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Analysis of an Adaptive E-Learning System with the Adjustment of the Felder-Silverman Model in Moodle

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Abstract. In the digital era, adaptive e-learning has become essential in addressing students' diverse learning preferences. This study aims to develop an adaptive e-learning system that integrates the Felder-Silverman Learning Style model (FSLSM) into Moodle using fuzzy logic and case-based reasoning. The system extracts behavioral attributes from student activity logs and classifies learning styles into four dimensions: processing, perception, input, and understanding. The experimental evaluation, conducted with and without substitution of the (ILS) questionnaire values, demonstrated varying levels of accuracy. Accuracy improved with ILS substitution as follows: processing (82.86%), perception (80.00%), input (80.00%), and understanding (74.29%). Without ILS substitution, the accuracies were as follows: processing (80.00%), perception (80.00%), input (74.29%), and understanding (62.86%). These findings confirm the system's potential to support personalized learning by accurately identifying learning styles.

Keywords: *e-learning adaptive, Learning Style, Felder-Silverman, fuzzy logic, case-based reasoning, Moodle*

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1. Introduction

In the current digital learning environment, e-learning systems have become essential components of education [1]. However, these systems often lack personalization features that can accommodate the individual differences in learning preferences. Adaptive e-learning, which tailors learning experiences according to student characteristics, is a promising solution to this challenge [2]–[7]. One model used to analyze individual learning styles is the Felder-Silverman model [8]–[10]. This model classifies learners into four dimensions of learning style: visual-verbal, active-reflective, sensory-intuitive, and sequential-global. However, in the context of e-learning, the implementation of the Felder-Silverman model has still not been widely explored.

The term learning style refers to the concept that each individual has differences in determining the most effective learning method [2]. Research related to the learning process focuses on accommodating the various learning styles of students [11]. One way to determine students' learning styles is to use questionnaires based on learning style model theory [12]. Although this instrument is reliable and supported by good validity, it has some shortcomings that can hinder the identification process. These shortcomings include the lack of student motivation when filling out questionnaires, and the inability of instruments to provide valid information as a basis for determining learning styles.

Along with the development of learning technology, the field of Automatic Detection of Learning Style (ADLS) has emerged, triggered by advances in the development of intelligent tutoring and adaptive e-learning. However, this system still has a drawback, namely, the difference in activity log data in the learning management system (LMS), which is the basis of the system, making it difficult to compare the performance of different approaches [13]. In the ADLS, the learning style model is used as a basis to group students according to their learning style and preferences in receiving and processing information [5]. Learning style models that are widely known among researchers include the Honey and Mumford learning style model [14], Kolb model [15]–[17], and

Felder-Silverman learning style model [10], [18], [19]. Theories related to learning style models can help develop learning materials tailored to students' preferences, experiences, and learning styles [20].

Moodle [21] is one of the most popular and flexible e-learning platforms that offers the potential to integrate the Felder-Silverman model in the design of adaptive e-learning systems. By utilizing the Moodle feature, which can track participants' learning behavior, adaptive adjustments based on the Felder-Silverman model can be applied to present learning content that suits the preferences and needs of each individual.
This study aims to develop and evaluate an adaptive e-learning system that classifies students' learning styles based on the Felder-Silverman Learning Style Model (FSLSM) using fuzzy logic and case-based reasoning. The specific objectives are:

1. To identify students’ learning styles from the Moodle activity log data across four FSLSM dimensions: processing, perception, input, and understanding.
2. To measure and compare the classification accuracy of learning styles with and without the substitution of Learning Style (ILS) questionnaire values.
3. To evaluate the effectiveness of fuzzy similarity and nearest-neighbor methods in determining learning style similarity

The proposed system analyzes students' interactions with Moodle to infer their learning style preferences across FSLSM dimensions. This data-driven approach aims to provide a more accurate and dynamic assessment of learning styles than static questionnaires. By implementing fuzzy logic and case-based reasoning, the system can handle the inherent uncertainty in learning style classification and provide personalized recommendations for content presentation.

2. Methods

The proposed system aims to revolutionize the assessment of students' learning style preferences by leveraging their interactions with Moodle’s learning management system. This innovative approach analyzes various aspects of student behavior within the platform, including resource access patterns, engagement with different types of content, and participation in online activities. By examining these interactions across the dimensions outlined in the Felder-Silverman Learning Style Model (FSLSM), the system can infer individual learning-style preferences with greater accuracy and granularity.

