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Fuzzy TOPSIS-Based Group Decision Model for Selecting IT Employees

Abigail Vania[1,*], Ditdit Nugeraha Utama[2]

[1,2]*Computer Science Department, BINUS Graduate Program – Master of Computer Science, Bina Nusantara University, Jakarta, Indonesia*

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Abstract

In the era of digitalization, the demand for competent IT employees is growing rapidly. However, the IT employee selection process often faces various challenges, such as biased selection criteria, many applicants, and difficulty in objective assessment. These challenges can lead to inaccurate selection decisions and have a negative impact on company performance. This research aims to develop a Group Decision Support Model (GDSM) for IT Employee Selection using the Fuzzy TOPSIS method to enhance objectivity and reliability in decision-making. This GDSM combines assessments from HRD and User IT groups by considering the weight of each criterion. The proposed model overcomes bias, uncertainty, and subjectivity in judgments from both groups. The GDSM is constructed with 8 parameters/sub-criteria (2 criteria) from the HRD group and 12 parameters (5 criteria) from the User IT group from interviews and research. Thus, the total is 20 assessment parameters, consisting of coding test, education, certification, computer literacy, openness to experience, conscientiousness, extroversion, agreeableness, neuroticism, verbal, numerical, ability to learn, appearance & attitude, work experience, communication skills, time management, job knowledge, motivation to apply, decision making, and service orientation. The methodology involves determining parameters, weights, fuzzification and this GDSM was tested through a limited simulation of IT employee selection using 11 respondents from Computer Science students for evaluation of the model. The result of this model is a ranking of the candidates. The best candidate is Cand. 8, with a closeness coefficient (CC) value of 0.896. The worst candidate is Cand. 3, with CC 0.241. The model is acceptable because it has no difference value between coding and manual for all candidates. This study contributes to increasing objectivity in IT employee selection and offers an implementation model for companies that want to improve the effectiveness of the recruitment process.

Keywords: IT Employees Selection, Fuzzy TOPSIS, Group Decision Support Model, HRD, User IT

1. Introduction

The most important aspect of human resource management is employee recruitment. Difficulties often faced include the very large number of applicants, biased criteria in recruiting employees, and many other challenges. Many companies experience difficulties in recruiting to determine suitable candidates who meet their needs [1], [2], [3]. Standard criteria that determine the qualifications of candidates for the intended position are very important in the personnel decision-making process. The requirements for employees in the IT sector are also not the same from the perspective of human resources and the perspective of IT users. Personality traits that are widely adopted by human resources include; openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism [4], [5]. On the other hand, IT users need to understand and be equipped with certain skills, for example communication skills and computer skills, analytical skills and problem-solving skills, coding skills, time management skills and computer understanding [6], [7].

The concept of setting criteria for IT employees remains important today, especially as information technology has taken center stage as businesses grapple with the modern digital environment. In a LinkedIn report (2023), demand for deputy software engineers and deputy artificial intelligence engineers is still high. Other professions that will be in high demand include data scientists, information security analysts, web developers, software developers, and database administrators will also be more in demand especially in 2023. Indeed, all the vacancies mentioned above require computer science or any IT courses. The growth in demand for IT jobs is estimated to increase job opportunities by 15% from 2021 to 2031 [8]. To handle recruitment challenges, Multi-Criteria Decision Making (MCDM) methods can

***Corresponding author: Abigail Vania (abigail.vania@binus.ac.id)**
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be employed. MCDM is a method that helps make decisions based on various criteria MCDM is a method that helps make decisions based on various criteria [9]. MCDM is also a general problem-solving approach that requires the analysis of various options to produce alternative choices. Problems that need to be solved using MCDM can occur in fields such as engineering, business, etc [10], [11]. Several MCDM methods are often used, including AHP, TOPSIS, PROMETHEE, and others.

AHP is a method discovered by Saaty, uses a hierarchy with a top-down structure to show the relationship between alternatives, criteria, and goals. The AHP method is usually used to calculate criteria weights. AHP also uses a pairwise comparison matrix to assess the relationship between criteria based on their level of importance and employs a consistency ratio to ensure that the pairwise comparison values in the given criteria matrix are consistent [12]. Previous research utilized AHP-ELECTRE to select IT employees based on 8 IT skill criteria (without criteria from the Human Resources side). The results obtained also include rankings of the candidates based on the assessments conducted [13].

Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) is a method developed by Brans. PROMETHEE applies binary comparisons at decision points based on evaluation factors. This method also considers internal relationships with evaluation factors in addition to importance weights that indicate the level of relationship between evaluation factors. [14]. Despite being simpler than AHP because it doesn't require a pairwise comparison matrix, PROMETHEE still involves somewhat complex calculations.

Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is an MCDM method developed by Hwang and Yoon. This method ranks alternatives based on their proximity to both a positive ideal solution and a negative ideal solution. TOPSIS is known for its simplicity and ease of implementation. It calculates the Euclidean distance between each alternative and these ideal solutions, then ranks them based on their preference index value sorted from largest to smallest [15], [16]. Unlike AHP, TOPSIS does not require a comparison matrix or involve multiple phases, making it straightforward to determine preferences compared to methods like PROMETHEE [15]. Additionally, Fuzzy TOPSIS has been used to develop employee selection strategies, highlighting cooperative versus selfish behavior [17].

Nowadays, problems are becoming increasingly complex, requiring group decisions rather than decisions by a single individual. However, each decision-maker in a group often has different levels of interest and preferences [18]. GDSM can help group decision-makers make the right decisions despite these differing interests and preferences.

The main aim of this study is to develop a Group Decision-Making System (GDSM) for selecting IT personnel from the perspectives of Human Resources (HR) and IT users. This approach combines the TOPSIS and Fuzzy TOPSIS methods, as no previous research has utilized this combination for IT employee selection involving multiple perspectives. The study was conducted to help companies in making rational decisions about suitable IT staff and intends to serve as a new reference in the field.

2. Literature Review

2.1. Related Works

Other times, previous research has been conducted several times employing different techniques for selecting employees. Such studies were mainly centered on hiring employees in accordance to the needs of the users. However, selecting employees is different since several factors need to be taken into consideration apart from the user. In this research, the Fuzzy TOPSIS technique is used to identify the optimum IT employees while taking the views of both HRD and User IT into consideration.

In 2020, in conducting the selection of logistics specialists using the Intuitionistic fuzzy TOPSIS method. There are 7 assessment criteria in the selection of logistics specialists, including, graduation, professional experience, computer literacy, fluency in foreign languages, communication skills, analytical thinking, teamwork. This study used 6 candidates, with the highest Closeness Coefficient of 0.774 (on candidate A1). [19] This study used 6 decision makers to determine the weight of each criterion, even each decision maker itself has a weight that affects the assessment of the weight of their criteria. The assessment of candidates is carried out by 3 decision makers. So that the assessment carried out can be said to be quite objective, both the assessment of the weight and the assessment of the candidate itself.

