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Traditional-Enhance-Mobile-Ubiquitous-Smart: Model Innovation in Higher Education Learning Style Classification Using Multidimensional and Machine Learning Methods

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Abstract

Learning achievement is undoubtedly impacted by each person's unique learning style. The assessment pattern is less focused due to the intricacy of the current components. In fact, general elements like VARK are thought to create complexity that can impair focus when combined with elements like environmental conditions, teacher effectiveness, and stakeholder policies. Although it is only ideal in specific areas, the application of supported information technology has so far yielded positive results. This essay attempts to be creative in evaluating how well students learn in higher education settings. An assessment framework that uses multidimensionality and simplifies features is the innovation that is being offered. Method, Material, and Media (3M) are the three categories into which simplification of aspects is separated. However, the Dimensions are categorized into five groups: Traditional, Enhance, Mobile, Ubiquitous, and Smart (TEMUS). Approximately 1200 respondents consisting of students and lecturers formed into a dataset in 2 types of data, namely test data and training data. The trial was conducted using 4 models, namely Random Forest, SVM, Decision Tree, and K-Nearest. The test results were interpreted in MSE, R-Square, Accuracy, Recall, Precision, and F1-Score. Based on the comparison of test results, it states that Random Forest has the most optimal results with MSE values of 0.46, R Square 0.99, Accuracy 0.86, Recall 0.86, Precision 0.87, F1 Score 0.84. Based on the results obtained, it proves that in addition to being able to carry out the classification process, the TEMUS Dimensional Framework can form a pattern of compatibility with each other, between the learning styles of Lecturers and Students. According to this TEMUS framework, teacher and student performance will be deemed suitable and effective when the 3M components are assessed from both perspectives in the same way. If not, a review will be conducted.

Keywords: Innovation, Learning Style, Multidimensional, Classification, Machine Learning

1. Introduction

Education was one of the industries whose operations were restricted when the epidemic era began four years ago. Of course, every teaching and learning activity is impacted by these constraints. The pandemic period compelled rapid changes in education [1]. Because education must go on, these advancements and inventions have a purpose. Learning outcomes that align with the goals are the result of ongoing development efforts in education, particularly in the area of learning [2]. Humans require education to enhance their capacity for general knowledge acquisition, behavior, and thought [1]. Education itself transforms learning into an activity. Education develops effectively and efficiently through a variety of learning methods and approaches [2], [3]. Learning certainly has a target achievement that is the goal of people who study certain sciences. At the higher education level, of course, learners or students are certain to have a vision or projection of goals with their learning [4], [5]. This is in contrast to the lower levels, which include elementary, middle, and high schools, where the learning paradigm emphasizes fundamental concepts like self-development, soft skills, mental attitudes, and other general topics [4]. However, at the college level, people have more freedom to choose,

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determine, and live according to their personal needs. Studying learning at the educational level in higher education still presents challenges, such as determining the effectiveness of learning based on its outcomes, the degree of influence of learning outcomes, the areas of learning weakness, and the choices that are suitable for learning development or improvement [6], How big is the influence of the implemented learning outcomes [7], where the weaknesses lie in learning, and what decisions are appropriate for improvement or development in learning [8]. Then, on the learning aspect side, there are aspects including external factors such as teachers or lecturers, teaching materials, environment, curriculum, technology, and internal factors such as motivation, interest, cognitive ability, physical condition, and others [2], [9]. Since the interactions between these components are complicated due to their numerous facets, we may simplify them by dividing them into three categories: method, material, and media. Thus, we may separate each cycle into three indications [10]. The first definition that may be applied to this 3M aspect is method. A method is a technique or approach used to present learning materials, such as a lecture, discussion, instruction, and the like [11]. The second is the material which is the content taught from various relevant sources, such as examples: concepts, facts, procedures, skills [12]. The third is media which can be said to be a supporting tool or means used to implement learning, such as: textbooks, videos, presentations, software and others [13]. At the tertiary level, implementing a learning style that is appropriate to learning outcomes will have a major effect on the objectives' outcomes [14], therefore, to see which cycle we implement becomes a very important thing. There are many facts in the field in terms of implementing learning, there is often a mismatch between learning styles and learning objectives [15]. A person's learning effectiveness will be impacted by this. In a variety of educational environments, integrating learning styles with learning models has demonstrated the ability to enhance academic achievement and student happiness [16]. Teachers can design more successful and interesting learning experiences by modifying their teaching strategies to suit each student's unique learning preferences [17]. For instance, student learning results can be greatly enhanced by an adaptive learning system that considers learning styles. For instance, by dynamically adapting content to students' learning preferences, virtual reality techniques demonstrate a good impact on learning motivation and performance. This virtual approach makes it possible to evaluate whether the learning model being used is part of the Smart Learning cycle [18], [19].