Unlike traditional static questionnaires, which provide a snapshot of learning styles at a single point in time, this data-driven method offers a dynamic and evolving assessment. It continuously updates its understanding of each student's preferences, based on their ongoing interactions with the learning environment. This adaptability ensures that the system remains responsive to changes in learning styles that may occur as students progress through their educational journeys. The implementation of fuzzy logic in the proposed system addresses the inherent complexity and uncertainty involved in categorizing the learning styles. Fuzzy logic allows for a more nuanced classification that acknowledges the spectrum of preferences, rather than forcing students into rigid categories. This approach recognizes that learners may exhibit varying degrees of alignment with different style dimensions, thereby providing a more realistic representation of individual learning tendencies.

Furthermore, the integration of case-based reasoning enhances a system's ability to make personalized recommendations for content presentation. By drawing upon a repository of past cases and successful learning experiences, the system can suggest tailored learning materials and instructional strategies that align with each student's inferred learning-style preferences. This personalization aims to optimize the learning experience by presenting information in formats and sequences that resonate with the cognitive processes of individual students. The combination of these advanced techniques, data-driven analysis, fuzzy logic, and case-based reasoning promises to create a robust and adaptive system for learning style assessments and personalized education. Moving beyond the limitations of traditional methods, this approach has the potential to significantly enhance the effectiveness of online learning environments and support improved learning outcomes for diverse student populations.

3. Results and Discussion

In this study, we developed a system that can provide learning style recommendations as part of the automatic detection of learning style (ADLS), which uses inputs in the form of student behavior patterns obtained from the results of extracting data from the activity log data of the learning management system (LMS). The output produced by the system was classified into four dimensions according to the Felder-Silverman learning style model (FSLSM). The details of the FSLSM learning-style model are shown in Table 1.

Table 1. Dimension Felder Silverman Learning Style Model (FSLM)

Dimension	Learning Style
Dimension 1 (processing)	Active/Reflective

Dimension 2 (Perception)	Sensing/Intuitive
Dimension 3 (Input)	Verbal/Visual
Dimension 4 (Understanding)	Sequential/Global

Broadly speaking, the learning style recommendation process consists of several stages: collecting learning management system (LMS) activity logs, extracting student behavior patterns, examining the contents of the case content/case library, fuzzy logic (fuzzification, inference, defuzzification), similarity function, testing, confirmation, and evaluation using the confusion matrix equation. Extraction of student behavior patterns using Table 2.

Table 2. Data Learning Management System (LMS)

Date	Time	User Full Nama	Event Context	Compose	Even Nama
03/09/24	10.00	Student 1	Page: A*	Page	Course Modul Viewed
03/09/24	12.16	Student 2	Page: A*	Page	Course Modul Viewed

Eleven attributes were used as the learning style recommendation instruments. Activity logs obtained from *learning management systems* (LMS) are shown in Table 3.

Table 3. Data Attributes

Input	Behavior Pattern Names
A1	Number of visit material (content object)
A2	Time taken to read material (content object)
A3	Number of visits to discussion forum
A4	Number of self-assessment-test
A5	Time taken to self-assessment-test
A6	Number of visit result pages of self-assessment-test
A7	Number of visit material (example)
A8	Time taken to read material (example)
A9	Number of revisions performed before handing in a test
A10	Time spent in a discussion forum
A11	Number of skipped learning objects

Table 4. The Influence of 11 Behavioral Pattern Attributes on the Learning Style Dimension

Dimension	Learning Style	Behavior Patterns
Dimension 1 (processing)	Active	Number of self-assessment-test
	Reflective	Number of visit material (content object), number of visits on a discussion forum, time taken to self-assessment test, number of visit result pages of the assessment test
Dimension 2 (Perception)	Sensing	Number of visit material (example), time taken to read material (example), number of revisions performed before handling in a test, number of visit result pages of self-assessment test
	Intuitive	Number of visits to material (content object), time taken to read material (content object)
Dimension 3 (Input)	Visual	-
	Verbal	Number of visits to a discussion forum, time spent in a discussion forum, number of visits to material (content object)
Dimension 4 (Understanding)	Sequential	-
	Global	Number of skipped learning objects

Table 4 Influence of 10 attributes of students' behavior patterns on learning style preferences in each dimension. Meanwhile, five attributes that are not used in the process of extracting student behavior patterns have a dominant influence if the value of these attributes is at a high frequency, as shown in Table 5.

