

Decision Support System for Determining Student Specializations using Fuzzy Tsukamoto and Topsis Methods
(Case Study: Informatics Engineering Undergraduate Program-FTI UKSW Salatiga)

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ABSTRACT

This study aims to design a decision support system that assists students in selecting a specialization that aligns with their abilities and interests, thereby supporting timely graduation. The selection of specialization is often based on self-assessment that tends to be subjective, or even follows the choices of peers without objective evaluation of personal abilities, making it necessary to adopt an approach capable of accommodating such uncertainty systematically. Therefore, the methods employed are Fuzzy Tsukamoto and TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution). This research was conducted to obtain the most appropriate specialization recommendation for students based on the established criteria. The criteria used in this study include academic grades of compulsory courses relevant to each specialization, technical skills, and programming abilities. The results of system testing on a student data sample indicate that the Network specialization obtained the highest TOPSIS preference value of 1.0, followed by Data Science and Software each with a value of 0.5, proving that the system is capable of generating a systematic specialization ranking based on the predetermined criteria.
Keywords: *Decision Support System, Tsukamoto, TOPSIS, Fuzzy, Students*

1. INTRODUCTION

In the world of education, choosing a specialization is an important step for students to achieve success in their studies. The right specialization not only affects academic achievement, but also influences timely graduation. Many students face difficulties in determining a specialization that suits their abilities and interests. For example, a student who is interested in information technology may feel confused in choosing between specializations in software engineering, network engineering, or data science, which ultimately leads them to follow the choices made by their friends [1]. Without the right assistance, the decisions made can cause students to experience difficulties in learning, which ultimately results in delays in graduation. To overcome this problem, a system is needed that is capable of providing support to students in determining specializations that suit their abilities and interests. A Decision Support System is a computer-based system designed to assist the decision-making process by presenting choices or alternative decisions. This system works by processing relevant data and information using specific models, allowing users to consider various possibilities before making a final decision [2], [3]. In the context of specialization selection, SPK can be an effective solution because it can provide recommendations based on relevant criteria. In this study, researchers will use the Fuzzy Tsukamoto and TOPSIS methods to design the system. Although the Fuzzy Tsukamoto and TOPSIS methods have been around for quite some time, they are still frequently used because they have clear advantages. Fuzzy Tsukamoto is suitable for handling uncertain or subjective data [4], [5]. In this study, Fuzzy Tsukamoto was used by considering several input variables, namely the grades of compulsory courses related to specialization, skills possessed, and student interests. On the other hand, the TOPSIS method is suitable for sorting and ranking alternatives based on predetermined criteria [6]. In this study, TOPSIS was used to determine the most suitable specialization by considering the results of the variables that had been analyzed. This method works by comparing each alternative to the best and worst ideal solutions, thereby producing an objective and easy-to-understand ranking [7]. Both methods remain relevant because they are flexible, easy to apply, and still capable of producing robust results even when more variables are used.

Several studies have shown that the Tsukamoto Fuzzy method is effective for processing and analyzing uncertain or qualitative data. Research by [8] used the Tsukamoto Fuzzy method to determine the amount of bread production based on demand and supply variables. Each variable is processed using a specific membership function to determine its contribution to the final result. Based on the fuzzy calculation

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results, this method has been proven to be effective in determining the amount of bread production with a high level of accuracy. In addition, [9] applied the Tsukamoto Fuzzy method to determine the price of car coatings. This study utilizes two input variables, namely car size and number of layers, and one output variable in the form of coating price. The processing begins with fuzzyfication to calculate the membership degree of each variable, followed by fuzzy inference based on predetermined rules, and ends with defuzzyfication to obtain crisp values as estimates of the final price. The results of this study indicate that this method is capable of providing accurate coating price predictions according to car conditions [9]. Furthermore, [10] used the Tsukamoto Fuzzy method to determine the best mobile phone technicians based on five assessment criteria. This method proved to be effective in producing accurate rankings through 20 fuzzy rules and weighted average defuzzification. On the other hand, several studies show that the TOPSIS method is effective in solving problems involving the selection of the best alternative from among many alternatives with different criteria weights. Research by [11] applied the AHP–TOPSIS method in a decision support system to determine the priority of village development programs. Through the AHP method, the weight of each development criterion was obtained, which was then used in the TOPSIS calculation process to assess and rank program alternatives. The results of the study show that the combination of these two methods helps produce more objective decisions in determining programs that are feasible to be prioritized in the RKPDes. Furthermore, [12] applied the TOPSIS method to assist the decision-making process in selecting housing based on several criteria, such as price, location, facilities, environment, and house design. The application of this method has been proven to provide consistent assessment results that are in line with consumer needs in determining the best alternative. Furthermore, [13] applied the TOPSIS method combined with Rank Order Centroid (ROC) weighting to develop a decision support system for ranking teachers based on the use of digital media. The study, which involved 26 teachers at the high school, vocational school, and Islamic high school levels, used eight assessment criteria with a Likert scale and proved capable of producing objective, transparent, and measurable rankings as a basis for strategic decision-making in improving teachers' digital competencies. Finally, [14] used the AHP and TOPSIS methods in designing a decision support system for selecting the best employees at PT. Arion Tech Indonesia. The AHP method was used to determine the weight of criteria such as productivity, discipline, and cooperation, while TOPSIS was used to rank employee alternatives based on their proximity to the ideal solution. The combination of these two methods provides more accurate results and helps companies determine the best employees objectively.