There are 3 things in the identification results that we can obtain by considering the background of the problem. First, namely Increasing Complexity: The increasing number of aspects used as benchmarks makes the evaluation process too complex and less focused on the main objectives of learning. Second, namely Factors that Influence: In addition to aspects that are assessed based on general aspects, other factors such as teacher ability, institutional vision, and student characteristics also influence the evaluation results and make the process more complex. Third, namely in development efforts: By utilizing various methods ranging from physical use such as sensors, and non-physical such as formulation and algorithms have been carried out, but the complexity of certain aspects and data used only produces approaches to the objectives of learning evaluation. Once the issues identified by the identification findings are known, they can be stated in two ways: The first is about how to create a system framework for efficient and successful learning evaluation while keeping the most important elements in mind and taking into account the complexity of the different elements that influence the learning process. Without neglecting other facets of learning evaluation in general, the second question is how to maximize the use of technology in this process.

2. Literature Review

2.1. Learning Style Aspects

Generally speaking, the three types of learning styles that we currently understand are kinesthetic, visual, and auditory [19]. Recent years have seen the addition of supporting elements, such as personal traits, which are evaluated according to the individual's preference for either social or autonomous learning [20], [10]. Educational observers believe that a person's learning style is greatly influenced by the elements of Method, Material, and Media. These three interconnected factors influence how an individual takes in, interprets, and retains information [5]. Difficulties with the complexity of factors that lead to a lack of attention to learning evaluation, together with extraneous factors including environmental factors, educator performance, and stakeholder policies. It is required to make simplifications in light of this. It should be possible to simplify without losing the true essences and characteristics. Simplifying certain aspects indicated in the review results is necessary to improve concentration while evaluating learning outcomes. We attempt to depict the highlighted issues in figure 1 as follows in order to make them easier to understand:

Figure 1. Visualization of the complexity of learning aspects

There are three ways to understand the link between the three elements. First, the learning process will be more successful if the approach is chosen to fit the content and the learning preferences of the students. Second, even if the approach is not as well suited to the students' learning style, engaging content will increase their motivation to study. Third, using a variety of media will improve comprehension of the subject matter for students with varying learning styles [10]. Furthermore, based on the cited sources, an individual's preferred method of learning will be significantly influenced by their learning style. In order to create efficient learning, it is crucial to comprehend the relationship between learning styles and the 3M elements. The study's theory states that there are seven different types of learning styles. Table 1 is a detailed explanation of the relationship between aspects based on the previous review which is simplified into 3 main aspects.

Table 1. Correlation of learning styles with 3M aspects

Learning Style	Appropriate Methods	Appropriate Materials	Appropriate Media
Auditory	Discussions, presentations, lectures, audio recordings.	Materials involving sound, such as poems, songs, dramas.	Podcasts, audio recordings, musical instruments.
Visual	Demonstrations, mind maps, graphs, diagrams.	Materials that use a lot of pictures, diagrams, graphs, maps.	Videos, visual presentations, picture books.
Kinesthetic	Practicals, experiments, role-playing, simulations.	Materials that involve physical activity, such as projects, games, sports.	Propagation aids, labs, exercise equipment.
Verbal	Discussions, debates, writing, reading.	Materials that use a lot of words, such as texts, poems, articles.	Books, magazines, dictionaries, word processing software.
Logical	Problem solving, data analysis, experiments.	Materials that are abstract, conceptual, and logical.	Graphs, tables, diagrams, simulation software.
Inter-personal	Group discussions, collaboration, role-playing.	Materials related to social interaction, such as case studies, group games.	Classrooms, discussion spaces, online platforms for collaboration.
Intra-personal	Self-reflection, journals, individual projects.	Materials that are personal, such as biographies, philosophy.	Diaries, quiet spaces, self-reflection tools.

The conclusion is that a person's learning style is greatly influenced by the interrelated elements of Method, Material, and Media. Teachers or instructors can establish a supportive learning environment and assist students in realizing their full learning potential by being aware of these three factors.