Table 5. The Influence of 5 Behavioral Pattern Attributes on the Learning Style Dimension

Dimension	Learning Style	Behavior Patterns
Dimension 1 (processing)	Active	Number of posts on the discussion forum
	Reflective	-

Dimension 2 (Perception)	Sensing	-
	Intuitive	-
Dimension 3 (Input)	Visual	-
	Verbal	Performance on the question about graphic
Dimension 4 (Understanding)	Sequential	Performance on the question about text
	Global	-

Table 5. It is the influence of five attributes of student behavior patterns that cannot be used in the extraction process because it has a value of 0 for each attribute on learning style preferences in each dimension. In the second stage, student behavior patterns are extracted. The activity logs obtained from the learning management system (LMS) were then extracted according to the attributes in Table 3. The extraction process aims to obtain values as characteristics of an object that can describe the characteristics of students' behavioral patterns.

Table 6. Stages of Extraction of Student Behavior Patterns

Input	Behavior Patterns	Extraction stage
A1	Number of visit material (content object)	Calculating the amount of student data that has components in the form of pages and events in the form of course modules viewed
A2	Time taken to read material (content object)	Calculate the average time difference on each page of material (content object) visited
A3	Number of visit on discussion forum	Counting the amount of student data that has components in the form of forums and event names in the form of discussions viewed
A4	Number of self assessment-test	Counting the amount of student data that has a component in the form of a quiz and an event name in the form of a quiz attempt started
A5	Time taken to self-assessment-test	Calculate the average time difference from the quiz with the event quiz attempt started and quiz attempt submitted on the quiz component
A6	Number of visit result pages of self-assessment-test	Counting the number of students who have components in the form of troublesome users and event names new grade user reports viewed
A7	Number of visit material (example)	Counting the number of students who have components in the form of page and event names and new course module views and events that have example information
A8	Time taken to read material (example)	Calculate the average time difference on each visited example page
A9	Number of revisions performed before handing in a test	Calculate the average number of revisions made in the event name in the form of quiz attempt started and quiz attempt submitted in the quiz component
A10	Time spent in a discussion forum	Calculate the time difference between the event name in the form of discussion viewed and the next accessed event name
A11	Number of skipped learning objects	Counting the number of different event contexts at the same time

Table 6. It is an extraction stage for each student behavior pattern obtained from the activity log of the learning management system. If the extraction stage of student behavior patterns was completed based on the rules in Table 6, the results obtained were mapped into 11 attributes, as shown in Table 7.

Table 7. Results of Behavior Pattern Extraction

Student	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11
Student 1	21	5.90	0	21	8.05	5	0	0	0.17	0	6

Table 7 shows an example of data from the results of behavioral pattern extraction based on the 11 attributes used as system inputs or inputs. An unbalanced range of values for each attribute can affect the quality of data processing results. An imbalance in the value range of the attribute causes the results to be skewed upward or downwards. Therefore, normalization and transformation using min-max normalization are required to obtain better results. The following is the equation used in the normalization process of extracting student behavior patterns

$$MinMax = \left(\frac{v - minA}{maxA - minA}\right)(newMax - newMin) + newMin \qquad (1)$$

In Equation 1, ν is the value of the attribute, *minA* is the smallest value of an attribute, *maxA* is the largest value of an attribute, *newMax* = the new largest value to replace the old largest value, and *newMin* is the new smallest value to replace the old smallest value. The value range for attributes 1 through 11 is normalized to 0 for the lower bound and 1 for the upper bound, where 1 represents a strong positive preference, and 0 represents a strong negative preference. The normalization results obtained from *the MinMax* calculation are listed in Table 8.

Table 8. Normalization Results

Student	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11
Student 1	0.49	0.54	0.00	0.71	0.09	0.42	0.00	0.00	0.29	0.00	0.49

Table 8. This is an example of data resulting from normalization using the *MinMax* method, which converts the value of an attribute into a value range of 0 to 1. The third stage is to check the contents of the *content case library*, where there is a case in the form of input values from 11 attributes, along with solutions in the form of learning styles divided into four dimensions. The case content can contain data that have been processed at least 1 time. If there are no case data or a solution in the *case content*, then the input value in the form of the result of the extraction of behavior patterns will be processed using the fuzzy logical method first. The fourth stage is classification using the fuzzy logic method with input in the form of values from student behavior patterns that have been divided into 11 attributes. Table 9. This is the threshold for student behavior patterns in e-learning used in the fuzzification process.