Based on previous studies, the use of the Fuzzy Tsukamoto and TOPSIS methods has been proven effective in solving decision-making problems involving subjective data and relatively complex criteria. These studies form the basis for combining the two methods in this study. The combination was carried out because Fuzzy Tsukamoto produces values for each specialization on each criterion variable, making it possible for there to be different results between variables. To overcome this, TOPSIS is used to integrate and rank all output values produced by Fuzzy Tsukamoto objectively. Through this research, it is hoped that appropriate specialization recommendations can be obtained for students, so that they can make better decisions in choosing a specialization and increase their chances of graduating on time.

2. RESEARCH METHOD

The research will be conducted in several stages, namely problem formulation, data collection, model creation, model testing, and evaluation of research results, as illustrated in Figure 1.

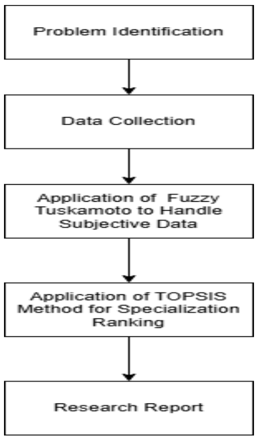

Figure 1. Research Flowchart

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Data Collection

The second stage is data collection, which includes data required for this study, such as grades for compulsory courses relevant to the three available specializations, namely Networking, Data Science, and Software. In addition, students were also asked to list the skills they have mastered, such as technical abilities that support these specializations and programming language skills they have mastered. Data collection was carried out using a Google Form distributed to students enrolled in the 2021 to 2024 Information Technology Study Program, Faculty of Information Technology, as it was considered practical and able to reach a large number of respondents [15]. From the collected data, one student data was selected as a sample for system testing because the complexity of the variables and rules used resulted in a large number of rules, so that testing was carried out in depth on one data to ensure that each stage of the process ran correctly. This approach is expected to provide a clear picture of student abilities so that it can help in providing more appropriate specialization recommendations. The first input data required is the input data for compulsory course grades, which can be seen in Table 1 below.

Table 1. Grade Input Data

Code	Course Name	Description
DS AI ML	Database System Artificial Intelligence Machine Learning	Compulsory Courses Relevant to the Data Science Specialization
CN NPF DS	Computer Networks Network Programming Fundamentals Data Security	Compulsory Courses Relevant to the Networking Specialization
SE WP OP	Software Engineering Web Programming Object-Oriented Programming	Compulsory Courses Relevant to the Software Specialization

The next input data required is the skills input data, which can be seen in Table 2.

Table 2. Skills Input Data

Code	Technical Skills	Description
DA ML BD DPP DV	Data Analysis *Machine Learning* *Big Data* Data Processing with Python/R Data Visualization	Skills Related to the Data Science Specialization
CNS SNA EH CC NCM	Computer Networks and Security Server and Network Administration Ethical Hacking Cloud Computing Network Configuration and Management	Skills Related to the Networking Specialization
WD MAD SD OP DC	Web Development Mobile Application Development Software Development Object-Oriented Programming DevOps dan CI/CD	Skills Related to the Software Specialization

The last input data required is the programming skill data, which can be seen in Table 3.

Table 3. Programming Language Input Data

Code	Programming Language	Description
R	*R*	Programming Languages Supporting the Data Science Specialization
JS	*Javascript*	Programming Languages Supporting the

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PHP J	*PHP* *Java*	Software Specialization
C	*C++*	Programming Languages Supporting the Networking & Software Specialization
PY SQL	*Python* *SQL*	Neutral / Supports All Specializations

Application of Fuzzy Tsukamoto to Handle Subjective Data

The third stage is the application of Fuzzy Tsukamoto to address subjective data. Data obtained from students, such as course grades, interests, and technical skills, are often difficult to interpret directly due to their subjective nature. In this stage, course grades are processed using Fuzzy logic to be categorized into low or high levels, making them more measurable and easier to analyze. Meanwhile, interests and technical skills are still considered directly to provide a more comprehensive picture. This process ensures that the system can provide specialization recommendations that match students' potential and preferences. Table 4 is the Fuzzy Set input table, while Table 5 is the Fuzzy Set output table.