2.2. Dimensions of Learning Styles

Numerous variations in learning models have been recognized by earlier scholars, as is well known. The various dimensions of learning that are known include inquiry-based, cooperative, integrated, problem-based, and thematic learning. In the simplification of the 3M aspects, the correlations indicated in table 1 represent the relationship between common aspects. [20]. The maturity level at which technology starts to enter education is reviewed in this study. The numerous factors result in less-than-ideal efficacy and efficiency when adjusting to the technological age. Grouping into more general dimensions is the appropriate course of action to make it simpler to assess how well learning styles apply to the execution of learning, especially when considering the function and development of technology in conjunction with the maturity level. Learning has an influence on the process of developing knowledge for a person. As shown in figure 2, there are now five learning activity cycles that can be used as preferences to gauge learning objectives. Traditional Dimension (T), Enhanced Dimension (E), Mobile Dimension (M), Ubiquitous Dimension (U), and Smart Dimension (S), or TEMUS for short, are the five categories of the learning cycle itself [20].

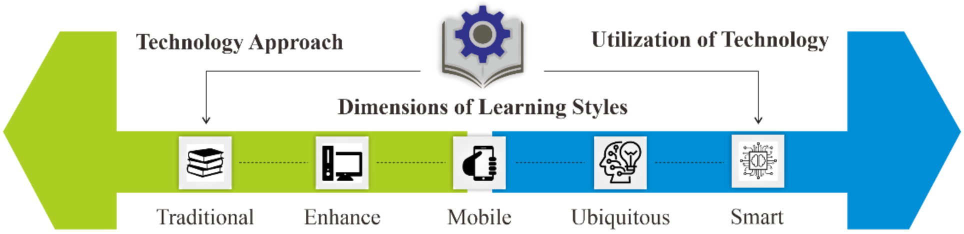


Figure 2. Dimensions of Learning Between Information Technology Approaches and Implementation

The learning model in these 5 cycles can be said to be a sector in seeing the learning style that is being carried out [20]. In the 5 cycles mentioned, of course, each cycle has a specific definition of purpose. In the traditional cycle, the goal tends to be the direct transfer of knowledge from teacher to student. Emphasis on factual mastery of the material [21]. The Enhance cycle can be interpreted as a cycle that enhances or enriches the learning process. The focus of this cycle lies in online learning, digital materials, and interaction through internet network media [22]. Mobile Cycle, the goal is to provide flexibility in learning, so that students can learn anytime and anywhere. Emphasis on independent learning and use of technology. Ubiquitous Cycle, the goal is to integrate learning into everyday life. Emphasis on learning that is meaningful and relevant to real life contexts [23]. The purpose of Smart Cycle is to personalize learning so that every student can study at their own pace and in their own way. a focus on using technology to improve learning effectiveness. We can see it through 3 aspects which are generally known, namely the Method, Material and Media aspects or abbreviated as 3M [24].

2.3. Propose Framework Model

This study will, in general, classify instructors and students according to how they implement their learning styles. While students are viewed through the classification of learning styles, lecturers are viewed through the lens of teaching style. The suitability of each of these classification groupings will be evaluated. The following is figure 3 which illustrates the concept of the classification framework model that has been created:

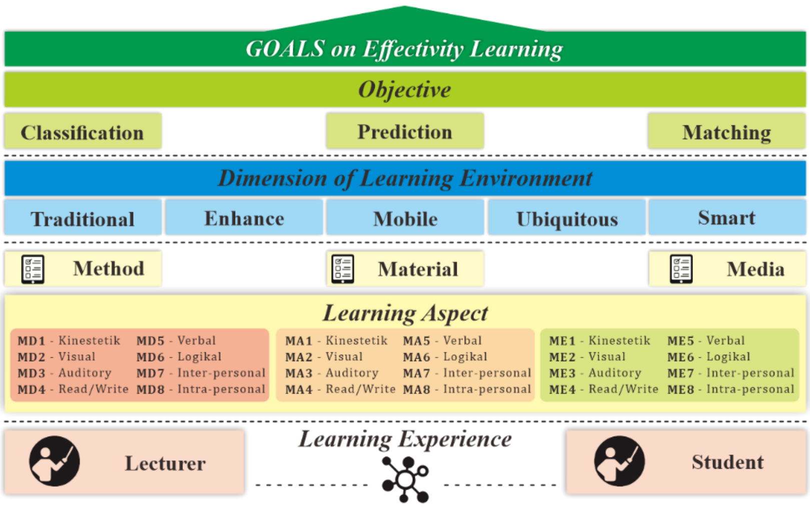


Figure 3. Framework TEMUS for Classification Model

Generally speaking, groups are formed using the structure shown in figure 2 based on five TEMUS cycles. The correlation and suitability case tests on the adopted learning style serve as the basis for the categorization. Although they both deal with the relationship between two things, suitability and correlation are generally distinct from one another [25]. Specifically, suitability refers to how appropriate or complementary two or more things are to one another, whereas correlation is quantitative and can quantify the statistical relationship between two variables [26].