Table 9. Behavioral Pattern Thresholds

Input	Behavior Pattern Names	Threshold
A1	Number of visit material (content object)	10% (0.01) and 20% (0.20)
A2	Time taken to read material (content object)	50% (0.05) and 75% (0.75)
A3	Number of visits to discussion forum	7 and 14 visits per week
A4	Number of self-assessment-test	25% (0.25) and 75% (0.75)
A5	Time taken to self-assessment-test	50% (0.05) and 75% (0.75)
A6	Number of visit result pages of self-assessment-test	10% (0.01) and 20% (0.20)
A7	Number of visit material (example)	25% (0.25) and 75% (0.75)
A8	Time taken to read material (example)	50% (0.05) and 75% (0.75)
A9	Number of revisions performed before handing in a test	10% (0.01) and 20% (0.20)
A10	Time spent in the discussion forum	5 and 10 minutes per week
A11	Number of skipped learning objects	25% (0.25) and 75% (0.75)

The results of the fuzzification stage are in the form of membership values and degrees. After the fuzzification process is completed, the results are passed to the fuzzy rule stage (IF... THEN). The output of the fuzzy rule stage is in the form of a level or level of fuzzy results along with a minimum feasibility value. Then, in the last stage of the fuzzy logic, namely defuzzification, a feasibility score calculation is carried out to determine the solution of student behavior patterns in the form of student learning styles for each dimension. This solution is then stored in a case library in the form of a case consisting of 11 attributes and a solution in the form of a student learning style.

The fifth stage is the similarity function, where the system calculates the similarity value using two scenarios in the form of fuzzy similarity and nearest-neighbor, if the case content has been filled with cases and solutions. In the first scenario**,** the fuzzy similarity method was used to determine the level of similarity of the data. Fuzzy similarity is performed after the system completes the fuzzification stage using the membership function and membership value. Fuzzy similarity is used to find similarities between the new and completed cases using the following equations:

$$x[i] = \frac{F}{H}$$

$$Sim(v, x[i]) = 1 - |v - x[i]| \qquad (2)$$

In Equation 2, x[i] is the i_{th} value of a set, H is the fuzzy set, F is the fuzzified value of set H, and v is the input/input value.

In the second scenario**,** the *nearest-neighbor method* is used to determine the level of similarity of the data. *The nearest neighbor* is operated before the system performs the fuzzification stage using the value of the data extraction results. *The nearest neighbor* is used to look for similarities between new cases and cases that have been processed using the following equation [9]:

$$Sim(v, x[i]) = 1 - \frac{|v - x[i]|}{N} \quad (3)$$

In Equation 3, x[i] is the i_{th} value of a set, v is the input/input value, and N is the highest value of a set. The results of the similarity calculations are listed in Table 10.

Table 10. Similarity Calculation Results

Student	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11
Student 1	1.0	0.94	1.0	1.0	1.0	1.0	1.0	1.0	0.8	1.0	1.0

If new data are considered similar to previous cases, this process is called *retrieval* or the stage of retrieving data with the highest level of similarity or similarity. If the results of the similarity calculation show the highest level of similarity, then the solution in the form of learning styles from old cases that have been previously processed will be reused to fill in the solutions in the form of learning styles from new cases. This process is called *reusing*.

The sixth stage is submission, where if there are data with a higher similarity value, the solution in the form of a learning style from a new case that already has a solution from the reuse process will be revised and replaced until the case in the case content shows the last index; the process is called revised. The seventh stage is the confirmation stage, when the revision process reaches the final index of the case content. At this stage, the solution in the form of student learning styles is included in the case library, along with input values that have been categorized into 11 learning style attributes. Cases containing the input value of this solution can be reused in the similarity function calculation if there are data with the highest level of similarity. The processes of *retrieving*, *reusing*, *revising*, and *retaining* are stages. When the data processing process reaches the last iteration, the results from the case library are issued in the form of learning styles classified by four dimensions, as shown in Table 11.

Table 11. Hasil Fuzzy Case-Based Reasoning

Student	Dimension 1 Active)	Dimensions 2 (Intuitive)	Dimension 3 (Visual)	Dimension 4 (Sequential)
Student 1	Active	Intuitive	Visual	Sequential

Table 11 is an example of a system output in the form of a learning style that is divided into four dimensions of learning styles. The final stage is an evaluation carried out to determine the accuracy of student behavior patterns in e-learning as material for learning style recommendations by comparing the output results with and without the substitution condition of the index of learning style (ILS) questionnaire value because the input attributes used could not meet the input recommended by previous research [22].