Table 4. Fuzzy Tsukamoto Set Input

Function	Variable	Category	Range	Domain
Input	Course Grade	High Low	20-100	[60-100] [20-70]
	Skill	High Low	0-5	[3-5] [0-2]
	Programming Language Skill	High Low	0-5	[3-5] [0-2]

Table 5. Fuzzy Tsukamoto Set Output

Function	Variable	Category	Range	Domain
Output	Course Grade Variable Results	High Low	60-70	[70] [60]
	Skill Variable Results	High Low		[70] [60]
	Programming Language Skill Variable Results	High Low		[70] [60]

In this system, each fuzzy variable uses a different membership function shape, namely a left shoulder shape to represent the Low category and a right shoulder shape for the High category. The variables and their membership functions are presented as follows.

a. Course Grade Variable

Each course grade is converted into a specific weight according to a predetermined scale, namely A = 100, B = 80, C = 60, D = 40, and E = 20. These grades are then grouped into two fuzzy categories, namely LOW and HIGH. The range of 20–60 is considered LOW because it generally indicates a lack of understanding, while 70–100 falls into the HIGH category because it reflects good learning outcomes. This division is made to make assessment easier and in line with general academic assessment standards. In the 60–70 range, there is a transition area where scores can gradually belong to both categories, LOW and HIGH. Therefore, the domain is divided as follows:

- LOW, domain = [20 – 70]
- HIGH, domain = [60 – 100]

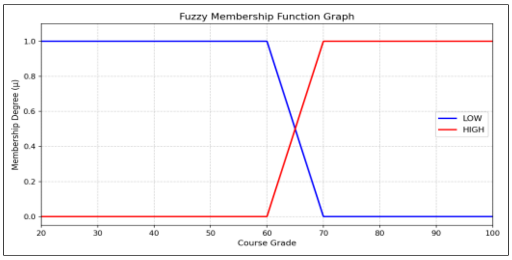

Figure 4. Membership Function of the Course Grade Weight Variable

The membership function for each set is given in Equation 1 and 2.

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$$\mu Low(x) = \begin{cases} 1 \ , & x \le 60 \\ \frac{70-x}{10} \ , & 60 < x \le 70 \\ 0 \ , & x > 70 \end{cases} \quad (1)$$

$$\mu High(x) = \begin{cases} 0 \ , & x \le 60 \\ \frac{x-60}{10} \ , & 60 < x \le 70 \\ 1 \ , & x > 70 \end{cases} \quad (2)$$

b. Skill Variable

Skill variables are grouped into two fuzzy sets, namely Low and High. This division is used to represent the level of mastery of students' skills, as shown in Figure 5.

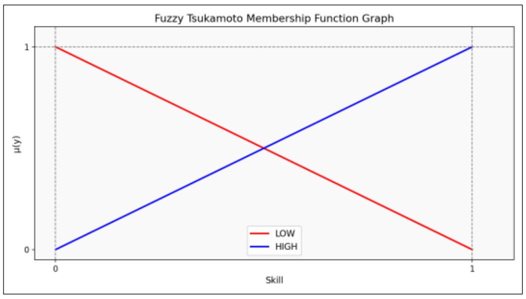

Figure 5. Membership Function of the Skill Variable

The membership function for each set is given in Equation 3 and 4.

$$\mu Low(x) = 0 \quad (3)$$

$$\mu High(x) = 1 \quad (4)$$

c. Programming Language Skill Variable

The Programming Language Skill variable is divided into two fuzzy sets, namely Low and High, to represent the level of mastery of students, as shown in Figure 6.

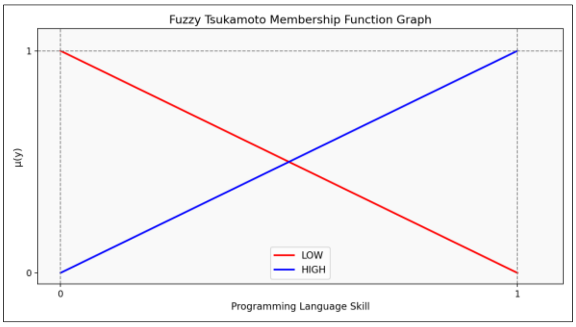

Figure 6. Membership Function of the Programming Language Skill Variable

The membership function for each set is given in Equation 5 and 6.

$$\mu Low(x) = 0 \quad (5)$$

$$\mu High(x) = 1 \quad (6)$$

The following are several Fuzzy rule designs for course grades, which can be seen in Figure 7.