3. Methodology

Before carrying out the completion steps, the author first compiles the stages to be able to carry out the classification to the matching process between variables. In the stages that are compiled using the method that has been determined according to the process. The following figure 4 shows the stages:

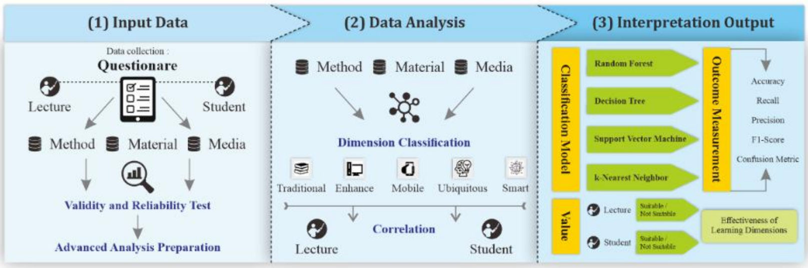


Figure 4. Stages of the completion process.

3.1. Input Data

It should be mentioned up front that, according to individuals who answered the questionnaire, the sample dataset used was drawn from many samples from different universities in the province of Central Java. However, a small-scale sample will be employed as test data in order to evaluate the sample. In order to demonstrate that the framework provided can work as intended, the author of this research article uses a limited sample, specifically the district level with three highly regarded universities. The outcomes will then be tested by contrasting the test data with more extensive training data, including Central Javan provincial-level data. We chose samples from the learning process that had been carried out in the previous semester so as not to seem too focused in this study. There are 2 types of statement values that have reversed values in the category cycle, namely the Positive and Negative value scales, as in the example in table 2, and table 3 below:

Table 2. Example of a Likert statement in a data acquisition questionnaire

Aspect Code	Statement	Cycle Category
Method	You implement learning with one-way interaction (+)	1(S), 2(U), 3(M), 4(E), 5(T)
MD1 – MD8	When you work on assignments, they are done online (-)	1(T), 2(E), 3(M), 4(U), 5(S)
Material	You use textbooks, articles and the like as the main material. (+)	1(S), 2(U), 3(M), 4(E), 5(T)
MA1 – MA8	Utilizing the surrounding environment as a source of learning materials (-)	1(T), 2(E), 3(M), 4(U), 5(S)
Media	Using whiteboard or projector media (+)	1(S), 2(U), 3(M), 4(E), 5(T)
ME1 – ME8	Using LMS or MOOC platform media (-)	1(T), 2(E), 3(M), 4(U), 5(S)

Note: (T) Traditional, (E) Enhance, (M) Mobile, (U) Ubiquitous, (S) Smart; 1-Never, 2-Rarely, 3-As needed, 4-Often, 5-Very often

Questions having values in a normal sequence are known as positive scale questions. They are also selecting the next values, which are 1 for the traditional dimension, 2 for the enhance value, 3 for the mobile value, 4 for the ubiquitous value, and 5 for the smart value. On the other hand, questions with a negative scale have a reverse answer: if the respondent selects a value of 5, the value is conventional; if they select a value of 4, the value is enhanced; if they select a value of 3, the value is mobile; if they select a value of 2, the value is ubiquitous; and if they select a value of 1, the value is smart.

Table 3. Table of specific student questions regarding learning experiences

Student Experience	Value Scale	Description
Learning style – E1	1. Auditory	Easier to understand just by listening
	2. Visual	Easier to understand by observing
	3. Kinesthetic	Easier to understand by practicing directly

Student Experience	Value Scale	Description
Characteristic of learning – E2	1. Socialist	Learning in groups
	2. Solitary	Learning independently
Time and Place – E3	1. Closed	Time and place are limited or bound
	2. Open	Time and place can be anywhere and anytime
Course Characteristic – E4	1. Factual	Prefer real things or facts
	2. Conceptual	Prefer conceptual things like formulas
	3. Procedural	Prefer procedural things or using steps
	4. Principal	Prefer experimental things
Course Material – E5	1. Physical	Prefer physical sources like books, journals, articles
	2. Non-physical	Prefer sources from the internet, websites, or electronic media
	3. Expert	Prefer direct sources from experts or teachers