The evaluation stage was also carried out to determine the accuracy of the similarity function of case-based reasoning by comparing the accuracy level of the results of fuzzy similarity and nearest-neighbor. The nearest-neighbor similarity function is used to obtain case similarity through numerical/symbolic values, whereas fuzzy similarity linguistically obtains case similarity. The calculation of the accuracy level was carried out to determine the accuracy of the learning style using the confusion matrix based on the index of learning style (ILS) questionnaire data as the data that was considered correct.

Table 12. Confusion Matrix

Data classes	**Mold Classes**	**Mold class**
	Positive	Negative
Classification Classes Positive	True Positive (TP)	False Positive (FP)
	False Negative (FN)	True Negative (TN)
	Positive (P)	Negative (N)

Table 12 is a confusion matrix with TP, FP, FN, and TN, which is used to measure the accuracy of the data classification results using fuzzy logic and case-based reasoning methods. Here, is the equation used to calculate the accuracy [23].

$$\text{Akurasi} = \frac{TP + TN}{TP + FP + TN + FN} \times 100 \quad (4)$$

In Eq. (4),

- TP is the number of positive outputs that are classified as positive (correctly classified data),
- TN is the number of positive outputs that are classified negatively (incorrectly classified data),
- FP is the number of negative outputs that are classified as positive (data classified incorrectly), and

- FN is the number of negative outputs classified as negative (incorrectly classified data).

In this study, the researcher conducted a test twice by calculating the accuracy level of each learning style from the four dimensions. This test uses a system that has been substituted with the results of the index of learning style (ILS) questionnaire to determine the accuracy of student behavior patterns in the learning style recommendation process. The results of the system test built using the fuzzy-logic classification method and case-based reasoning were evaluated using a confusion matrix.

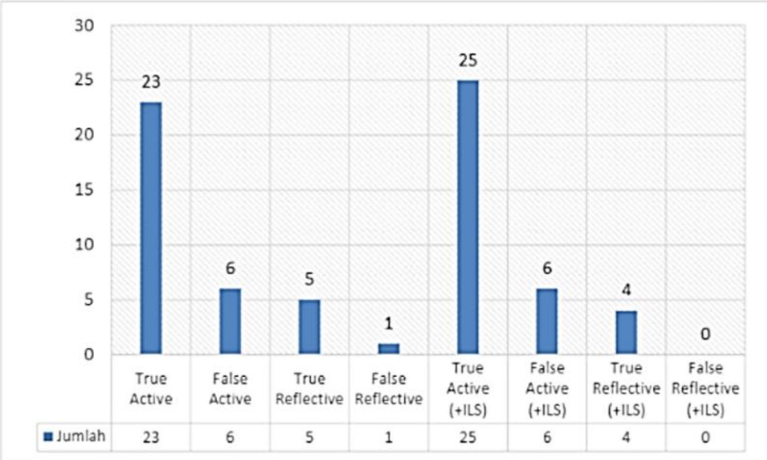

Figure 1. Results of Fuzzy Case-Based Reasoning Classification (non-ILS substitutions) and Results of Fuzzy Case-Based Reasoning (with-ILS substitutions) Classification in the Processing Dimension

Figure 1 shows that the number of data points from fuzzy case-based reasoning classification in the processing dimension with no substitution of values from the index of learning style (ILS) is as follows: true active 23, false active 6, true reflective 5, and false reflective 1. Meanwhile, the results of fuzzy case-based reasoning classification in the processing dimension with value substitution conditions from the ILS showed true active 30, false active 1, false reflective 0, and true reflective 4.

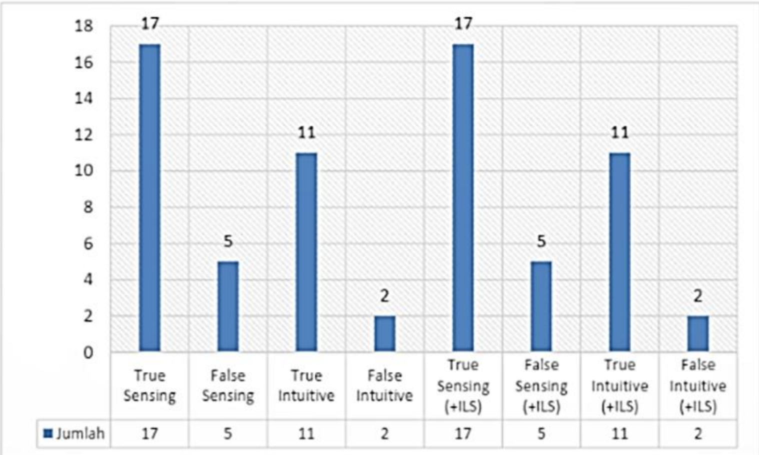

Figure 2. Results of Fuzzy Case-Based Reasoning Classification (non-ILS substitution) and Fuzzy Case-Based Reasoning Classification Results (with-ILS substitutions) in the Perception Dimension

Figure 2 shows that the amount of data resulting from the classification of fuzzy case-based reasoning in the perception dimension with the condition without substitution of values from the index of learning style (ILS) is as follows: true sensing 17, false sensing 5, true intuitive 11, and true intuitive, 2. Meanwhile, the results of fuzzy case-based reasoning classification in the perception dimension with value substitution conditions from ILS indicated true sensing in 17, false sensing in 5, true intuitive in 11, and false intuitive in 2.