A. Rule Design for Data Science Course Grades
[R1] IF DS Low AND AI Low AND ML Low THEN Data Science SpecializationLow
[R2] ----------------
[R8] IF DS High AND AI High AND ML High THEN Data Science Specialization High

B.Rule Design for Networking Course Grades
[R1] IF CN Low AND NPF Low AND DS Low THEN networking Specialization Low
[R2] ----------------
[R8] IF CN High AND NPF High AND DS High THEN networking Specialization High

C. Rule Design for Software Course Grades
[R1] IF SE Low AND WP Low AND OP Low THEN Software Specialization Low
[R2] ----------------
[R8] IF SE High AND WP High AND OP High THEN Software Specialization High

Figure 7. Fuzzy Rule Design for Course Grades

The following are several Fuzzy rule designs for Skills, which can be seen in Figure 8.

A. Rule Design for Skills in the Data Science Field
[R1] IF DA Low AND ML Low AND BD Low AND DPP Low AND DV Low THEN Data Science Specialization Low
[R2] ---------------
[R7] IF AD High AND ML High AND BD High AND DPP High AND DV Low THEN Data Science Specialization High

B. Rule Design for Skills in the Networking Field
[R1] IF CNS Low AND SNA Low AND EH Low AND CC Low AND NCM Low THEN Networking Specialization Low
[R2] ---------------
[R7] IF CNS High AND SNA High AND EH High AND CC High AND NCM High THEN Networking Specialization High

C. Rule Design for Skills in the Software Field
[R1] IF WD Low AND MAD Low AND SD Low AND OP Low AND DC Low THEN Software Specialization Low
[R2] ---------------
[R7] IF WD High AND MAD High AND SD High AND OP High AND DC High THEN Software Specialization High

Figure 8. Fuzzy Rule Design for Skills

The following are Fuzzy Programming Language Skill Rule Designs, which can be seen in Figure 9.

A. Rule Design for Programming Language Skills in the Data Science Field
[R1] IF R Low AND C Low AND PY Low AND SQL Low THEN Data Science Specialization Low
[R2] ---------------
[R7] IF R High AND C High AND PY High AND SQL High THEN Data Science Specialization High

B. Rule Design for Programming Language Skills in the Networking Field
[R1] IF C Low AND PY Low AND SQL Low THEN Networking Specialization Low
[R2] ---------------
[R7] IF C High AND PY High AND SQL High THEN Jaringan Specialization High

C. Rule Design for Programming Language Skills in the Software Field
[R1] IF J Low AND JS Low AND PHP Low AND C Low AND PY Low AND SQL Low THEN Software Specialization Low
[R2] ---------------
[R7] IF J High AND JS High AND PHP High AND C High AND PY High AND SQL High THEN Software Specialization High

Figure 9. Fuzzy Rule Design for Programming Language Skills

Application of the TOPSIS Method for Ranking Specializations

The fourth stage is the application of the TOPSIS method to rank the specializations. After each criterion variable is processed using Fuzzy Tsukamoto, the defuzzification process produces crisp values for each specialization in each criterion, namely the values for compulsory courses, skills, and programming language skills. These crisp values are then arranged into a decision matrix that serves as the initial input in the TOPSIS process, where each specialization acts as an alternative and each criterion variable acts as an assessment criterion. With TOPSIS, the specialization that best suits the student's abilities will be placed at the highest rank based on its relative proximity to the ideal solution, so that students can easily see the specialization that is most suitable for them. This study applies the TOPSIS series of stages:

- Constructing the Decision Matrix

At this stage, data from each specialization, such as compulsory course grades, skills, and programming skills, are entered into a decision matrix that forms the basis for subsequent calculations.

- Normalizing the Decision Matrix

Normalization is performed to standardize the scale of values for each criterion. The goal is to ensure that all data can be compared fairly and objectively, even if they have different value ranges.

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- Constructing the Weighted Normalized Matrix

After normalization, each criterion is given a weight according to its level of importance. This weight helps highlight the criteria that are more influential in determining the best specialization.