In 2020, fuzzy TOPSIS with Triangular Fuzzy Number (TFN) was applied to assess the business consequences of undertaking the choice of among the employees as well as recognize the best approaches towards selection of employees. This research only used two datasets (Employee A and Employee B) with three criteria: academic experience, technical knowledge, teamwork [17]. Therefore, this research only considers basic factors for selecting an optimal strategy and defining a strategy. Furthermore, there is a lack of identified criteria for the analysis of texts used by the identified journals. Also, the following important issues are revealed Further, the model implementation results are not pointed out clearly. However, it has revealed that the Fuzzy TOPSIS model can be applied to identify appropriate candidates for employment.

In 2020, conducting IT personnel selection using the entropy and divergence measures based method to determine the weight of the criteria and using the Intuitionistic Fuzzy ARAS method for the selection model. There are 3 criteria, including Individual Qualifications, Technical Specifications and General Features. Individual Qualifications has 5 sub-criteria including, Expression and communication, Emotional balance, Quality oriented, Internal and external customer oriented, Crisis management, Basic computer skills, General information about economy and business world. Technical Support has 4 sub-criteria, including, Adaptation level to new technology, software and hardware, Competence of required software, Continuous development and technological relevance, Experience. While General Features has 4 sub-criteria, including Microsoft Office abilities, Foreign language skills, Social activities, Extra achievements. In this study, 5 candidates were used and the assessment of the candidates was carried out by 3 decision makers and the weight of the assessment of each decision maker depends on the level of qualification of the decision maker itself. The best candidate was obtained by Candidate X_4 with the highest degree of utility value, which is 0.9623 [20]. In this study, there is also an objective assessment of candidates because it used more than 1 decision maker and the assessment weight of each decision maker is different. In addition, this study overcomes ambiguity by using Intuitionistic Fuzzy. However, it is very unfortunate that this study focuses too much on non-numerical (qualitative) data.

In 2021, conducted idle-level managers' selection of Dongfeng Commercial Vehicle Co. using the Weighted Cross-Entropy TOPSIS of Hesitant Picture Fuzzy Linguistic Sets method. There are 4 criteria, including negotiation and communication skills, business development capability, sales and marketing capability, and technical background. This study used 4 candidates and the first rank was obtained by Candidate a_4. The assessment of candidates was carried out by 4 departments, including HR, technical, sales, and financial departments [21]. This study uses hamming distance in determining the weight of the criteria, so that it can be used dynamically and the weight of the criteria remains if there is a missing value or no information about the weight. Using the Hesitant Picture Fuzzy Linguistic Sets (HPFLSs) method can overcome the ambiguity of evaluation and is more flexible than traditional fuzzy sets. However, it is unfortunate that the calculation is very complex and highly dependent on the parameters n and θ for calculating HPFLSs.

In 2023, programmers were selected using the AHP-ELECTRE method with 8 criteria. AHP was used to obtain weights, and ELECTRE was used to prioritize recommendations. The criteria used included abstract depiction, conceptual design, logical data model, physical data model, region sets, cyclomatic logic, speed coding, and logical matrices. The dataset consisted of 23 candidates [13]. Based on the criteria obtained, it appears that they only focused on IT skills. Meanwhile, companies may need a suitable personality, not only IT skills. Additionally, ELECTRE is a more complex calculation method compared to TOPSIS. This study produced a ranked list of candidates

There are several methods for selecting employees based on related works. Most of them use TOPSIS or Fuzzy TOPSIS for employee or personnel selection. TOPSIS and Fuzzy TOPSIS have the same basis but differ in their approach; Fuzzy TOPSIS can handle qualitative or subjective values. Most studies either make the criteria too specific or too general for making decisions in employee selection. Additionally, it is rare to find research that uses Fuzzy TOPSIS to select IT employees. A model, especially a GDSM, must be able to help make IT employee selection decisions from various perspectives, including HRD and IT Users. The model using the Fuzzy TOPSIS method can solve problems in selecting IT employees.

3. Methodology

The first step was case analysis. One of the most important aspects of conducting research is understanding the problem. By comprehending the problem, it can serve as the foundation for building the right model. This step was carried out by conducting a literature review to find and understand the case. From the literature study, we can derive research questions and understand the existing issues. We began with the existing theories from the HRD perspective and the technical qualifications of IT employees for selecting IT personnel. However, a model that combines both the HRD and IT user perspectives has not yet been found.

After that, the second step was parameterizing. In building a model, parameters are very important to achieve the goal (selecting candidates). Incorrect parameters can impact candidate selection. Therefore, parameter selection must be determined before the model is created. At this stage, appropriate parameters for selecting IT employees were identified. Parameter search was done by studying literature, such as looking for parameters from the HRD side based on psychological theory and looking at the qualifications of candidates from IT job vacancies as parameters from the IT User side. Additionally, interviews were conducted with HRD experts and IT users to determine and select the necessary parameters for selecting IT employees. The HRD side selected employees based on personality (big five personality or five-factor model) [5] and the candidate's basic abilities. Meanwhile, the IT User side focused more on skills. After determining the parameters, the experts also determined the importance value of each parameter to obtain parameter weights from the perspectives of HRD and IT Users. Apart from that, it also determined fuzzy boundaries based on interviews by experts for big five personality and based on the literature for interview (User IT side) [22].

The third step was data collecting. This data collection was carried out by simulating IT employee selection. The simulation was conducted on 11 computer science students from BINUS University. This simulation included a psychological test, basic ability test, interview, and coding test, lasting for 2 hours. The psychological test has 60 questions; the basic ability test consists of 17 verbal test questions, 15 numerical test questions, and 15 learning ability questions. Psychological test questions and basic abilities were obtained from the internet with expert approval.

After getting the data, the forth step was GDSM constructing. In the model constructing step, the model was developed using a combination of the Fuzzy TOPSIS and TOPSIS methods. The data used was fuzzy only for assessments from the HRD side for psychological tests and from IT Users for interviews because this data often could not be measured standardly. The fuzzy logic is usually implemented in problems that have elements of uncertainty, imprecision, etc. Examples of words indicating uncertainty are "somewhat," "more or less," and "a little.". Apart from these parameters, TOPSIS was used. The model combining the TOPSIS and Fuzzy TOPSIS methods was built using the Python programming language, and the code was run on Google Colab.

Because this research used Fuzzy logic, and there are several membership functions that can be used, we use the Triangular Fuzzy Number, which is one type of membership function [23]. Combination of two linear curves, specifically a descending linear curve and an ascending linear curve is Triangular Fuzzy Number (figure 1). The triangular curve has three parameters: the starting point (a), the peak point (b), and the endpoint (c). The membership function of the triangular curve is formulated as in (1). This function determines the degree of membership of each value in the fuzzy set, giving the highest value at the peak of the triangle and decreasing linearly towards the starting point and endpoint.