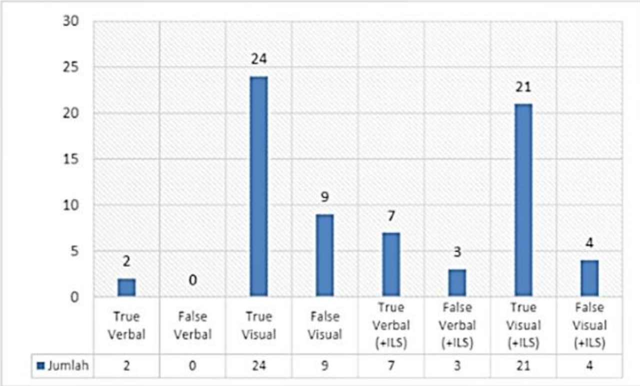

Figure 3. Results of Fuzzy Case-Based Reasoning Classification (non-ILS substitution) and Fuzzy Case-Based Reasoning Classification (with-ILS substitutions) in the Input Dimension

Figure 3 shows that the amount of data resulting from fuzzy case-based reasoning classification in the input dimension without substitution of the value of the index of learning style (ILS) is as follows: true verbal 2, false verbal 0, true visual 24, and false visual 9. Meanwhile, the results of fuzzy case-based reasoning classification in the input dimension with value substitution conditions from ILS show true verbal 7, false verbal 3, true visual 21, and true visual 4.

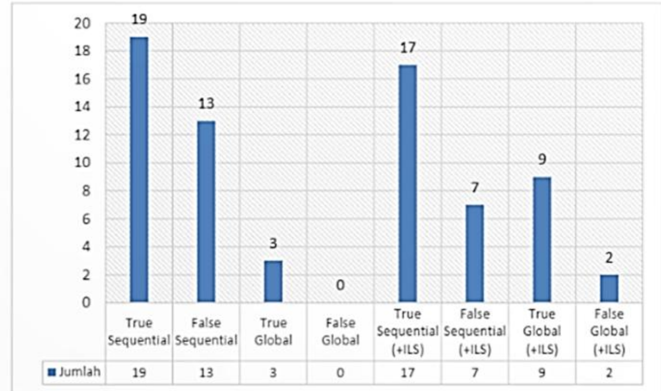

Figure 4. Results of Fuzzy Case-Based Reasoning Classification (non-ILS substitutions) and Fuzzy Case-Based Reasoning (with-ILS substitutions) Classification Results in the Understanding Dimension

Figure 4 shows that the amount of data from fuzzy case-based reasoning classification in the understanding dimension with no substitution of values from the index of learning style (ILS) is as follows: true sequential 19, false sequential 13, true global 3, and false global, 0. Meanwhile, the results of fuzzy case-based reasoning classification in the understanding dimension with the value substitution condition of ILS showed true sequential 17, false sequential 7, true global 9, and false global 2.

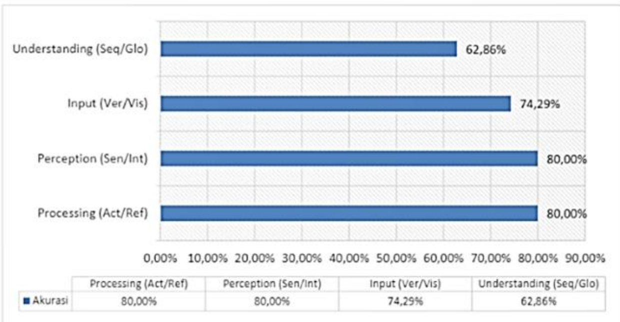

Figure 5 Results of accuracy calculation using confusion matrix for four dimensions of the Felder–Silverman learning style model without substitution of ILS values.