- Determining the Positive and Negative Ideal Solutions

At this stage, the positive ideal solution (the highest value for each criterion) and the negative ideal solution (the lowest value for each criterion) are calculated. These two solutions will be used as a reference to measure the extent to which each alternative approaches the best solution.

- Calculating the Distance to the Ideal Solution

Each specialization will be calculated based on its distance from the positive and negative ideal solutions. Specializations that are closer to the positive ideal solution and further from the negative ideal solution will have a greater chance of becoming the best choice.

- Calculating the Final Preference Value

The final stage in the TOPSIS method is to calculate the preference scores for each alternative. These values represent the level of suitability of each alternative compared to the others. The alternative with the highest preference value is considered the most recommended alternative.

Research Report

The fifth stage is the research report. After going through the data collection process, using fuzzy logic to handle subjective data, and applying the TOPSIS method to rank specializations, this research report was compiled to present the results obtained. This report will include an explanation of the research process, data analysis, and recommendations for specializations that are in line with the criteria and abilities of students. Thus, this research is expected to provide the right solution in helping students choose specializations that suit their potential.

3. RESULTS AND DISCUSSION

The problem identification process was carried out through observation at the Informatics Engineering Undergraduate Program, Faculty of Information Technology, Satya Wacana Christian University. It was found that many students who should have graduated had not yet completed their studies. Some of the obstacles or problems encountered included difficulty in achieving adequate grades, obstacles in completing their thesis, and low motivation to study. The main assumption of this problem is the lack of compatibility between students and their chosen specializations. Therefore, this study aims to develop a data-based specialization recommendation system that can help students choose specializations that suit their interests and abilities, thereby improving academic performance and accelerating graduation. Data on students in the Information Technology Study Program, Faculty of Information Technology, was obtained through a questionnaire. The data collected included grades for compulsory courses, technical skills, and programming language skills mastered by students. The data was used for calculations using the Fuzzy Tsukamoto method, as shown in Table 6.

Table 6. Sample Grade Data

ID	DS	AI	ML	CN	NPF	DS	SE	WP	OP
672021051	A	A	B	A	A	A	A	A	C

The following sample data shows the technical skills mastered by students based on the results of self-assessment through questionnaires, as shown in Table 7.

Table 7. Sample Skill Data

ID	DA	ML	BD	DPP	DV	CNS	SNA	EH	CC	NCM	WD	MAD	SD	OP	DC
672021051	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0

The latest sample data shows the technical skills mastered by students based on the questionnaire results, as shown in Table 8.

Table 8. Sample Programming Language Skill Data

ID	R	JS	J	C	PHP	PY	SQL
672021051	0	0	0	0	1	1	1

Input Variable Sets

In the Tsukamoto Fuzzy method, each input variable is converted into a fuzzy set. This process is carried out to determine the degree of membership of each variable based on predetermined criteria. Fuzzy sets are created for three input variables, namely compulsory course grades, technical skills, and programming skills. The value variable shows the results of compulsory courses related to specializations. These values are converted into fuzzy sets based on predetermined membership degrees. The results of

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forming fuzzy sets for the value variable from one of the data sets with student ID number 672021051 can be seen in Table 9.

Table 9. Input Variable Sets for Course Grades

Variable	Low	High
DS	0	1
AI	0	1
ML	0	1
CN	0	1
NPF	0	1
DS	0	1
SE	0	1
WP	0	1
OP	1	0

The results of fuzzy set formation for student skill variables using the same data can be seen in Table 10.

Table 10. Input Variable Sets for Skills

Variable	Low	High
DA	0	1
ML	0	1
BD	1	0
DPP	0	1
DV	0	1
CNS	1	0
SNA	1	0
EH	1	0
CC	1	0
NCM	1	0
WD	1	0
MAD	1	0
SD	1	0
OP	1	0
DC	1	0

The results of fuzzy set formation for the Programming Language Skills variable of students with the same data can be seen in Table 11.

Table 11. Input Variable Sets for Programming Language Skills

Variable	Low	High
R	1	0
JS	1	0
PHP	0	1
J	1	0
C	1	0
PY	0	1
SQL	0	1

Determining the α-predicate and Z Value for the Course Grade Variable

The process begins by determining the α-predicate based on the degree of membership (μ) of the input variable, namely the compulsory course grades. At the implication stage, the Min method is used to take the smallest value from the fuzzy set in accordance with the applicable rules. After that, the Z value is calculated as the final result to see the interest in the fields of Data Science, Networking, or Software.

a. Calculation of α-predicate and Z for the Evaluation of Data Science Specialization Course Grades.