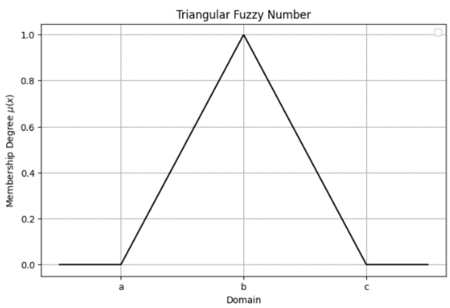

Figure 1. The membership Function of The Triangular Fuzzy Number

Fuzzy TOPSIS is a method developed in 1981. It is one of the most widely used MCDM methods. This method is used to optimize decision-making by calculating the distance between each alternative and the positive ideal solution, as well as the distance from the negative ideal solution [24]. The result is a ranking of the alternatives. The following are the steps for implementing Fuzzy TOPSIS [24], [25]. First, forming decision matrix is shown as (2). Where $\widetilde{D}$ is the matrix of alternative evaluations against the criteria, A_m is the m-th alternative, C_n is the n-th criterion and $x_{i,j}$ is the value of the i-th alternative against the j-th criterion in fuzzy form.

$$\mu[x] = \begin{cases} 0, x \leq a \cup x \geq c \\ \frac{x-a}{b-a}, a < x < b \\ 1, x = b \\ \frac{c-x}{c-b}, b < x < c \end{cases} \tag{1}$$

Second, forming the fuzzy normalization decision matrix is shown as (3) and (4). If the criterion is a benefit criterion, normalize it as in as (3). If the criterion is a cost criterion, normalize it as in as (4). Here, $\tilde{r}_{i,j}$ represents the normalized value in the i-th row and j-th criterion. c_j^* is the maximum of the upper bounds in the matrix for the j-th criterion. Then, $a_{i,j}$ represents the lower bound in the matrix for the i-th alternative and j-th criterion. Additionally, there is $b_{i,j}$ represents the peak value in the matrix for the i-th alternative and j-th criterion and $c_{i,j}$ is the upper bound in the matrix of the i-th alternative and j-th criterion. Then, a_j^- is the minimum of the lower bounds in the matrix for the j-th criterion.

$$\widetilde{D} = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & C_3 & C_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} & \begin{bmatrix} \tilde{x}_{1,1} & \tilde{x}_{1,2} & \tilde{x}_{1,3} & \tilde{x}_{1,n} \\ \tilde{x}_{2,1} & \tilde{x}_{2,2} & \tilde{x}_{2,3} & \tilde{x}_{2,n} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m,,2} & \tilde{x}_{m,3} & \tilde{x}_{m,n} \end{bmatrix} \end{array} \tag{2}$$

$$\tilde{r}_{i,j} = (\frac{a_{i,j}}{c_j^*}, \frac{b_{i,j}}{c_j^*}, \frac{c_{i,j}}{c_j^*}) \tag{3}$$

$$\tilde{r}_{i,j} = (\frac{a_j^-}{c_{i,j}}, \frac{a_j^-}{b_{i,j}}, \frac{a_j^-}{a_{i,j}}) \tag{4}$$

Third, calculating the weights with normalized matrix. In this stage, the weights are multiplied with the normalized matrix as shown in (5). Where, $\tilde{v}_{i,j}$ is the result of the multiplication of the normalized matrix for the i-th alternative and the j-th criterion with the weight of the j-th criterion and w_j is the weight value for the j-th criterion. Fourth, finding positive and negative ideal solution as shown in (6) and (7). S^+ represents positive ideal solution and S^- represents negative ideal solution. $\tilde{v}_j$ is the maximum value from the multiplication of the normalized matrix for the i-th alternative and the j-th criterion with the weight of the j-th criterion. $\tilde{v}^-{}_j$ is the minimum value from the multiplication of the normalized matrix for the i-th alternative and the j-th criterion with the weight of the j-th criterion.

$$\mathrm{\tilde{v}_{i,j} = \tilde{r}_{i,j} \times w_j} \tag{2}$$

$$\mathrm{S^+ = \{\tilde{v}_{1,}\tilde{v}_{2,}\tilde{v}_{3,} \ldots, \tilde{v}_n\}} \tag{3}$$

$$\mathrm{S^- = \{\tilde{v}^-{}_{1,}\tilde{v}^-{}_{2,}\tilde{v}^-{}_{3,} \ldots, \tilde{v}^-{}_n\}} \tag{4}$$

Fifth, calculating the distance between each alternative and the ideal and anti-ideal solution as shown in (8) and (9). Where $[\tilde{x} - \tilde{y}]^2$ can be obtained by $(a_1 - a_2)^2 + (b_1 - b_2)^2 + (c_1 - c_2)^2$, considering $\tilde{x}$ as (a_1, b_1, c_1) and $\tilde{y}$ A (a_2, b_2, c_2). Then, d_i^+ is the ideal solution for the i-th alternative and d_i^- is the anti-ideal solution for the i-th alternative. Sixth, calculating the closeness coefficient as shown in (10). Where, CC_i represents the closeness coefficient for the i-th alternative. After that, ranking the alternative based on closeness coefficient. The alternatives are ranked from the highest (most recommended alternative) to the lowest value of the closeness coefficient. The fifth step was model verifying and validating. This stage is carried out to evaluate the model. The process involved verifying the methods, algorithms, and parameters used to ensure they are in accordance with applicable theory and interview results. Validation is conducted by comparing the data to determine whether it aligns with reality or actual data. In this research, verification includes 4 indicators: parameters, fuzzy TOPSIS process, TOPSIS process, TOPSIS merging process, and

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fuzzy TOPSIS. Meanwhile, validation includes 2 indicators: input and output data. The result of this stage will have a verification value of 1, which means that the data used in the model is 100% correct. Similarly, for the validation value, the expected value is 1 (indicating a 100% correct value).

$$d_i^{+} = \sqrt{\sum_{j=1}^{n}\left[\tilde{v}_{i,j} - \tilde{v}_j\right]^2} \tag{5}$$

$$d_i^{-} = \sqrt{\sum_{j=1}^{n}\left[\tilde{v}_{i,j} - \tilde{v}^{-}{}_j\right]^2} \tag{6}$$

$$CC_i = \frac{d_i^{-}}{d_i^{-} + d_i^{+}} \tag{7}$$

Lastly, documenting GDSM for selecting IT employees. This documentation takes the form of a thesis and journal. It is hoped that this documentation can serve as a reference for future researchers and as evidence of the contributions made Result and Discussion.

3.1. Decision Parameters

Parameters are very important in building a model. To identify these parameters, a parameterization step is conducted. After conducting literature reviews and interviews, 20 parameters were identified. These parameters form a GDSM for selecting IT employees, providing recommendations in the form of rankings. The development of the IT employee selection model involves two groups: HRD and User IT.