As previously stated, a small sample test data set—more precisely, a trial carried out at three prestigious colleges in Central Java—will be used for the TEMUS evaluation framework test. Eight questions each were used to analyze the 48 questions, which were grouped based on the 3M aspect categories. All participants—lecturers and students alike—were given two sets of questions. To clarify the data obtained, we can visualize the training dataset with the test dataset that will be used as research material in this paper. Details of the questionnaire distribution can be seen in figure 5 below:

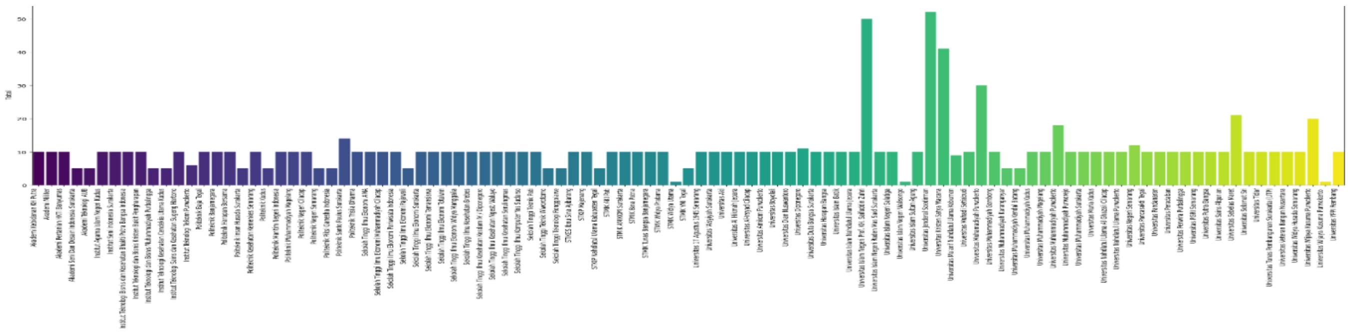


Figure 5. Training dataset based on universities in Central Java region

The total number of respondents at Central Java universities was 1,200. Five colleges had the highest number of respondents to the questionnaire, as shown in figure 5. The first university had 340 responders, followed by the second with 312; the third with 230; the fourth with 156; and the fifth with 118 individuals. The test data collecting comes next. As seen in figure 6, the author uses test data in this study by selecting samples from one region for universities 1, 2, and 4.

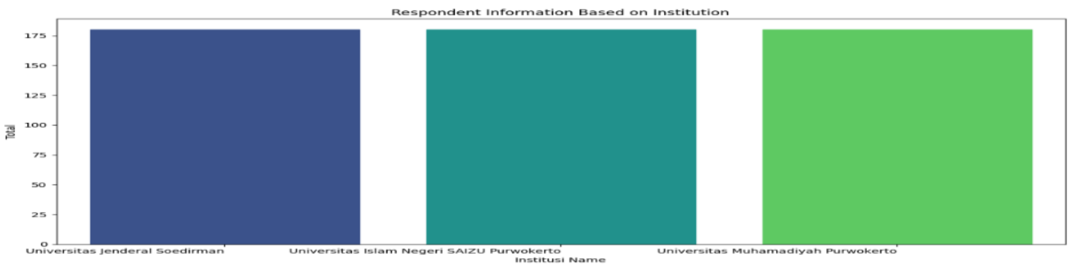


Figure 6. Test Dataset for certain regional level universities in Central Java

The next step after choosing to use test data is to balance the numbers to make the process of dimension matching and categorization easier. A total of 540 samples, 180 from each university, were identified as test data. Following the data-gathering process, we evaluate each questionnaire instrument's validity and reliability. The author applies the following Pearson formula in the validity test:

$$r = \sum((x - \bar{X})(y - \bar{Y}))/\sqrt{[\sum(x - \bar{X})^2 \sum(y - \bar{Y})^2]} \quad (1)$$

Description: r: Pearson correlation coefficient; x : The mean (average) of all the values of variable X; X̄ : The mean (average) of all the values of variable X; y : Individual value for the second variable (Y); Ȳ : The mean (average) of all the values of variable Y

Then to test reliability the author uses the following formula:

$$\alpha = \left(\frac{k}{k} - 1\right) * \left(1 - \frac{\sum si^2}{st^2}\right) \quad (2)$$

Description: k: number of items; s_i^2: variance of item score I; s_t^2: total score variance

The correlation value will show that it is important to ensure that the variables are related to each other. Probability or p-value is to ensure how likely a result is to occur by chance. In the context of research, this probability value is crucial to determine whether the results we get are statistically significant or just happen by chance. Finally, the Cronbach alpha value measures the extent to which items in an instrument (such as a questionnaire) are interrelated and consistent in measuring the same construct.