[R1] IF DS Low AND AI Low AND ML Low THEN Data Science Specialization Low
α- Predicate 1 = *Min* (0, 0, 0) = 0
Z1 = 60 + (0 × 10) = 60

[R2] ----------------

[R8] IF DS High AND AI High AND ML High THEN Data Science Specialization Highi
α- Predicate 8 = *Min* (1, 1, 1) = 1
Z8 = 60 + (1 × 10) = 70

b. Calculation of α-predicate and Z for the Evaluation of Networking Specialization Course Grades.

[R1] IF CN Low AND NPF Low AND DS Low THEN Networking Specialization Low
α- Predicate 1 = *Min* (0, 0, 0) = 0

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Z1 = 60 + (0 × 10) = 60
[R2] ----------------
[R8] IF CN High AND NPF High AND DS High THEN Networking Specialization High
α- Predicate 8 = *Min* (1, 1, 1) = 1
Z8 = 60 + (1 × 10) = 70

c. Calculation of α-predicate and Z for the Evaluation of Software Specialization Course Grades.
[R1] IF SE Low AND WP Low AND OP Low THEN Software Specialization Low
α- Predicate 1 = *Min* (0, 0, 1) = 0
Z1 = 60 + (0 × 10) = 60
[R2] ----------------
[R8] IF SE High AND WP High AND OP High THEN Software Specialization High
α- Predicate 1 = *Min* (1, 1, 0) = 0
Z1 = 60 + (0 × 10) = 60

d. Defuzzification Process

The defuzzification process is carried out using the weighted average method. The final value is determined from the Z result in each fuzzy rule in each specialization. The following is the defuzzification process for the Data Science, Networking, and Software specializations:

- Z Value for the Data Science Specialization : 70
- Z Value for the Networking Specialization : 70
- Z Value for the Software Specialization : 60

Based on the results of calculations using the Fuzzy Tsukamoto FIS method with student sample data, the specializations that can be considered for these students are Data Science and Networking, each with a defuzzification value of 70, while the Software specialization has a value of 0, which is lower than the other two specializations.

Determining the α-predicate and Z Value for the Skill Variable

The α-predicate determination stage for the programming skill variable is carried out by referring to the membership degree (μ) of the skills possessed by students. This process follows the same flow as in the previous variables. Next, in the implication stage, the Min method is applied to obtain the smallest value from the fuzzy set based on the applicable rules. Finally, the Z value is calculated to determine students' interest in Data Science, Networking, or Software.

a. Calculation of α-predicate and Z for the Evaluation of Data Science Specialization Skills.
[R1] IF DA Low AND ML Low AND BD Low AND DPP Low AND DV Low THEN Data Science Specialization Low
α- Predicate 1 = *Min* (0, 0, 1, 0, 0) = 0
Z1 = 60 + (0 × 10) = 60
[R2] ----------------
[R7] IF AD High AND ML High AND BD High AND DPP High AND DV Low THEN Data Science Specialization High
α- Predicate 7 = *Min* (1, 1, 0, 1, 1) = 0
Z7 = 60 + (0 × 10) = 60

b. Calculation of α-predicate and Z for the Evaluation of Networking Specialization Skills.
[R1] IF CNS Low AND SNA Low AND EH Low AND CC Low AND NCM Low THEN Networking Specialization Low
α- Predicate 1 = *Min* (1, 1, 1, 1, 1) = 1
Z1 = 60 + (1 × 10) = 70
[R2] ----------------
[R7] IF CNS High AND SNA High AND EH High AND CC High AND NCM High THEN Networking Specialization High
α-Predicate 7 = *Min* (0, 0, 0, 0, 0) = 0
Z7 = 60 + (0 × 10) = 60

c. Calculation of α-predicate and Z for the Evaluation of Software Specialization Skills.
[R1] IF WD Low AND MAD Low AND SD Low AND OP Low AND DC Low THEN Software Specialization Low
α- Predicate 1 = *Min* (1, 1, 1, 1, 1) = 1

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Z1 = 60 + (1 × 10) = 70
[R2] ----------------
[R7] IF WD High AND MAD High AND SD High AND OP High AND DC High THEN Software Specialization High
α- Predicate 7 = *Min* (0, 0, 0, 0, 0) = 0
Z7 = 60 + (0 × 10) = 60

d. Defuzzification Process

The defuzzification process was carried out using the weighted average method. The final value was obtained from the Z result in each fuzzy rule in each specialization. The following are the defuzzification results for the Data Science, Networking, and Software specializations:

- Z Value for the Data Science Specialization : 60
- Z Value for the Networking Specialization : 70
- Z Value for the Software Specialization : 70

Based on the results of calculations using the Fuzzy Tsukamoto FIS method with sample data on student skills, the specializations that can be considered for these students are Networking and Software, each with a defuzzification value of 70, while the Data Science specialization has a value of 60, which is lower than the other two specializations.

