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Decision Support System Modeling for Determining Thesis Advisors Using Profile Matching

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Abstract

This study aims to develop a decision support system based on the Profile Matching method to provide automatic, objective, and systematic recommendations for determining thesis advisors. The background of this research is the advisor selection process that is commonly conducted manually by students, which often leads to an imbalance in lecturer workload and incompatibility between students' research topics and lecturers' areas of expertise. Such conditions can reduce the effectiveness of the thesis supervision process. The proposed system applies the Profile Matching method to compare lecturer competency profiles with student research needs by analyzing several criteria. These criteria are divided into Core Factors and Secondary Factors, which include the suitability of research fields, supervisory experience, and the number of students currently being supervised. Data used in this study were collected from students and lecturers in the Computer Science study program. The system's recommendations were then tested and validated through manual calculations to evaluate their accuracy and reliability. The results of this study indicate that the developed decision support system is capable of generating an advisor ranking that aligns well with students' research interests while also distributing supervision workloads more evenly among lecturers. Overall, this research demonstrates that implementing a decision support system using the Profile Matching method can enhance objectivity, fairness, and efficiency in determining thesis advisors. Furthermore, the system can serve as a foundation for the future development of academic recommendation systems in higher education institutions.

Keywords: Decision Support System, Profile Matching, Thesis Advisor Recommendation, Academic Supervision, Lecturer Workload Distribution

1. Introduction

The process of determining thesis advisors in many study programs is still predominantly carried out manually, where students are given the freedom to choose their advisors based on personal preferences. While this approach offers flexibility and autonomy for students in selecting lecturers they feel comfortable working with, it also gives rise to a number of significant challenges. In practice, students often select advisors based on factors such as popularity, familiarity, or prior personal interactions, rather than on an objective assessment of the lecturer's academic expertise or relevance to the chosen research topic.

As a result, mismatches frequently occur between students' research fields and the competencies of their assigned advisors, which can hinder the quality and direction of the thesis guidance process. Furthermore, this selection mechanism often leads to an unequal distribution of supervisory workloads among lecturers. Certain lecturers become overwhelmed with a large number of supervisees, while others are assigned only a few or none at all. Such workload imbalances can reduce the effectiveness of supervision, limit the amount of time and attention lecturers can provide to each student, and potentially delay the completion of theses. Overall, these issues not only affect individual students and lecturers but also have broader implications for academic quality assurance and the efficiency of the thesis completion process within higher education institutions.

These problems indicate that the process of selecting thesis advisors based solely on student preferences does not necessarily ensure an objective and appropriate match between the chosen thesis topics, the academic competencies of lecturers, and the number of students supervised by each lecturer. The absence of clear assessment criteria and measurable parameters often leads to subjective decisions that may overlook important academic considerations. Consequently, this condition can negatively affect the effectiveness of the supervision process, as well as the quality of guidance received by students.

Therefore, it is essential to implement a more structured, systematic, and measurable approach to support the determination of thesis advisors. Such an approach should be capable of objectively evaluating the suitability between students' research needs and lecturers' areas of expertise, while also considering supervisory capacity and workload balance. By applying a well-defined method, the advisor selection process can become more transparent, fair, and efficient. Ultimately, this structured approach is expected to contribute to a more equitable distribution of supervision responsibilities among lecturers and to improve the overall academic quality and timely completion of students' theses.

One of the problems that often occurs is that the process of determining thesis supervisors is still based on subjectivity. Therefore, a decision support system that uses appropriate methods is needed to help determine supervisors more objectively, while ensuring a fairer distribution of supervision and improving academic effectiveness [1]. The role of the thesis advisor is very important in the process of writing a thesis by students. The thesis advisor is responsible for determining the direction or topic of the student's research. Critical discussions between lecturers and students are essential for producing a quality thesis. Without effective written feedback from the thesis advisor, students may find it difficult to achieve the expected academic writing standards [2].

The basic concept of a recommendation system is a system used to facilitate the process of assigning thesis advisors to students. This approach is considered appropriate because it can help match the title or topic of a student's thesis with the field of expertise or research of the thesis advisor [3]. A Decision Support System (DSS) is an information system designed to assist the decision-making process in an organization. DSS facilitates decision-making by presenting structured and relevant information. The data and information available in DSS are processed using mathematical or statistical methods to generate recommendations or decision alternatives [4].