The group of HRD has two criteria: 'psychological test' (based on literature reviews and expert reviews) and 'basic competency test' (based on expert reviews). The 'psychological test' includes five sub-criteria: 'openness to experience' (A1), 'conscientiousness' (A2), 'extroversion' (A3), 'agreeableness' (A4), and 'neuroticism' (A5). The ‘psychological test’ uses the Big Five Personalities theory, and this assessment is very important for working as an IT employee. Like ‘openness to experience’ is needed in IT employees because technology continues to develop so that IT employees must continue to want to learn something new. In ‘conscientiousness’ IT employees are needed because they complete tasks on time and maintain the quality of the work results. ‘’Extroversion’’ is needed because it helps IT employees communicate so that they can work in teams or consult with users. IT employees need a friendly, cooperative attitude to reduce conflict in the work environment called ‘Agreeableness’. IT employees also need emotional stability in doing their work in order to produce maximum results because often tasks for IT employees have very tight deadlines, therefore ‘Neuroticism’ is needed. The 'basic competency test' includes three sub-criteria: 'verbal' (B1), 'numeric' (B2), and 'ability to learn' (B3). ‘Verbal’ is needed because as an IT employee it is necessary to understand reading, and be able to explain such as instructions or technical documentation, project requirements and conditions. In the IT world, often solving problems requires logic, so that a ‘numerical’ assessment is needed. The IT world continues to move and develop very quickly, so IT employees are needed who are able to adapt quickly to change so that the ‘ability to learn’ is needed.

The group of User IT consists of five criteria: 'interview', 'coding test' (D1) (to see the ability to solve problems using logic and how to express the solution in coding), 'education' (E1) (to find out whether the candidate has basic theory about IT based on the major they took), 'certification' (F1) (when the candidate has certification, it means their ability has been tested and validated), and 'computer literacy' (G1) (to find out what programming languages they have mastered and can adjust the programming language that is often used in a company). The 'interview' criterion is further divided into eight sub-criteria: 'appearance & attitude' (C1) (good attitude and appearance, can improve the work atmosphere to be more productive and collaborative), 'work experience' (C2) (the experience that employees have can provide varied solutions and adapt more quickly), 'communication skills' (C3) (IT employees are required to have the ability to explain something without using technical language to the team, or users or other parties), 'time management' (C4) (not a few tasks for IT employees have tight deadlines, so this parameter is needed), 'job knowledge' (C5) (when candidates really understand the field of work they are applying for, they will be able to solve problems more quickly), 'motivation to apply' (C6) (seeing the seriousness of the candidate's application so that they can work seriously and optimally), 'decision making' (C7) (IT employees need decision-making skills because they are faced with various options to determine solutions and think about the positives and negatives of the solutions they provide), and 'service orientation' (C8) (needed to prioritize satisfaction and think about customer needs in developing products such as application development). ‘Interview’ parameters are based on expert reviews while ‘coding test’ parameter is based on literature reviews and expert reviews, ‘education’, ‘certification’ and ‘computer literacy’ are based on literature reviews.

Thus, there are a total of 20 parameters: 8 from the HRD group and 12 from the User IT group. Descriptions of the parameter values and types are provided in table 1. For example, the sub-criterion "Openness to Experience" is coded as A1, with the explanation that "openness to experience" refers to high levels of curiosity, creativity, and imagination, measured on a scale from 0 to 100%. This will be calculated using fuzzy logic, and its criterion type is classified as a benefit. The same applies to the other sub-criteria.

Table 1. Details of Parameters

Code	Description	Value	Type/Criteria Type
A1	High curiosity, creativity, imagination	0-100 (in percentage)	Fuzzy/Benefit
⋮	⋮	⋮	⋮
G1	Knowledge of IT (number of programming languages known)	≥ 0 (Programming languages known)	Non-fuzzy/Benefit

After determining the parameters, the next step is to determine the weight of each parameter. Weighting is carried out to determine the level of importance of each parameter. There are several ways to determine parameter weights, one of which is by conducting interviews. This interview is conducted in an expert manner, with experts giving a rating between 1 (not important) and 5 (very important). Each group (HRD and IT User) has 3 experts who assess the level of importance of the parameters. The assessment uses more than 1 expert and count the assessment using average to avoid bias in the assessment. In addition, the experts who conduct the assessment are experts who have experience in their respective fields for more than 5 years (HRD experts have 10 years of experience in conducting IT employee selection in a digital marketing company that has web development, application hosting, website design, and digital advertising services, while the User IT experts work as the head of the IT department at a foundation of one of the best schools in Jakarta for more than 10 years and work as a data engineer for more than 5 years at one of the e-commerce companies in Indonesia). The scores given by the experts for each group are averaged for each group, criteria, and sub-criteria. After averaging, a weight is obtained for each group, criterion, and sub-criteria. For example, average weight of ‘HRD’ group is 3.333 (get it from $\frac{3.000+4.000+3.000}{3} = 3.333$) and average weight of ‘User IT’ is 5.000 (get it from $\frac{5.000+5.000+5.000}{3} = 5.000$). So, the final weight for ‘User IT’ group is 0.400 (get it from $\frac{3.333}{3.333+5.000} = 0.400$) as shown in table 2.

Table 2. Weights by Group

No	Group	Count Expert 1	Count Expert 2	Count Expert 3	Average	Weight
1	HRD	3.000	4.000	3.000	3.333	0.400
2	User IT	5.000	5.000	5.000	5.000	0.600

Likewise, the same method is used to obtain the criteria weights in the 'HRD' group as in table 3 and the criteria weights in the 'User IT' group as in table 4.

Table 3. Weight of Criteria from The HRD Group

No	Criteria	Count Expert 1	Count Expert 2	Count Expert 3	Average	Weight
1	Psychological test	3.000	3.000	3.000	3.000	0.391
2	Basic Competency Test	5.000	4.000	5.000	4.667	0.609

Table 4. Weight of Criteria from The User IT Group

No	Criteria	Count Expert 1	Count Expert 2	Count Expert 3	Average	Weight
1	Interview	5.000	4.000	4.000	4.333	0.206
2	Coding Test	5.000	5.000	5.000	5.000	0.238
3	Education	4.000	3.000	3.000	3.333	0.195
4	Certification	3.000	4.000	3.000	3.333	0.159
5	Computer Literacy	5.000	5.000	5.000	5.000	0.238

The same calculation method is also used to obtain weights on the sub-criteria of the 'The Psychological Test' criteria as in table 5, the sub-criteria of the 'The Basic Competency Test Criteria' criteria as in table 6, and the sub-criteria of the 'The Interview Criteria' criteria as in table 7.