Determining the α-predicate and Z Value for the Programming Language Skill Variable

As with the previous variables, the α-predicate for the programming skill variable is based on the degree of membership (μ) of the skills possessed by students. In the implication process, the Min method is used to determine the smallest value of the fuzzy set in accordance with the predetermined rules. Next, the Z value is calculated to determine the direction of students' interest in the fields of Data Science, Networking, or Software.

a. Calculation of α-predicate and Z for the Evaluation of Data Science Specialization Programming Language Skills.

[R1] IF R Low AND C Low AND PY Low AND SQL Low THEN Data Science Specialization Low
α- Predicate 1 = *Min* (1, 1, 0, 0) = 0
Z1 = 60 + (0 × 10) = 60
[R2] ----------------
[R7] IF R High AND C High AND PY High AND SQL High THEN Data Science Specialization High
α- Predicate 7 = *Min* (0, 0, 1, 1) = 0
Z7 = 60 + (0 × 10) = 60

b. Calculation of α-predicate and Z for the Evaluation of Networking Specialization Programming Language Skills.

[R1] IF C Low AND PY Low AND SQL Low THEN Networking Specialization Low
α- Predicate 1 = *Min* (1, 0, 0) = 0
Z1 = 60 + (0 × 10) = 60
[R2] ----------------
[R7] IF C High AND PY High AND SQL High THEN Networking Specialization High
α- Predicate 7 = *Min* (0, 1, 1) = 0
Z7 = 60 + (0 × 10) = 60

c. Calculation of α-predicate and Z for the Evaluation of Software Specialization Programming Language Skills.

[R1] IF J Low AND JS Low AND PHP Low AND C Low AND PY Low AND SQL Low THEN Software Specialization Low
α- Predicate 1 = *Min* (1, 1, 0, 1, 0, 0) = 0
Z1 = 60 + (0 × 10) = 60
[R2] ----------------
[R7] IF J High AND JS High AND PHP High AND C High AND PY High AND SQL High THEN Software Specialization High
α- Predicate 7 = *Min* (1, 0, 1, 0, 1, 1) = 0
Z7 = 60 + (0 × 10) = 60

d. Defuzzification Process

The defuzzification process was carried out using the weighted average method. The final value was obtained from the Z result in each fuzzy rule in each specialization. The following are the defuzzification

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results for the Data Science, Networking, and Software specializations:

- Z Value for the Data Science Specialization: 60
- Z Value for the Networking Specialization : 60
- Z Value for the Software Specialization : 60

The result remains 60 because all α-predicates ultimately produce 0 in the high-value rules. This makes the calculation Z = 60 + (0×10) = 60 in each specialization. Based on the calculation results using sample data on students' programming skills, the specializations that can be considered for these students are Data Science, Networking, and Software because all three have the same value.

Application of the TOPSIS Method

After obtaining the results from the Fuzzy Tsukamoto method, the next step is to apply the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method to determine the best specialization. This process begins with compiling a decision matrix based on the data obtained, including the values of compulsory courses, skills, and programming skills in each specialization. This matrix will be the basis for calculating and determining the ideal solution. The decision matrix used is shown in Table 12.

Table 12. Decision Matrix Table

Alternative (Specialization)	Course Grade	Skill	Programming Language Skill
Data Science	70	60	60
Networking	70	70	60
Software	60	70	60

The next step is to normalize the decision matrix. This normalization aims to equalize the scale of values for each criterion so that the comparison is more fair and balanced. That way, each specialization can be assessed objectively even though the initial values are different. The normalization process begins by calculating the sum of squares of each value in each column, which is then used as the basis for the normalization calculation, as follows:

- Course Grade:

$$\sqrt{70^2 + 70^2 + 60^2} = \sqrt{4900 + 4900 + 3600} = \sqrt{13.400} = 115.76$$

- Skill:

$$\sqrt{60^2 + 70^2 + 70^2} = \sqrt{3.600 + 4900 + 4900} = \sqrt{13.400} = 115.76$$

- Programming Language Skill:

$$\sqrt{60^2 + 60^2 + 60^2} = \sqrt{3.600 + 3.600 + 3.600} = \sqrt{10.800} = 103.92$$

Next, each value in the decision matrix is divided by the square root of the sum of squares in each column. This step aims to obtain normalized values so that all data is on the same scale. This calculation is performed using the formula shown in Table 13.