The developed decision support system aims to address specific problems by providing appropriate solutions and supporting more effective decision making [5]. This system works by presenting various decision- es obtained through data processing and the application of analytical models, without replacing the main role of the decision maker [6]. A Decision Support System (DSS) is a system designed to assist students or decision makers in making decisions, especially in semi-structured situations [7]. DSS uses various methods in the decision-making process, one of which is the profile matching method. This method has been widely applied by other researchers, both in education and other fields [8].

The Profile Matching method is a technique that compares an individual's profile with established competency standards, with the aim of identifying gaps between the required criteria and the candidate's characteristics [9]. The Profile Matching method is a method in a decision support system that compares the actual value of a profile with the expected profile value [10]. The Profile Matching method is widely used because it is relatively easy to understand in supporting decision making. This method works by comparing the GAP (difference) between the actual value and the expected value, and assessing alternatives based on predetermined criteria [11].

The Profile Matching process begins with the selection of the necessary criteria and the setting of Target Values for each aspect. Next, the individual's abilities are compared with the predetermined qualifications to obtain a GAP value. The smaller the GAP value, the greater the weight given. The next stage involves calculating the Core Factor and Secondary Factor, with a certain percentage given to each factor as the basis for determining the final score [12].

GAP is the difference between the job profile or established criteria and the individual profile score, which is measured based on predetermined attributes. Determination of GAP Value Weighting: At this stage, the value weighting for each attribute is determined based on predetermined weights. Once the weighting for each attribute has been determined, the attributes are then divided into two groups, namely Core Factors and Secondary Factors. Core Factors are the most important or prominent attributes of a position and are expected to contribute the most to optimal performance. Secondary Factors include attributes other than Core Factors. The final result of the Profile Matching method is a ranking of candidates that shows their order of suitability to become academic advisors [13].

This study aims to develop a system capable of automating the recommendation of thesis advisors in an accurate and measurable manner, replacing the manual selection process previously carried out by students. With this system, it is hoped that the distribution of students under supervision will be more balanced, the suitability of lecturer competencies will be optimized, and the quality of the thesis supervision process will improve. The potential benefits of this research include improved thesis supervision quality through competency matching and the creation of a more objective and measurable advisor placement mechanism. Several studies [14], [15] have discussed the Profile Matching method for lecturer recommendations, but these studies only matched one field for students. Students only had one field of study, whereas in this study, students could choose one to three fields of study, which were then matched with the lecturers' areas of expertise. The Secondary Factors in both studies used aspects such as position, level of education, and length of service of the lecturer. In contrast, this study uses Secondary Factors such as the number of students the lecturer has supervised and the number of students currently under their supervision. These factors were chosen because they can improve the match between students and supervisors if the lecturer has frequently supervised students in the same field. It also avoids having too many students under the guidance of the lecturer. That is why the researcher uses the Secondary Factors of mentoring experience and the lecturer's mentoring load.

Thus, this study not only adapts the existing Profile Matching method but also develops it for real-world conditions where students can choose more than one research field and additional factors are used to optimize the distribution of supervision. This approach is expected to provide a more objective, measurable, and effective solution in the process of determining thesis supervisors.

2. Methodology

This study uses the Profile Matching method to build a thesis advisor recommendation system. The research data was obtained through digital sources, specifically from the UINSU Computer Science Study Program website. The data used consisted of lecturer data in the form of areas of expertise or competence, as well as student data in the form of research topics or fields. All data was collected through digital documentation techniques and processed into a research dataset.

The system design stage was carried out by preparing a process architecture consisting of data processing, Profile Matching calculations, and presentation of recommendation results. The ideal value for each criterion was determined in advance, then the actual value of the lecturer was calculated based on the gap between the ideal value. The gap value is converted into a weight using a gap table, then the final value is calculated using the criteria weights: 70% for field suitability, 20% for testing experience, and 10% for workload. The calculation results in a lecturer ranking, and the lecturer with the highest score is recommended as a supervisor.