Table 5. Weight of Sub-Criteria from The Psychological Test Criteria

No	Sub-criteria	Count Expert 1	Count Expert 2	Count Expert 3	Average	Weight
1	Openness to experience	5.000	5.000	5.000	5.000	0.254
2	Conscientiousness	4.000	4.000	4.000	4.000	0.203
3	Extroversion	2.000	3.000	3.000	2.667	0.136
4	Agreeableness	4.000	4.000	4.000	4.000	0.203
5	Neuroticism	4.000	4.000	4.000	4.000	0.203

Table 6. Weight of Sub-Criteria from The Basic Competency Test Criteria

No	Sub-criteria	Count Expert 1	Count Expert 2	Count Expert 3	Average	Weight
1	Verbal	4.000	3.000	3.000	3.333	0.250
2	Numeric	5.000	5.000	5.000	5.000	0.375
3	Ability to Learn	5.000	5.000	5.000	5.000	0.375

Table 7. Weight of Sub-Criteria from The Interview Criteria

No	Sub-criteria	Count Expert 1	Count Expert 2	Count Expert 3	Average	Weight
1	Appearance & attitude	4.000	4.000	3.000	3.667	0.131
2	Work experience	4.000	5.000	4.000	4.333	0.155
3	Communication Skills	3.000	4.000	3.000	3.333	0.119
4	Time Management	4.000	3.000	3.000	3.333	0.119
5	Job knowledge	4.000	4.000	4.000	4.000	0.143
6	Motivation to apply	3.000	2.000	2.000	2.333	0.083
7	Decision making	3.000	4.000	3.000	3.333	0.119
8	Service orientation	4.000	3.000	4.000	3.667	0.131

Then, to get the final weight, it is obtained by multiplying at each level. For example, the sub-criteria 'openness to experience' is from the 'HRD' group and the 'psychological test' criterion. The weight of the 'HRD' group is 0.4, the weight of the 'psychological test' criteria is 0.391, and the weight of 'openness to experience' is 0.254. Then the final weight is 0.4 * 0.391 * 0.254, which results in 0.040 as shown in table 8.

Table 8. Final Weight

Code	Final Weight	Code	Final Weight
A1	0.040	C3	0.412
A2	0.032	C4	0.412

Code	Final Weight	Code	Final Weight
A3	0.021	C5	0.494
A4	0.032	C6	0.288
A5	0.032	C7	0.412
B1	0.061	C8	0.453
B2	0.091	D1	0.143
B3	0.091	E1	0.095
C1	0.453	F1	0.095
C2	0.536	G1	0.143

Some parameters use fuzzy because they are considered unable to be measured in a standard way. The parameters that use fuzzy are in the 'psychological test' and 'interview' criteria because these criteria are assessed subjectively. By using fuzzy on the 'psychological test' and 'interview' criteria, you can provide a more objective and more certain assessment. The ‘psychological test’ has 3 levels of importance. The importance levels are: ‘Low’ with fuzzy number (0, 0, 50), ‘Medium’ with fuzzy number (20, 50, 80) and ‘High’ with fuzzy number (50, 100, 100). The ‘interview’ has 5 levels of importance. The importance levels are: ‘Very Bad’ with fuzzy number (1,1,3), ‘Bad’ with fuzzy number (1, 3, 5), ‘Enough’ with fuzzy number (3, 5, 7), ‘Good’ with fuzzy number (5, 7, 9) and ‘Very Good’ with fuzzy number (7, 9, 9) [22]. Because the parameters in the 'psychological test' and 'interview' criteria will be calculated using fuzzy, the weights in these criteria must also be changed to fuzzy weights with a membership function as shown in figure 2. The fuzzy weights have 7 levels of importance. The importance levels are: 'Very Low' with fuzzy number (0, 0, 0.1), 'Low' with fuzzy number (0, 0.1, 0.3), 'Medium Low' with fuzzy number (0.1, 0.3, 0.5), 'Medium' with fuzzy number (0.3, 0.5, 0.7), 'Medium High' with fuzzy number (0.5, 0.7, 0.9), 'High' with fuzzy number (0.7, 0.9, 1.0), and 'Very High' with fuzzy number (0.9, 1.0, 1.0) [21].

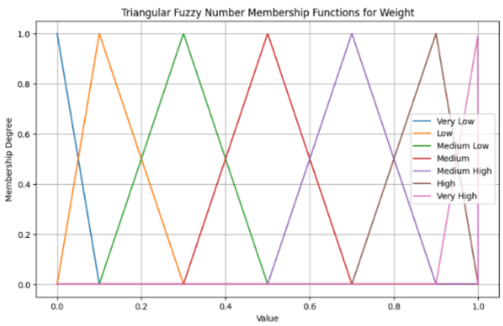

Figure 2. Membership Function for Weight

Fuzzy weight calculations use the Zadeh extension (multiplication of fuzzy numbers). For example, to obtain the fuzzy weight for the 'openness to experience' sub-criterion, you must multiply the fuzzy weight of the 'HRD' group, the fuzzy weight of the 'psychological test' criterion, and the fuzzy weight of the 'openness to experience' sub-criterion. The weight of the 'HRD' group is 0.4, which is then converted to fuzzy values (0.3, 0.5, 0.7). The weight of the 'psychological test' criterion is 0.391, with fuzzy values (0.1, 0.3, 0.5), and the weight of the 'openness to experience' sub-criterion is 0.254, with fuzzy values (0.1, 0.3, 0.5). Thus, the final fuzzy value obtained for the 'openness to experience' parameter is $(0.3 * 0.1 * 0.1, 0.5 * 0.3 * 0.3, 0.7 * 0.5 * 0.5) = (0.003, 0.045, 0.175)$. Similarly, calculations for other parameters are performed.

3.2. Raw Data

The data used for the simulation is primary data, collected as if selecting IT employees using Computer Science student respondents from BINUS University. This data collection was carried out by having respondents complete a series of tests, such as psychological test, basic competency test, and coding test. The questions for the psychological tests, basic ability tests, and coding tests were sourced from the internet and then validated by experts. Additionally, respondents also underwent interviews, which were conducted and assessed by experts. The data obtained is as shown in the table 9.

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Table 9. Raw Data

	Cand. 1	Cand. 2	…	Cand. 10	Cand. 11
A1	79.000	81.000	…	75.000	79.000
⋮	…	…	…	…	⋮
G1	3.000	3.000	…	4.000	4.000

3.3. Model and Algorithm

This section discusses the algorithm for building models using the Fuzzy TOPSIS method. In building the model, specific steps were needed to achieve the goal of developing the GDSM for IT employee selection, as shown in figure 5. First of all, the data was read. Then, it is determined which parameters will be calculated using fuzzy logic and which will not. If the parameter is fuzzy, the membership function needs to be read. Next, the value of the parameter is read and the value and weight are fuzzified. This fuzzification process is used to overcome subjective problems. Such as the assessment of the parameter 'motivation' in the 'interview' criteria, often the assessment is difficult to measure, so changing the crisp value to fuzzy, easier to interpret based on categories and easier to understand. For example, a candidate has a value of 8 out of 10, the value can be said to be 'Good' but also can be said to be 'Very Good' based on figure 4, this is where fuzzy plays a role. Since the value has two assessment categories, fuzzy considers the two categories. If there is another candidate with a value of 8.1, then this fuzzification process also makes the difference minimal by combining them in the same category. So, by using fuzzy logic, it can make the assessment more objective and more reliable. Membership function for 'psychological test' criteria as in the figure 3 and 'interview' criteria as in the figure 4. Then, calculations were performed using the method's formula to obtain the square of the ideal solution and the square of the anti-ideal solution.