3.2. Data Analysis

Following the acquisition of the relevant validity and reliability data, the author proceeds with additional analysis. Classification of the 3M questionnaire findings against the TEMUS dimensions will be done in the subsequent analysis stage. Four models will be used in this classification procedure, and the best model will be compared afterwards. Among the models used in the categorization are Random Forest, Decision Tree, Support Vector Machine, and k-Nearest Neighbor. However, the author focuses on one model that is considered possible and more accurate, namely random forest. We can see the concept of random forest used in this research case. The classification form that was used with the Random Forest model is shown in figure 7. The classification form that was used with the Random Forest model is shown in figure 7.

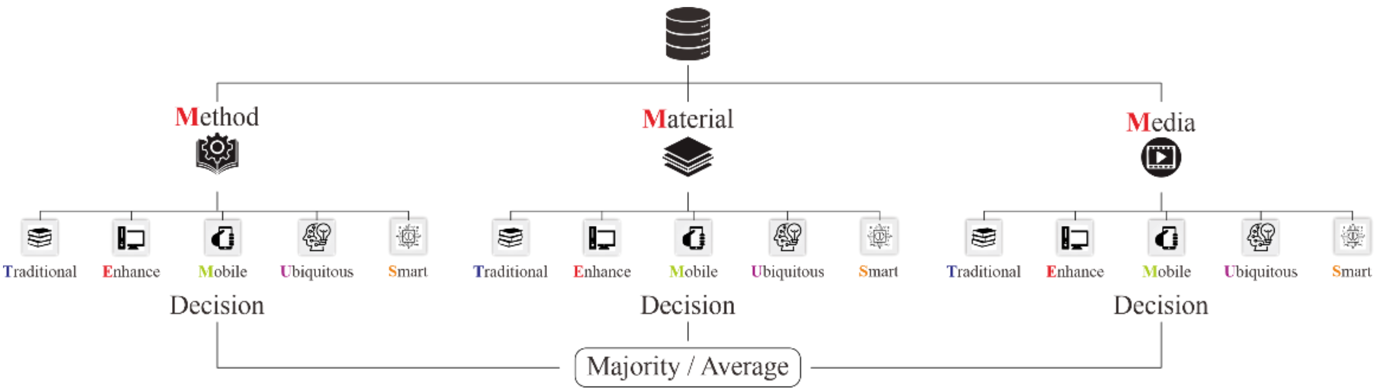


Figure 7. Random forest scheme in this study

Random forest is a technique that resembles a number of decision trees that form an ensemble algorithm like a forest. The final choice is the result of combining all decision trees, each of which has its own splitting rule. No single formula can adequately capture the Random Forest process due to its complexity and adaptability. The entire process in this analysis is done using machine learning. After the classification results are known, the next step is to combine the suitability of the results of the TEMUS classification analysis with the student experience analysis. So the final concept will be as in figure 8 below:

Figure 8. Match Level between TEMUS Classification (X) and Student Experience (Y)

3.3. Interpretation of Analysis Results

The explanation of the classification analysis's findings from the previous step is covered in the interpretation stage. The author employs indicators between the levels of accuracy, recall, precision, and confusion metrics to derive interpretation results for the TEMUS classification results. Among the indications used will be a comparison of the random forest model with other models, such as decision trees, support vectors, and k-nearest neighbors. In addition to classifying, the author also analyzes the findings of the match between the lecture and student classifications, determining the efficacy of the learning process according to the dimensions employed.

4. Results and Discussion

Next discussion the author will then discuss the definition, description of data in the collection, data analysis steps, and finally data interpretation.

4.1. Data Processing

The appropriateness of learning between lecturers and students is determined by two variables in data gathering. Student learning experience is the basis for variable Y, while TEMUS dimensions are the basis for variable X. The TEMUS categorization questionnaire's validity and reliability are the subject of the first finding. Previously, the correlation test between variables and model dependability the most fundamental statistical model in general—was employed in validity and reliability testing. Interpretation of validity and reliability test results according to general guidelines We use the first guideline, namely the correlation value. Correlation is a value where the variables used in the model have a level of relationship with each other, while also proving that if one variable changes, it will affect changes in the other variable. The rule is to be guided by the correlation value (R) ranging from -1 to +1. If the resulting value is close to +1, then interpret a strong positive correlation value. If the resulting value is close to -1, then interpret a strong negative correlation. If the value is close to 0, then interpret a weak correlation or no correlation. As for the p value <0.05, then interpret there is a significant correlation. Cronbach's Alpha, is the Alpha value that will prove that the model is reliable and can be used in general. The rule is if the value> 0.60: Usually considered reliable. If the value> 0.70: Considered quite reliable. While the value> 0.80: Considered very reliable. The outcomes of the validity and reliability tests are shown in table 4.