Figure 5 shows that the results of the calculation of the accuracy of the classification results with the condition without substitution of the Index of Learning Style (ILS) value are as follows: for dimension 1 (processing) of 80.00%, dimension 2 (perception) of 80.00%, dimension 3 (input) of 74.29%, and dimension 4 (understanding) of 62.86%

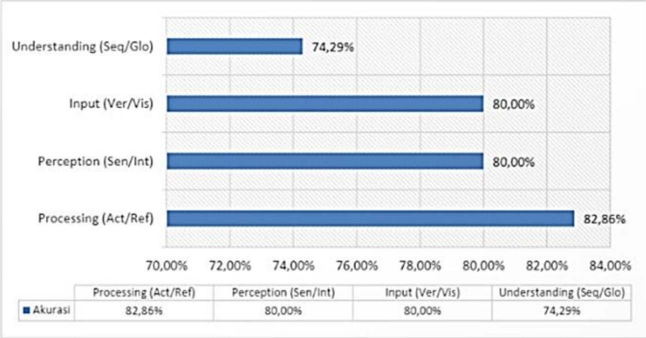

Figure 6. Results of Accuracy Calculation Using the Confusion Matrix for the Four Dimensions of FSLSM Learning Style (Index of Learning Style Substitution)

Figure 6 shows that the results of the calculation of the accuracy of the classification results with the substitution conditions of the Index of Learning Style (ILS) values are as follows: for dimension 1 (processing) of 82.86%, dimension 2 (perception) of 80.00%, dimension 3 (input) of 80.00%, and dimension 4 (understanding) of 74.29%.

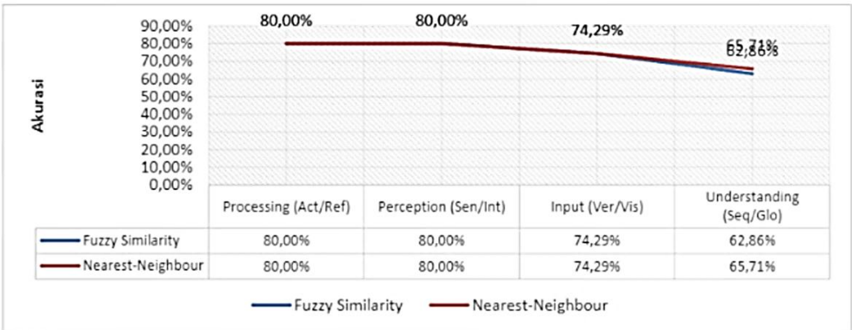

Figure 7. Comparison Results of Similarity Function Accuracy Comparison

Figure 7 shows that the results of the accuracy calculation in Scenario 1 with the condition of using the fuzzy similarity function are as follows: for dimension 1 (processing), 80.00%; dimension 2 (perception), 80.00%; dimension 3 (input), 74.29%; and dimension 4 (understanding), 62.86%. Meanwhile, the calculation of accuracy in Scenario 2 with the condition of using the nearest-neighbor similarity function is as follows: for dimension 1 (processing), 80.00%; dimension 2 (perception), 80.00%; dimension 3 (input), 74.29%; and dimension 4 (understanding), 65.71%.

The results obtained in figure 6 show that the recommendation of an active learning style in the condition of no substitution of ILS scores recorded the highest number. This is due to input data or input with a low membership level that tends to be more, as well as solutions that are in accordance with the results of the index of learning style (ILS) with a conformity level of 79.31% However, reflective learning style recommendations tend to be few, but do not affect the level of reflective conformity which reaches 83.33%. In Figure 6, the recommendation of active learning styles in the condition of ILS substitution still shows the highest number and has increased by two points compared to the condition without ILS substitution.

This increase was triggered by a decrease in false reflective learning styles by 1 and a decrease in true reflective learning style recommendations by 1; thus, the level of active learning style suitability increased to 80.64% or increased by 1.33%, while reflective learning style suitability increased to 100%. The accuracy level obtained from dimension 1 (processing) in the condition without ILS value substitution was 80.00%, which tended to be lower compared to the condition where dimension 1 used ILS value substitution, which showed an accuracy level of 82.86%. The decrease in conformity and accuracy values in dimension 1 in the condition of no substitution of ILS values was influenced by inputs or inputs in the form of six attributes out of the seven recommended attributes. By authorizing 1 ILS attribute in the system, the accuracy level can be increased by 2.86% by increasing the acquisition of active learning style recommendation numbers from reflective learning style recommendation errors

The results obtained in Figure 2 show that the sensing-learning style recommendation recorded the highest number of recommendations. This is due to more input data or input with a low membership level, and is formed from solutions that are in accordance with the results of the Index of Learning Style (ILS), which reaches a conformity level of 77.27%. However, this only slightly affected the acquisition rate of reflective learning styles but did not have an impact on the level of conformity of reflective learning styles to ILS, which reached 84.61%. The magnitude of the difference is influenced by the number of false senses, which is superior by three points compared with false intuition. The accuracy level obtained from dimension 2 (perception) was 80.00%. There was no change in the level of conformity and accuracy in dimension 2, which was reflected in the input in this dimension in the form of the seven recommended attributes.