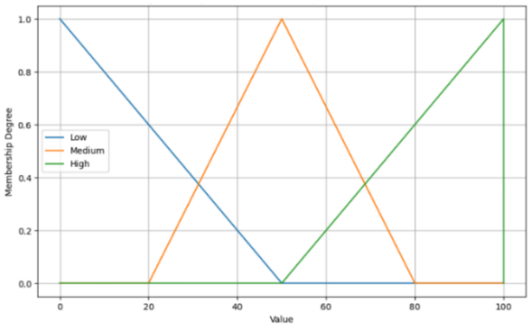

Figure 3. Membership function for Psychological Test

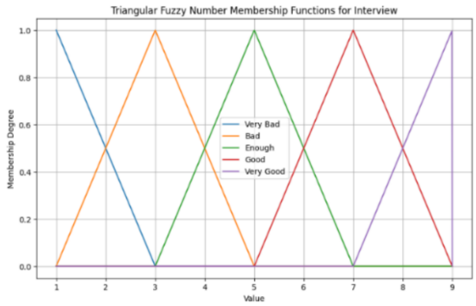

Figure 4. Membership function for Interview

Meanwhile, for non-fuzzy parameters, following the steps for fuzzy parameters involved only a slightly different formula. After reading the non-fuzzy parameter values, perform min-max normalization as in (11) for the benefit parameters and as in (12) for the cost parameters, where $r_{i,j}^{norm}$ is normalization value in the i-th row and j-th criterion, x_{ij} is value on the i-th alternative and j-th criteria, $x_{max\ j}$ is maximum value on the i-th alternative and j-th criterion, $x_{min\ j}$ is minimum value on the i-th alternative and j-th criterion. Then, multipled the normalized matrix for the i-th alternative and j-th criterion (r_{ij}) by the weight of the j-th criterion (w_j) as in (13). Next, find the positive ideal solutions (S^+) and negative ideal solutions (S^-) as shown in (14) and (15), where v_j is $\underset{i}{max}\{v_{i,j}\}$ which means the maximum value of the result of multiplying the normalization matrix on the i-th alternative and the j-th criterion with the weight of the j-th criterion on the j-th criterion, where $v^-{}_j$ is $\underset{i}{min}\{v_{i,j}\}$ which means the minimum value of the result of multiplying the normalization matrix on the i-th alternative and the j-th criterion with the weight of the j-th criterion on the j-th criterion.

$$r_{i,j}^{norm} = \frac{x_{ij} - x_{min\ j}}{x_{max\ j} - x_{min\ j}} \tag{11}$$

$$r_{i,j}^{norm} = \frac{x_{max} - x_{ij}}{x_{max\ j} - x_{min\ j}} \tag{12}$$

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$$v_{ij} = r_{ij} \times w_j \tag{13}$$

$$S^+ = \{v_1, v_2, v_3, \dots, v_n\} \tag{14}$$

$$S^- = \{v_1^-, v_2^-, v_3^-, \dots, v_n^-\} \tag{15}$$

$$(dnf_i^+)^2 = \sum_{j=1}^{n} \left(v_{i,j} - v_j\right)^2 \tag{16}$$

$$(dnf_i^-)^2 = \sum_{j=1}^{n} \left(v_{i,j} - v^-_j\right)^2 \tag{17}$$

Then, calculate the distance square of the ideal solution non-fuzzy ($(dnf_i^+)^2$) is the sum of the squared differences of each alternative ($v_{i,j}$) with the positive ideal solution on non-fuzzy parameters (v_j) as shown in (16) and the distance square of the anti-ideal solution non-fuzzy ($(dnf_i^-)^2$) is the sum of the squared differences of each alternative ($v_{i,j}$)with the negative ideal solution on non-fuzzy parameters (v_j^-) as shown in (17).

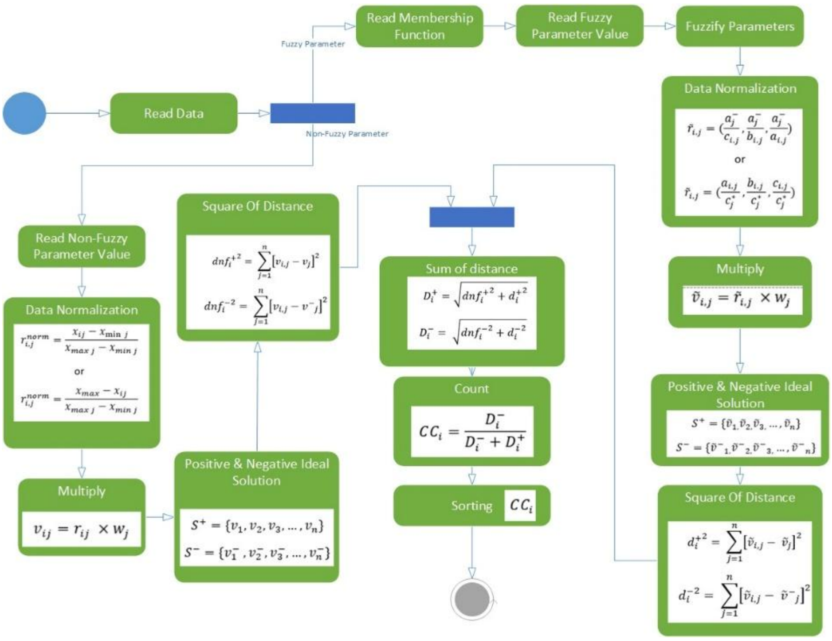

Figure 5. Model Activity Diagram

After obtaining the squares of the ideal and anti-ideal solutions from both fuzzy and non-fuzzy parameters, added up the squares of the ideal solutions and the squares of the anti-ideal solutions from both fuzzy and non-fuzzy parameters. After summing, obtain the combined ideal solution and the combined anti-ideal solution by taking the square root of the sums of the squares of the ideal and anti-ideal solutions from the fuzzy and non-fuzzy parameters. This is where the role of fuzzy and non-fuzzy values produces one value called distance. Then, calculate the closeness coefficient based on the distance value (a combination of root values from the squares of the ideal and anti-ideal solutions from the fuzzy and non-fuzzy parameters) and sorted the closeness coefficients from largest to smallest, where the largest closeness coefficient value indicates the most recommended alternative.