Table 4. Validity and reliability of the TEMUS Classification Variable (X)

Method				Material				Media			
Variable	**p-Value**	**Corr.**	**Cronbach-α**	**Variable**	**p-Value**	**Corr.**	**Cronbach-α**	**Variable**	**p-Value**	**Corr.**	**Cronbach-α**
MD1	-2.41	0.71	0.81	MA1	-3.06	0.80	0.72	ME1	-4.16	0.62	0.76
MD2	-4.25	0.74		MA2	-3.25	0.92		ME2	-2.65	0.72	
MD3	-7.08	0.61		MA3	-2.18	0.57		ME3	0.05	0.18	
MD4	-8.44	0.73		MA4	-4.41	0.59		ME4	-2.77	0.69	
MD5	-2.63	0.58		MA5	-1.98	0.51		ME5	-9.53	0.82	
MD6	-7.90	0.51		MA6	-7.90	0.80		ME6	-7.86	0.80	
MD7	-9.61	0.57		MA7	0.18	0.13		ME7	-9.61	0.84	
MD8	0.21	0.31		MA8	-1.33	0.52		ME8	-4.47	0.78	

The p-value for each of the indicators MD1, MD2, MD3, MD4, MD5, MD6, and MD7 in the Method Aspect is significantly less than 0.05. This indicates that the null hypothesis is strongly refuted by the evidence. Said another way, the groups compared based on the Total_MD variable show a statistically significant difference for each of the variables MD1 through MD7. MD8: The significance criterion of 0.05 is exceeded by the p-value (0.218). This shows that there is no way to rule out the null hypothesis. In other words, the MD8 variable's Total_MD variable does not offer enough compelling information to draw the conclusion that the groups under comparison differ statistically significantly. The average likelihood value, except for MD 8, is more than 50%. It may be inferred that every item in the method aspect is operating effectively because the alpha value of 0.81 is greater than 0.70.

The p-value is significantly less than 0.05 for each of the following indicators in the Material Aspect: MA1, MA2, MA3, MA4, MA5, MA6, and MA8. This suggests that the null hypothesis is refuted by a large amount of evidence. In other words, there is a statistically significant difference between the groups evaluated using the Total_MA variable for all variables MA1 through MA8, with the exception of MA7. MA7: Although the p-value (0.0189) is generally greater than 0.05, it is extremely close to the significance level. At the 0.05 significance level, this suggests that there might be a propensity for differences between the groups compared based on the Total_MA variable for variable MA7, but it is not significant enough to be considered statistical. With the exception of MA7, the average likelihood value is greater than 50%. Since the alpha value of 0.72 is greater than 0.70, it may be presumed that every component in the material aspect is operating as intended.

The p-value is significantly less than 0.05 for each of the following indicators in the Media Aspect: ME1, ME2, ME4, ME5, ME6, ME7, and ME8. This suggests that the evidence strongly contradicts the null hypothesis. In other words, based on the Total_ME variable, there is a statistically significant difference between the groups compared for all variables ME1 through ME8, with the exception of ME3. ME3: The p-value is somewhat higher than 0.05 (0.0542). According to the Total_ME variable for the ME3 variable, this suggests that there might be a propensity for a difference between the groups studied, but however, at the 0.05 significance level, it is not significant enough to be regarded as statistically significant. The average likelihood value is greater than 50%, with the exception of ME3. Since the alpha value of 0.76 is greater than 0.70, it may be presumed that every item in the method aspect is operating as intended. The result is shown in table 5.