Determination of ideal and actual values: each criterion is measured on a normalized scale (0-5) to be compared with the ideal value (SIdeal):

Field Suitability = Normalization: $\left(\frac{\text{Number of Matching Fields}}{\text{Total Student Fields}}\right) \times 5$

Supervisory Experience = Normalization: $\left(\frac{\text{Current Lecturer Experience}}{\text{Maximum Lecturer Experience}}\right) \times 5$

Guiding Load = Reverse Normalization: $5 - \left(\frac{\text{Actual Lecturer Load}}{\text{Maximum Lecturer Load}}\right) \times 5$

The number of matching fields refers to the number of fields that match between the lecturer's field and the student's thesis research field, and the total number of student fields is the sum of the student's research fields. Actual lecturer experience refers to the experience of the lecturer to be calculated, and maximum lecturer experience refers to the most experience of the lecturer in the data. The same applies to actual lecturer workload and maximum lecturer workload. In reverse normalization, the mentoring workload is a negative criterion. A score of 5 is given if the lecturer's workload is very light (close to zero), and a score close to 0 is given if the lecturer's workload is full (close to maximum).

Gap calculation (difference). This step is the core of Profile Matching. The difference between the actual and ideal scores is calculated and then rounded:

$G = \text{round}(SActual - SIdeal)$

$G = 0$: The actual value is exactly the same as the ideal value.

$G > 0$: Actual value exceeds ideal value.

$G < 0$: Actual value is less than ideal.

The final total score is calculated by converting each gap value (G) into a Value Weight (B) using a special mapping table (Core Factor Mapping). The weight reflects the level of conformity or performance of the lecturer to the predetermined ideal value.

Table 1. Gap Weights

GAP	Assigned Weight	Interpretation
0	5	Meets ideal target (Very Good)
1	4.5	Slightly better than target
-1	4	Slightly below target
2	3.5	Much better
-2	3	Much worse (needs improvement)
3	2.5	Far above target (inefficient)
-	2	Well below target (needs improvement)
Other	1	Not appropriate

The table shows eight gap levels from -3 to +3. Gap 0 receives the highest weight (5.0) because it is considered most in line with the ideal value. Negative gaps (-1 to -3) indicate values below the target, so their weights decrease to 4.0, 3.0, and 2.0. Meanwhile, positive gaps (+1 to +3) describe values that exceed the target, with weights of 4.5, 3.5, and 2.5, respectively. The greater the gap from 0, whether lower or higher, the smaller the weight given because it is considered less than ideal.

Calculation of the total recommendation score: after all Value Weights (B) for each criterion are obtained, these values are then combined using the Weighted Summation method. At this stage, each criterion is multiplied by its percentage weight (W), then all the multiplication results are added together to produce the final recommendation value.

$$S_{Total} = (0.7 \times B_{Field}) + (0.2 \times B_{Exp}) + (0.1 \times B_{Load})$$

The lecturer with the highest STotalvalue will be placed as the top recommendation, i.e., in first place for the student concerned. The testing in this study was conducted manually, namely by calculating all stages of Profile Matching using direct calculations without the aid of software. In addition, the study also evaluated whether the final results were in line with expectations based on the concept of lecturer expertise field suitability. This approach ensures that even though no external comparators are available, the recommendation results remain methodologically valid and in accordance with the basic principles of the Profile Matching method.

2.1 System Flowchart

Figure 1 illustrates the system flowchart of the thesis supervisor recommendation process using the Profile Matching method. The flowchart describes each stage, starting from data collection, score calculation, gap analysis, weighting, ranking, and ending with the final recommendation.

