)    | 3        | 0        |

Note. E = Expert. DFI = Direct Fuzzy Influence. C = Criteria.
Table A7. The corresponding triangle fuzzy numbers in Table A2.

|   | E9 | E10 | C1 (TFN) | C2 (TFN) | C3 (TFN) | C4 (TFN) | C5 (TFN) | C6 (TFN) | C7 (TFN) | C8 (TFN) | C9 (TFN) | C10 (TFN) | C11 (TFN) | C12 (TFN) | C13 (TFN) | C14 (TFN) | C15 (TFN) | C16 (TFN) | C17 (TFN) | C18 (TFN) | C19 (TFN) | C20 (TFN) |
|---|----|-----|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| C1 | 0  | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | C1 | 0  | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) |
| C2 | (0.25, 0.5, 0.75) | 0  | (0.25, 0.5, 0.75) | (0.5, 0.75, 1) | C2 | (0.25, 0.5, 0.75) | 0  | (0.25, 0.5, 0.75) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) |
| C3 | (0.75, 1, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | C3 | (0.75, 1, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) | (0.5, 0.75, 1) |

Note. TFN = Triangle Fuzzy Number. C = Criteria.
### Table A8. The corresponding triangle fuzzy numbers in Table A3.

| E1 | $C_{31}$ (TFN) | $C_{32}$ (TFN) | $C_{33}$ (TFN) | $C_{34}$ (TFN) | $C_{35}$ (TFN) | $C_{36}$ (TFN) | $C_{37}$ (TFN) | $C_{38}$ (TFN) | $C_{39}$ (TFN) | $C_{40}$ (TFN) | $C_{41}$ (TFN) |
|----|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|
| E1 | $C_{42}$ (TFN) | $C_{43}$ (TFN) | $C_{44}$ (TFN) | $C_{45}$ (TFN) | $C_{46}$ (TFN) | $C_{47}$ (TFN) | $C_{48}$ (TFN) | $C_{49}$ (TFN) | $C_{50}$ (TFN) | $C_{51}$ (TFN) | $C_{52}$ (TFN) |

Note. TFN = Triangle Fuzzy Number. C = Criteria.
Table A9. The corresponding triangle fuzzy numbers in Table A4.

|       | C_{31} (TFN) | C_{32} (TFN) | C_{33} (TFN) | 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) | (0.25, 0.5, 0.75) | C_{31} | 0            | (0, 0.25)    | (0.25, 0.5, 0.75) |
| C_{32} | (0, 0.25)    | 0            | (0.5, 0.75, 1)  | C_{32} | (0, 0.25)    | 0            | (0.25, 0.5, 0.75) |
| C_{33} | (0, 0.25)    | (0.25, 0.5, 0.75) | 0            | C_{33} | (0, 0.25)    | (0.5, 0.75, 1) | 0            |

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

|       | C_{31} (TFN) | C_{32} (TFN) | E2 | C_{31} (TFN) | C_{32} (TFN) |
|-------|--------------|--------------|----|--------------|--------------|
|       |              |              |    |              |              |
| C_{31} | 0            | (0, 0.25, 0.5) | C_{31} | 0            | (0.25, 0.5, 0.75) |
| C_{32} | (0.5, 0.75, 1) | 0            | C_{32} | (0.5, 0.75, 1) | 0            |
| C_{33} | (0.5, 0.75, 1) | 0            | C_{33} | (0.5, 0.75, 1) | 0            |
Table A11. The de-fuzzy values for Triangle Fuzzy Numbers in Table A6.

| E7  | C41 (TFN) | C42 (TFN) | E8  | C41 (TFN) | C42 (TFN) |
|-----|-----------|-----------|-----|-----------|-----------|
| C41 | 0         | (0.25, 0.5) | C41 | 0         | (0.25, 0.5, 0.75) |
| C42 | (0.75, 1, 1) | 0         | C42 | (0.25, 0.5, 0.75) | 0         |

| E9  | C41 (TFN) | C42 (TFN) | E10 | C41 (TFN) | C42 (TFN) |
|-----|-----------|-----------|-----|-----------|-----------|
| C41 | 0         | (0.25, 0.5, 0.75) | C41 | 0         | (0.25, 0.5, 0.75) |
| C42 | (0.5, 0.75, 1) | 0         | C42 | (0.5, 0.75, 1) | 0         |