The results shown in Figure 3 regarding the recommendation of visual learning styles in conditions without substitution of the Index of Learning Style (ILS) value show the highest number. This is because the input has a high membership rate, which corresponds to an ILS result of 72.77% in terms of suitability. Meanwhile, the results of the verbal learning style recommendation in conditions without substitution of ILS scores only decreased by two, with the level of conformity reaching 100%. This decline occurred because of the large amount of input, which reflected the high membership level. In Figure 8, the results of the recommendation of the true verbal learning style in the condition of ILS value substitution show an increase of five digits, while false verbal learning increases by three digits when compared to the condition without ILS value substitution. This increase was triggered by a decrease in false visuals by five and true visuals by 3, so that the level of verbal learning style suitability decreased to 70%, whereas the visual learning style suitability rate increased to 84%.

The accuracy level obtained from dimension 3 (input) in the condition of no substitution of the ILS value was 74.29%. This figure tends to be lower than that of dimension 3, which uses ILS value substitution and achieves an accuracy level of 80.00%. The low conformity and accuracy values in dimension 3 in the condition of no substitution of ILS values were influenced by inputs consisting of three out of five recommended attributes. By improving the results of the verbal learning style recommendations and reducing visual learning style recommendation errors, the two ILS attributes substituted in the system succeeded in increasing the accuracy level by 5.71%. The results shown in Figure 6 regarding sequential learning style recommendations in conditions without substitution of the Index of Learning Style (ILS) value shows the highest number. This is due to input data that have a low membership rate, which tends to be higher, as well as solutions that are in accordance with the ILS results, even though the level of conformity is very low, at 59.37%. This condition affects the low value of global learning styles. The global learning style recommendation has a conformity level of 100% because the value of the global false rate decreases to 0.

In Figure 9, the results of the global learning style recommendation under the condition of ILS substitution value show an increase of six digits when compared to the condition without ILS substitution. This increase was triggered by a decrease in the number of false sequentials by four and true sequentials by two, as well as an increase in global falsehoods of 1.46%. The level of sequential learning style conformity increased to 70.83%, with an increase of 11.46%, while global learning style conformity decreased to 81.81%. The level of accuracy obtained from dimension 4 (understanding) in the condition of no substitution of the ILS value was 62.86%. This figure tends to be lower than the condition where dimension 4 uses ILS value substitution, which shows an accuracy rate of 74.29%. The low value of conformity and accuracy in dimension 4 in the condition of no substitution of the ILS value is influenced by the input consisting of one of the three recommended attributes. By improving the results of the global learning style recommendations and reducing sequential learning style recommendation errors, the two ILS attributes substituted in the system succeeded in increasing the accuracy rate by 11.43%.

The accuracy results of the two similarity functions obtained showed the same values in dimension 1 (processing), dimension 2 (perception), and dimension 3 (input). However, there was a difference of 2.85% in the accuracy level of dimension 4 (understanding), which was influenced by the decrease in the results of false sequential learning style recommendations by one number and the increase in the results for true global learning style recommendations by one number, such that the accuracy level of dimension 4 in the nearest-neighbor similarity function increased to 65.71%.

4. Conclusions

This study successfully developed an adaptive e-learning system that identifies student learning styles based on FSLSM using behavioral data from Moodle. Sixteen behavioral attributes were extracted and processed through fuzzy logic and case-based reasoning to classify the students' learning styles into four dimensions. The system's classification accuracy significantly improved when the ILS questionnaire values were integrated, reaching up to 82.86% in the processing dimension. In comparison, the lowest accuracy without ILS substitution was found for the understanding dimension (62.86%). The findings highlight that integrating additional learner-specific data, such as the ILS questionnaire, enhances the classification performance of the system. Furthermore, the nearest-neighbor similarity function slightly outperformed the fuzzy similarity in the understanding dimension. These results align with the research objectives and indicate that behavioral data combined with machine learning techniques can effectively support personalized e-learning. Future work should explore hybrid similarity techniques and broader datasets to further improve classification reliability.

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