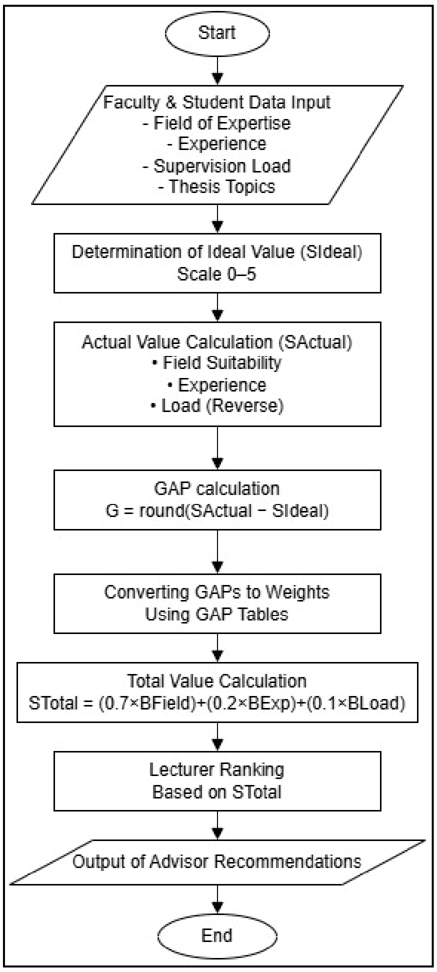

Figure 1. Flowchart of the Profile Matching Calculation Process

The flowchart illustrates the stages of the thesis supervisor recommendation process using the Profile Matching method. The process begins by collecting student profile data, particularly the student's research field interests, followed by the collection of lecturer profile data, which includes field of expertise, mentoring experience, and current mentoring workload. After the data are gathered, an ideal or standard profile is determined to serve as a reference for evaluating lecturer suitability. The system then calculates the actual scores (SActual) for each lecturer based on predefined formulas for each criterion, such as field suitability, mentoring experience, and mentoring load.

Next, the gap value is obtained by calculating the difference between the actual score and the ideal score for each criterion. These gap values are then converted into weighted scores using the Profile Matching gap weight table to ensure consistent evaluation. In this process, field suitability is treated as the Core Factor because it has the greatest influence on the effectiveness of thesis supervision, while mentoring experience and mentoring workload are considered Secondary Factors. The system subsequently calculates the final score for each lecturer by combining the weighted Core Factor and Secondary Factors according to their respective importance. Based on these final scores, the lecturers are ranked from the highest to the lowest, and the lecturer with the highest score is recommended as the most suitable thesis supervisor. This structured process ensures that the recommendation results are objective, measurable, and aligned with both student research needs and lecturer capacity.

3. Results and Discussion

3.1 Assessment Criteria & Percentage Weights

The Profile Matching method is used to find the most suitable lecturers based on lecturer profiles and student needs. There are three assessment criteria used, as shown in Table 2.

Table 2. Assessment Criteria & Percentage Weights

No.	Criteria	Weight	Category
1	Field Suitability	70 (0.7)	Core factor
2	Mentoring experience	20 (0.2)	Secondary factor
3	Faculty Workload	10 (0.1)	Secondary factor

The faculty advisor recommendation system uses the Profile Matching method by comparing the field of study in the student's thesis title, advising experience, and faculty workload. Field compatibility is calculated based on the number of matches between the lecturer's field of expertise and the field of the student's thesis title, experience is assessed based on how many students the lecturer has supervised, and workload is assessed based on how many students are currently being supervised by the lecturer at that time. Each actual value is compared to the ideal value and converted using a gap table, then weighted 70% for field suitability, 20% for experience, and 10% for workload. The final result is a ranking of lecturers, where the lecturer with the highest score is recommended as the most suitable supervisor.

3.2 Sample Lecturer Data

To perform manual calculations, the researcher uses three sample data sets of lecturers obtained from the Computer Science study program website of UINSU. These data are used to identify the field of competence of each lecturer based on their academic background and expertise. In addition, information regarding lecturers' supervisory experience and current supervisory workload is included as sample variables to support the evaluation process and illustrate the application of the proposed method. The following is the sample data for the 3 lecturers shown in Table 3.

Table 3. Data sample of lecturers

No.	lecturer's name	Field	Experience	Workload
1	Dr. Mhd. Furqan, S.Si., S.H., M.Comp.Sc	Probabilistic Computing Data Mining Teks Mining Data Visualization Process Optimization Machine Learning Image and Signal Processing Vision or Pattern Recognation Ubiquitous Computing	60	4
2	Ilka Zufria, M.Kom	Data Mining Teks Mining Informatics Retrieval Decission Suport System Expert System Process Optimization Virtual Reality Human-Computer Interaction	40	3
3	Sriani, M.Kom	Fuzzy Logic Computing Data Visualization Process Optimization Machine Learning Image and Signal Processing Human-Computer Interaction	45	3