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

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

| E1  | C1 (DCV) | C2 (DCV) | C3 (DCV) | C4 (DCV) | E2  | C1 (DCV) | C2 (DCV) | C3 (DCV) | C4 (DCV) | E3  | C1 (DCV) | C2 (DCV) | C3 (DCV) | C4 (DCV) | E4  | C1 (DCV) | C2 (DCV) | C3 (DCV) | C4 (DCV) | E5  | C1 (DCV) | C2 (DCV) | C3 (DCV) | C4 (DCV) | E6  | C1 (DCV) | C2 (DCV) | C3 (DCV) | C4 (DCV) | C5 (DCV) |
|-----|----------|----------|----------|----------|-----|----------|----------|----------|----------|-----|----------|----------|----------|----------|-----|----------|----------|----------|----------|-----|----------|----------|----------|----------|-----|----------|----------|----------|----------|-----|----------|----------|----------|----------|
### Table A13. The de-fuzzy Crisp values for Triangle Fuzzy Numbers in Table A8.

| E1       | C31 (DVC) | C32 (DVC) | C33 (DVC) | E2       | C31 (DVC) | C32 (DVC) | C33 (DVC) | E3       | C31 (DVC) | C32 (DVC) | C33 (DVC) | E4       | C31 (DVC) | C32 (DVC) | C33 (DVC) | E5       | C31 (DVC) | C32 (DVC) | C33 (DVC) |
|---------|-----------|-----------|-----------|---------|-----------|-----------|-----------|---------|-----------|-----------|-----------|---------|-----------|-----------|-----------|---------|-----------|-----------|-----------|
| Application and Installment cost (C31) | 0.00 | 0.50 | 0.73 | C31 | 0.00 | 0.27 | 0.50 | C31 | 0.00 | 0.50 | 0.50 | C31 | 0.00 | 0.27 | 0.73 | C31 | 0.00 | 0.73 | 0.50 |
| Operating cost (C32) | 0.97 | 0.00 | 0.97 | C32 | 0.73 | 0.00 | 0.27 | C32 | 0.50 | 0.00 | 0.73 | C32 | 0.50 | 0.00 | 0.73 | C32 | 0.73 | 0.00 | 0.73 |
| Training cost (C33) | 0.73 | 0.73 | 0.00 | C33 | 0.50 | 0.50 | 0.00 | C33 | 0.27 | 0.50 | 0.00 | C33 | 0.27 | 0.73 | 0.00 | C33 | 0.50 | 0.73 | 0.00 |

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

| E1       | C31 (DVC) | C32 (DVC) | C33 (DVC) | E2       | C31 (DVC) | C32 (DVC) | C33 (DVC) | E3       | C31 (DVC) | C32 (DVC) | C33 (DVC) | E4       | C31 (DVC) | C32 (DVC) | C33 (DVC) | E5       | C31 (DVC) | C32 (DVC) | C33 (DVC) |
|---------|-----------|-----------|-----------|---------|-----------|-----------|-----------|---------|-----------|-----------|-----------|---------|-----------|-----------|-----------|---------|-----------|-----------|-----------|
| Application and Installment time(C31) | 0.00 | 0.35 | 0.65 | C31 | 0.00 | 0.08 | 0.50 | C31 | 0.00 | 0.50 | 0.50 | C31 | 0.00 | 0.35 | 0.65 | C31 | 0.00 | 0.05 | 0.65 |
| Operating time (C32) | 0.03 | 0.00 | 0.73 | C32 | 0.05 | 0.00 | 0.65 | C32 | 0.05 | 0.00 | 0.65 | C32 | 0.03 | 0.00 | 0.73 | C32 | 0.03 | 0.00 | 0.73 |
| Training time (C33) | 0.05 | 0.65 | 0.00 | C33 | 0.03 | 0.73 | 0.00 | C33 | 0.03 | 0.73 | 0.00 | C33 | 0.03 | 0.73 | 0.00 | C33 | 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.

|     | \( C_{41} \) (DVC) | \( C_{42} \) (DVC) | \( C_{41} \) (DVC) | \( C_{42} \) (DVC) | \( C_{41} \) (DVC) | \( C_{42} \) (DVC) | \( C_{41} \) (DVC) | \( C_{42} \) (DVC) | \( C_{41} \) (DVC) | \( C_{42} \) (DVC) |
|-----|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| E1  | 0.00                | 0.27                | 0.00                | 0.50                | 0.00                | 0.27                | 0.00                | 0.50                | 0.00                | 0.73                |
|     | Internal safety \( C_{41} \) |                      |                      |                      |                      |                      |                      |                      |                      |                      |
| E2  | 0.73                | 0.00                | 0.50                | 0.00                | 0.73                | 0.00                | 0.73                | 0.00                | 0.73                | 0.00                |
|     | External safety \( C_{42} \) |                      |                      |                      |                      |                      |                      |                      |                      |                      |
| E6  | 0.00                | 0.50                | 0.00                | 0.27                | 0.00                | 0.50                | 0.00                | 0.50                | 0.00                | 0.50                |
|     | \( C_{41} \)        |                      |                      |                      |                      |                      |                      |                      |                      |                      |
| C42 | 0.50                | 0.00                | 0.97                | 0.00                | 0.50                | 0.00                | 0.73                | 0.00                | 0.73                | 0.00                |

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