Table 13. Normalization Table

Alternative	Course Grade	Skill	Programming Language Skill
Data Science	$\frac{70}{115.76} = 0.605$	$\frac{60}{115.5} = 0.518$	$\frac{60}{103.92} = 0.577$
Networking	$\frac{70}{115.76} = 0.605$	$\frac{70}{115.5} = 0.605$	$\frac{60}{103.92} = 0.577$
Software	$\frac{60}{115.76} = 0.518$	$\frac{70}{115.5} = 0.605$	$\frac{60}{103.92} = 0.577$

After obtaining the normalized decision matrix, the next step is to determine the weight for each criterion. The weights are distributed evenly, namely 0.333 for compulsory course grades, skills, and programming skills. This distribution is done because the three criteria are considered equally important in determining student specializations. This process produces a weighted matrix, as shown in Table 14.

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Table 14. Weighted Matrix Table

Alternative	Course Grade	Skill	Programming Language Skill
Data Science	0.333 × 0.605 = 0.200	0.333 × 0.518 = 0.171	0.333 × 0.577 = 0.190
Networking	0.333 × 0.605 = 0.200	0.333 × 0.605 = 0.200	0.333 × 0.577 = 0.190
Software	0.333 × 0.518 = 0.171	0.333 × 0.605 = 0.200	0.333 × 0.577 = 0.190

After obtaining the weighted matrix, the next step is to determine the positive and negative ideal solutions. The positive ideal solution is the best set of values for each criterion, while the negative ideal solution is the lowest set of values. This stage is carried out to compare each alternative with both solutions, in order to determine which alternative is closest to the ideal conditions and determine the specialization that best fits the following definition:

- Positive ideal solution (A^+); maximum value of each column

  A^+ = (0.200, 0.200, 0.190)

- Negative ideal solution (A^-); minimum value of each column

  A^- = (0, 171, 0.171, 0.190)

After the positive and negative ideal solutions are determined, the distance of each alternative from both solutions is calculated. This stage aims to determine the alternative that is closest to the best solution and furthest from the worst solution, as follows:

Data Science:

- $B^+=\sqrt{(0.200-0.200)^2+(0.171-0.200)^2+(0.190-0.190)^2}=\sqrt{0+0.000841+0}=0.029$
- $B^-=\sqrt{(0.200-0.171)^2+(0.171-0.171)^2+(0.190-0.190)^2}=\sqrt{0.000841+0+0}=0.029$

Networking:

- $B^+=\sqrt{(0.200-0.200)^2+(0.200-0.200)^2+(0.190-0.190)^2}=0$
- $B^-=\sqrt{(0.200-0.171)^2+(0.200-0.171)^2+(0.190-0.190)^2}=0.41$

Software:

- $B^+=\sqrt{(0.171-0.200)^2+(0.200-0.200)^2+(0.171-0.190)^2}=\sqrt{0.000841+0+0}=0.029$
- $B^-=\sqrt{(0.171-0.171)^2+(0.200-0.171)^2+(0.190-0.190)^2}=\sqrt{0+0.000841+0}=0.029$

The final stage in this analysis is the calculation of the final preference value. This value is obtained by comparing the distance of each alternative to the positive and negative ideal solutions. The alternative with the highest value is considered the best choice because it is closest to the positive ideal solution and furthest from the negative ideal solution. The results of this calculation will show the most suitable specialization for students:

- *Data Science*: $C=\frac{0.029}{0.029+0.029}=0.5$
- Networking: $C=\frac{0.041}{0+0.41}=1.0$
- *Software*: $C=\frac{0.029}{0.029+0.029}=0.5$

Based on the final preference value calculation using the TOPSIS method, the Networking specialization has the highest preference value of 1, making it the best choice. Meanwhile, the Data Science and Software specializations each received a score of 0.5, indicating that they are quite suitable but not as optimal as the Networking specialization.

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4. CONCLUSION AND RECOMMENDATIONS

Based on this study, the developed specialization recommendation system successfully provided objective recommendations in helping students choose specializations that suit their abilities. Fuzzy Tsukamoto was used to handle uncertainty in subjective data, while TOPSIS was used to generate specialization rankings based on the values of compulsory courses, skills, and programming skills mastered by students. The results of the system testing show that the Networking specialization received the highest preference score of 1.0, followed by Data Science and Software with 0.5 each, proving that the system is capable of producing a logical order of specialization priorities that matches the students' ability profiles. For further research, it is recommended to add other relevant variables such as student involvement in projects, organizational activities, or specific academic achievements, so can be more comprehensive and produce more accurate recommendations in accordance with the overall student profile.

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