The data are used as sample inputs for conducting manual calculations in this study. The field variable represents the lecturer's area of expertise, which is used to assess the suitability between the lecturer's competence and the student's research topic. The experience variable refers to the number of students that a lecturer has previously supervised, while the workload variable indicates the number of students currently under the lecturer's supervision. It is important to note that the experience and workload data used in this study are not based on actual institutional records. Instead, these values were entered by the researcher solely for simulation and calculation purposes. This approach was taken because reliable and publicly available data regarding lecturers' supervisory experience and current workload could not be obtained. Although the data are hypothetical, they are designed to represent realistic conditions and are sufficient to demonstrate the profile matching calculation process and evaluate the functionality of the proposed decision support method.

3.3 Manual Calculation

To conduct a manual calculation trial, the researcher used sample data from student final projects to perform the matching process using the Profile Matching method. These data represent students' research topics and requirements, which are then compared with lecturer profiles based on predetermined criteria. The sample data are used to illustrate the stages of calculation and to validate the accuracy of the matching results. The sample of student final project data used in this manual calculation is presented in Table 4.

Table 4. Data sample of lecturers

Name	Field of Thesis Title
Student A	Text Mining (TM) Machine Learning (ML) Data Mining (DM)

In the sample data, Student A selected three main thesis subject areas, namely Text Mining, Machine Learning, and Data Mining. These subject areas represent the primary research interests of the student and serve as the basis for determining advisor suitability. Based on the level of compatibility between the lecturers' competencies and these three research areas, the system then performs a profile matching process. This process evaluates the degree of alignment between student needs and lecturer profiles using predefined criteria. The following section presents a detailed manual calculation of the profile matching process to illustrate how the final advisor recommendations are generated.

Table 5. Calculation for Dr. Mhd. Furqan, S.Si, S.H, M.Comp.Sc

Criteria	Actual Data	SActual	G(Gap)	B	W x B
Field	Suitable: TM, ML, DM (3 out of 3)	$\left(\frac{3}{3}\right) \times 5 = 5.0$	round(5.0 – 5.0) = 0	5.0	0.7 × 5.0 = 3.5
Mentoring Experience	60 times	$\left(\frac{60}{60}\right) \times 5 = 5.0$	round(5.0 – 4.0) = 1	4.5	0.2 × 4.5 = 0.9
Mentoring Load	4 Guidance	$5 - \left(\frac{4}{4}\right) \times 5 = 0$	round(0 – 3.0) = -3	2.0	0.1 × 2.0 = 0.2
Total Score:					4.6

Table 6. Calculations for Ilka Zufria, M.Kom

Criteria	Actual Data	SActual	G(Gap)	B	W x B
Field	Suitable: TM, DM (2 out of 3)	$\left(\frac{2}{3}\right) \times 5 = 3.33$	round(3.33 – 5.0) = -2	3.0	0.7 × 3.0 = 2.1
Mentoring Experience	45 Times	$\left(\frac{50}{60}\right) \times 5 = 4.16$	round(4.16 – 4.0) = 0	5.0	0.2 × 5.0 = 1
Mentoring Load	3 Guidance	$5 - \left(\frac{3}{4}\right) \times 5 = 1.25$	round(1.25 – 3.0) = -2	3.0	0.1 × 3.0 = 0.3
Total Score:					3.4

Table 7. Calculations for Sriani, M.Kom

Criteria	Actual Data	SActual	G(Gap)	B	W x B
Field	Suitable: ML (1 out of 3)	$\left(\frac{1}{3}\right) \times 5 = 1.66$	round(1.66 – 5,0) = -3	2.0	$0.7 \times 2.0 =$ 1.4
Mentoring Experience	45 Times	$\left(\frac{45}{60}\right) \times 5 = 3.75$	round(3.75 – 4,0) = 0	5.0	$0.2 \times 5.0 =$ 1
Mentoring Load	3 Guidance	$5 - \left(\frac{3}{4}\right) \times 5 = 1.25$	round(1.25 – 3.0) = -2	3.0	$0.1 \times 3.0 =$ 0.3
Total Score:					2.7