4. Results and Discussion

4.1. Model Simulation

This section discusses simulating models from raw data in table 9. To build models from two groups using a combination of methods between Fuzzy TOPSIS and TOPSIS, we followed the algorithm in figure 5. The first step was to read the data. Then, read the weights and identify which parameters were fuzzy ('psychological test' and 'interview' criteria) and non-fuzzy. Next, fuzzify the values for the criteria parameters 'psychological test' (as in table 10) and 'interview' (as in table 11).

For example, Candidate 1 has an 'openness to experience' (A1) value of 79. When fuzzifying, a value of 79 on the 'psychological test' can belong to either the 'medium' (descending linear curve with fuzzy number (20, 50, 80)) or 'high' category (ascending linear curve, with fuzzy number (50, 100, 100)). If we categorize it as 'medium', we get the result $\frac{80-79}{80-50} = \frac{1}{30}$ (from formula (1), $\frac{c-x}{c-b}$, where c is 80, b is 50). If we categorize it as 'high', the result is $\frac{79-50}{100-50} = \frac{29}{50}$ (from formula (1), $\frac{x-a}{b-a}$, where a is 50, b is 100). From these results, the highest score is in the 'high' category, so the value of 'openness to experience' for Candidate 1 uses 'high' category fuzzy values, namely (50, 100, 100).

Table 10. Fuzzify Value of 'Psychological Test' Criteria

Cand.	**A1**	**A2**	**…**	**A4**	**A5**
Cand. 1	(50.000,100.000, 100.000)	(20.000,50.000, 80.000)	…	(50.000,100.000, 100.000)	(20.000,50.000, 80.000)
⋮	…	…	…	…	⋮
Cand. 11	(50.000,100.000, 100.000)	(20.000,50.000, 80.000)	…	(20.000,50.000, 80.000)	(20.000,50.000, 80.000)

Table 11. Fuzzify Value of 'Interview Criteria

Cand.	**C1**	**C2**	**…**	**C7**	**C8**
Cand. 1	(7.000,9.000, 9.000)	(7.000,9.000, 9.000)	…	(7.000,9.000, 9.000)	(7.000,9.000, 9.000)
…	…	…	…	…	⋮
Cand. 11	(7.000,9.000, 9.000)	(7.000,9.000, 9.000)	…	(7.000,9.000, 9.000)	(7.000,9.000, 9.000)

Next, normalize the data. For non-fuzzy parameters, use the formulas in (11) and (12), and for fuzzy parameters, use the formulas in (3) and (4). The results of normalization are shown in the table 12, table 13, table 14.

Table 12. Normalization of Non-Fuzzy Parameters

Cand.	**B1**	**B2**	**B3**	**D1**	**E1**	**F1**	**G1**
Cand. 1	0.875	1.000	0.000	1.000	0.000	0.000	0.500
…	…	…	…	…	…	…	…
Cand. 11	1.000	1.000	0.400	1.000	0.000	0.000	1.00

For example, the highest value in column A1 is 100. Since A1 is a benefit criterion, the fuzzy value in this column is divided by 100. Therefore, the value for Candidate 1 becomes $(\frac{50}{100}, \frac{100}{100}, \frac{100}{100}) = (0.5, 1, 1)$. Meanwhile, for B1, Cand. 1 obtains the result $\frac{14-7}{15-7} = 0.875$, because Cand. 1's value is 14, the maximum value in the verbal column is 15, and the minimum value is 7.

Table 13. Normalization of 'Psychological Test' Criteria

Cand.	**A1**	**A2**	**A3**	**A4**	**A5**
Cand. 1	(0.500,1.000, 1.000)	(0.200,0.500, 0.800)	(0.000,0.000, 0.500)	(0.500,1.000, 1.000)	(0.000,0.000, 0.000)
…	…	…	…	…	…
Cand. 11	(0.500,1.000, 1.000)	(0.200,0.500, 0.800)	(0.000,0.000, 0.500)	(0.200,0.500, 0.800)	(0.000,0.000, 0.000)

Table 14. Normalization of 'Interview' Criteria

Cand.	**C1**	**C2**	**…**	**C7**	**C8**
Cand. 1	(0.778,1.000, 1.000)	(0.778,1.000, 1.000)	…	(0.778,1.000, 1.000)	(0.778,1.000, 1.000)
⋮	…	…	…	…	⋮
Cand. 11	(0.778,1.000, 1.000)	(0.778,1.000, 1.000)	…	(0.778,1.000, 1.000)	(0.778,1.000, 1.000)

After normalization, both fuzzy and non-fuzzy parameters were multiplied by their respective weights. Then, determine the positive and negative ideal solutions. Next, calculated the squares of the distances to the ideal and anti-ideal solutions. Summed the squares of the fuzzy and non-fuzzy distances to the ideal solution and do the same for the anti-ideal solution, then took the square root of each summed. With the combined values of the ideal solution and the anti-ideal solution, a closeness coefficient could be obtained, with results as shown in table 15. Based on the closeness coefficient values obtained, the ranking was as follows: first place is Cand. 8, followed by Cand. 6, Cand. 7, Cand. 11, Cand. 2, Cand. 10, Cand. 9, Cand. 1, Cand. 5, Cand. 4, and lastly, Cand. 3.

Table 15. Fuzzy and Non-Fuzzy Distances with Closeness Coefficients (CC) for Candidates

Cand.	**non- fuzzy $(\mathbf{dnf}^{+})^{2}$**	**fuzzy $(\mathbf{d}^{+})^{2}$**	**non- fuzzy $(\mathbf{dnf}^{-})^{2}$**	**fuzzy $(\mathbf{d}^{-})^{2}$**	**$\mathbf{D}^{+}$**	**$\mathbf{D}^{-}$**	**CC**
Cand. 1	0.014	0.005	0.037	0.007	0.135	0.210	0.609
⋮	…	…	…	…	…	…	⋮
Cand. 11	0.003	0.006	0.054	0.006	0.097	0.245	0.716

4.2. Model Verification & Validation

One of the important stages in GDSM for selecting IT employees is validation and verification. Validation is carried out to ensure the correctness of the data in the model compared to actual data. Verification is carried out to ensure the correctness of the model compared to theory.

There were 4 verification assessment indicators, including parameters, the fuzzy TOPSIS process, the TOPSIS process, and the combined TOPSIS and fuzzy TOPSIS process. The parameter indicator has four sub-indicators: fuzzy, non-fuzzy, value range, and weight. The fuzzy and non-fuzzy sub-indicators are assessed by calculating the number of fuzzy and non-fuzzy parameters. The verification value is 1.00 if the model parameters match the reference parameters and is represented by (V) in the conformity column. For example, based on the reference, there were 13 fuzzy parameters, so the model also used 13 fuzzy parameters. Thus, the verification value is 1.00. This process is applied to the other sub-indicators as well.

The fuzzy TOPSIS process indicator had 5 sub-indicators: procedures before normalization, normalization formula, weight multiplication formula with normalized data, positive and negative ideal solution formula, and distance square formula. For example, the procedure before normalizing in the fuzzy TOPSIS process, based on references, involved reading the membership function for weights (as in figure 2), psychological test scores (as in figure 3), and interview scores (as in figure 4). Apart from reading the membership function, fuzzification was also performed. Another example, distance square formula used (18) for the distance square of the ideal solution fuzzy (d_i^{+2}) is the sum of the squared differences of each alternative in fuzzy value $(\tilde{v}_{i,j})$ with the positive ideal solution on fuzzy parameters $(\tilde{v}_j)$ and (19) for the distance square of the anti-ideal solution fuzzy (d_i^{-2}) is the sum of the squared differences of each alternative in fuzzy value $(\tilde{v}_{i,j})$ with the negative ideal solution on fuzzy parameters $(\tilde{v}^-{}_j)$. The verification value is 1.00 if the model matches the reference and is symbolized by (v) in the truth column.

The TOPSIS process indicator had 4 sub-indicators: the normalization formula, the weight multiplication formula with normalized data, the positive and negative ideal solution formula, and the distance square formula. All formulas in the sub-indicators were verified based on references. For example, the normalization formula used (12) for cost criteria and (11) for benefit criteria. If the model matches the reference, the verification value is 1.00 and the truth column is marked with the symbol (V).

The combined TOPSIS and fuzzy TOPSIS process indicator had 3 sub-indicators: procedure, distance combination formula, and closeness coefficient formula. The procedure for this combination consists of summing the distances from fuzzy TOPSIS and TOPSIS, calculating the closeness coefficient, and sorting the closeness coefficient. The distance combination formula and the closeness coefficient formula were based on references. For example, distance combination formula used (20), where distance of the ideal solution for the i-th alternative (D_i^+) is square root of sum of the distance square of the ideal solution fuzzy $((d_i^+)^2)$ and non-fuzzy $((dnf_i^+)^2)$ and (21) where distance of the anti-ideal solution for the i-th alternative (D_i^-) is square root of sum of the distance square of the anti-ideal solution fuzzy $((d_i^-)^2)$ and non-fuzzy $((dnf_i^-)^2)$. Another example, closeness coefficient formula used (22), where CC_i is closeness coefficient for i-th alternative. The verification value is 1.00 if the model and reference are in agreement and is symbolized by (V) in the conformity column.

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$$d_i^{+2} = \sum_{j=1}^{n}\left[\tilde{v}_{i,j} - \tilde{v}_j\right]^2 \tag{18}$$

$$d_i^{-2} = \sum_{j=1}^{n}\left[\tilde{v}_{i,j} - \tilde{v}^{-}{}_j\right]^2 \tag{19}$$

$$D_i^{+} = \sqrt{dnf_i^{+2} + d_i^{+2}} \tag{20}$$

$$D_i^{-} = \sqrt{dnf_i^{-2} + d_i^{-2}} \tag{21}$$

$$CC_i = \frac{D_i^{-}}{D_i^{-} + D_i^{+}} \tag{22}$$

The actual data were obtained from the simulation results of IT employee selection for 11 Computer Science students. All input data from the 11 students were validated during the validation process. The range of data values for each sub-criterion is shown in table 1. If the value used in the model matches the range of values in table 1, the validation value is 1.00, symbolized by (V) in the suitability column. The results of applying the model to each candidate will also be validated to ensure they have the same validation value as the input data. For example, for Candidate 1, with a code of criteria A1, the actual value is 0-100, and the input value is 79. Therefore, the validation value is 1.00, indicated by (V) in the Trueness column. For example, the output validation, Candidate 1 received a Closeness Coefficient value of 0.609 from coding and manual calculations. If the Closeness Coefficient value is the same from coding and manual calculations, it means that the difference in the Closeness Coefficient value from coding and manual calculations is 0. Thus, the validation value is 1.00 (it can be said that the model is in accordance with the actual), represented by (V) in the Trueness column.

4.3. Discussion

Compared to related works on employee selection, research from, [13], [17], [19], [20], [21] only carries out selection with criteria that are too specific (user needs criteria) as in research [13], [17], [19] or places too much on qualitative data as in [20] and [21]. When conducting selection, many people use Fuzzy TOPSIS/TOPSIS, but not for selecting IT employees. In previous research, the AHP-ELECTRE method was used for selecting IT employees, but with criteria originating from IT users (too specific) [13]. This research provides a solution by combining too general and too specific criteria for selecting IT employees, using GDSM to combine a general point of view (HRD with 8 criteria) and a specific point of view (IT User with 12 criteria) as decision criteria, using the Fuzzy TOPSIS method (11 criteria) and TOPSIS (9 criteria). The weight assessment was carried out by 3 experts from HRD and 3 experts from IT Users, then the scores were combined by averaging, and the candidate assessment was carried out by 1 expert from HRD and 1 expert from IT Users. Combining the Fuzzy TOPSIS and TOPSIS methods involves adding up the squares of the ideal solutions and the squares of the anti-ideal solutions from both fuzzy and non-fuzzy parameters, followed by calculating the closeness coefficient as usual. From the closeness coefficient value, candidate recommendations are obtained by sorting the values. The model can be improved by adding parameters from literature studies or interviews with experts. Additionally, more than one expert in each group can also assess candidates.

Currently, this study uses limited simulation using 11 respondents to conduct initial evaluation with the results that the model is in accordance with the actual. In addition, this study also does not compare with other methods. So, future studies could focus on larger data to evaluate and the effectiveness of the model. Additionally, it can also compare the model with other methods such as AHP, PROMETHEE, MOORA, and others to show its strengths and weaknesses.

5. Conclusion

This research has successfully selected IT employees using assessments from more than one group of decision-makers. A GDSM for IT employees' selection was built using the Fuzzy TOPSIS method. This GDSM was created using 20 parameters obtained from literature studies and interviews. The output from the resulting model can assist decision-makers in selecting candidates who are suitable for employment, along with the ranking results of the candidates. This model had been successfully tested on 11 respondents. The result is cand. 8 which is in first place with CC 0.896 (the alternative that is closest to the positive ideal solution) and cand. 3 which is in last place with CC 0.241 (the alternative that is farthest from the positive ideal solution). Additionally, it makes the assessment of IT employee selection more objective. It is hoped that in the future, modeling GDSM for IT employee selection will incorporate more parameters, utilize additional literature studies, and conduct more interviews with experts to improve the quality of the model, use large data and compare with other methods.

6. Declarations

6.1. Author Contributions

Conceptualization: A.V. and D.N.U.; Methodology: A.V.; Software: A.V.; Validation: A.V. and D.N.U.; Formal Analysis: A.V. and D.N.U.; Investigation: A.V.; Resources: A.V.; Data Curation: A.V.; Writing Original Draft Preparation: A.V. and D.N.U.; Writing Review and Editing: A.V. and D.N.U.; Visualization: A.V. Both authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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