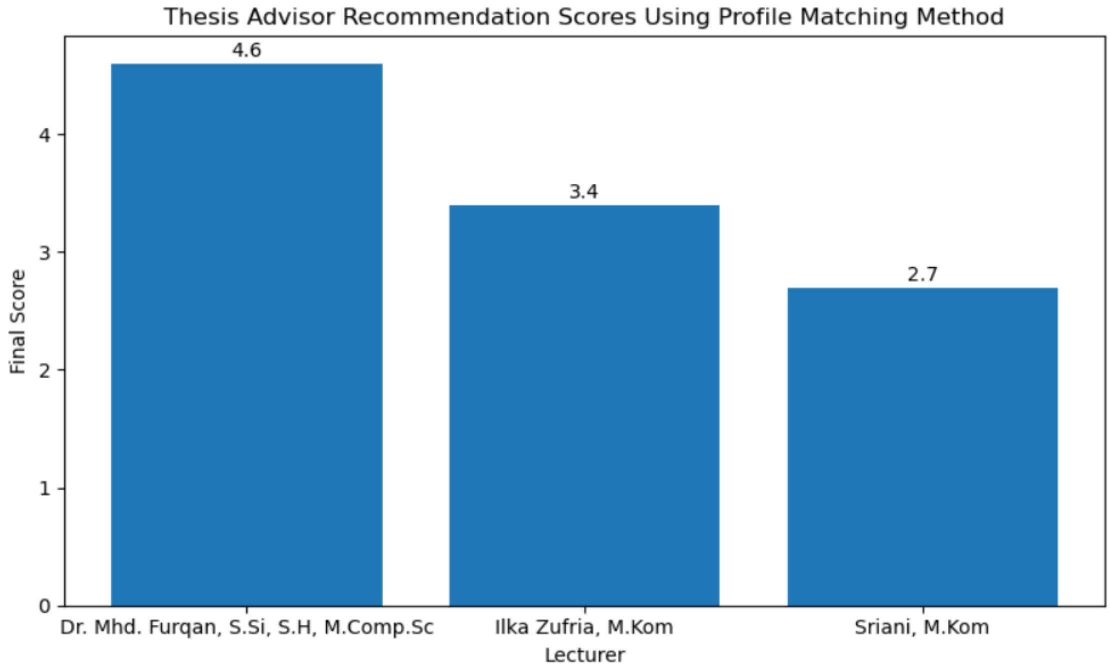

Figure 2. Lecturer Ranking Results Based on the Profile Matching Method

Based on the results of the manual calculations presented in the previous table, the lecturer who is most recommended to supervise Student A's thesis is Dr. Mhd. Furqan, S.Si, S.H, M.Comp.Sc, who achieved the highest ranking with a final score of 4.6. This result indicates that the lecturer's field of expertise is highly aligned with Student A's selected research areas, namely Text Mining, Machine Learning, and Data Mining. The second recommended supervisor is Ilka Zufria, M.Kom, who obtained a score of 3.4, reflecting a moderate level of suitability between her competencies and the student's research focus. Meanwhile, Sriani, M.Kom, received the lowest score of 2.7, indicating a lower level of compatibility based on the applied criteria.

The profile matching calculation process in this study prioritizes the suitability of the research field as the Core Factor, as it plays a crucial role in ensuring effective academic guidance and research quality. In addition, supervisory experience and current supervisory workload are considered as Secondary Factors to support fair workload distribution among lecturers. By combining these factors, the system is able to generate advisor recommendations that are more objective, structured, and measurable. This approach helps align faculty competencies with student research needs while also promoting a more balanced supervision system.

4. Conclusion

Based on the research results and discussion, it can be concluded that the decision support system based on the Profile Matching method is able to provide more objective and measurable recommendations for thesis supervisors compared to the manual method previously used by students who chose based on popularity or personal experience. This system successfully combines several criteria, including research field suitability, mentoring experience, and number of students under supervision, through Core Factor and Secondary Factor calculations.

By applying the Profile Matching method, the system can generate a ranking of supervisors that matches the competence and availability of supervising lecturers, while distributing the mentoring load more evenly. This study shows that the development of an expanded Profile Matching model that takes into account several research fields and lecturer experience factors can improve the effectiveness and quality of the thesis supervision process. Thus, the developed system makes a significant contribution as a decision-making tool that supports objectivity, efficiency, and fairness in determining supervising lecturers.

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