Table 5. Validity and reliability of the Student Experience Variable (Y)

Variable	p-Value	Correlation	Cronbach-α
Dimension	-8.59	0.67	
E1 - Learning style	-5.26	0.55	
E2 - Characteristic of learning	-4.25	0.69	
E3 - Time and Place	0.37	0.73	0.71
E4 - Course Characteristic	-5.73	0.61	
E5 - Course Material	-3.03	0.52	
Result	-4.45	0.73	

Then for the results of the validity and reliability test on Student Experience, it states that, Dimension, E1, E2, E4, E5, and Result: For all of these variables, the p-value is much smaller than 0.05. This means that there is very strong evidence to reject the null hypothesis. In other words, there is a statistically significant difference between the groups compared based on the Total_Score variable for each of these variables. For E3, the p-value (0.37) is much greater than 0.05. This indicates that the null hypothesis cannot be ruled out. To put it another way, the Total_Score variable for the Time variable does not provide enough compelling evidence to conclude that there is a statistically significant difference between the groups studied. A number of variables, including MD8, MA7, ME3, and E3, exhibit negligible p-Values in the submitted validity and reliability tests. Since the cause of these variables is understood to be a lack of data, they show that there aren't many differences that can be measured. The statistical test might not have enough power to identify the true differences if the sample size is too small or the variability in the data is relatively minor. To prove this cause, let's try to prove it with a validity and reliability test for a large scale on the number of respondents at the Central Java provincial level with a total of 1200 respondents. The results are shown in table 6.

Table 6. Validity and reliability of TEMUS Classification Variable (X) on Respondents at Provincial Level

Method				Material				Media			
Var.	p-Val	Corr.	Sig.	Var.	p-Val	Corr.	Sig.	Var.	p-Val	Corr.	Sig.
MD1	0.000	0.364	Significant	MA1	0.000	0.320	Significant	ME1	0.003	-0.15	Significant
MD2	0.000	0.525	Significant	MA2	0.033	0.744	Significant	ME2	0.000	0.452	Significant
MD3	0.000	-0.21	Significant	MA3	0.000	-0.15	Significant	ME3	0.040	0.679	Significant
MD4	0.005	0.594	Significant	MA4	0.000	0.459	Significant	ME4	0.000	0.447	Significant
MD5	0.000	0.515	Significant	MA5	0.000	0.724	Significant	ME5	0.000	-0.17	Significant
MD6	0.000	0.656	Significant	MA6	0.000	0.467	Significant	ME6	0.000	-0.22	Significant

Method				Material				Media			
Var.	**p-Val**	**Corr.**	**Sig.**	**Var.**	**p-Val**	**Corr.**	**Sig.**	**Var.**	**p-Val**	**Corr.**	**Sig.**
MD7	0.000	0.320	Significant	MA7	0.045	0.303	Significant	ME7	0.018	-0.23	Significant
MD8	0.002	0.744	Significant	MA8	0.000	-0.15	Significant	ME8	0.002	0.414	Significant
Cron-α	0.805			Cron-α	0.929			Cron-α	0.847		

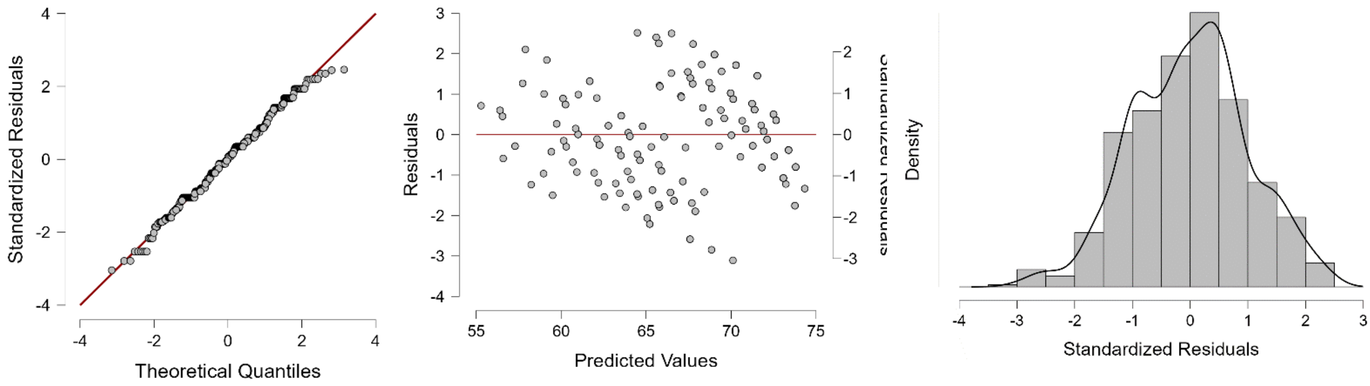
Then for the test results based on learning experience, namely E1 to E5 for a larger scale by reviewing respondents in the Central Java province area, can be seen in table 7 below:

Table 7. Validity and Reliability of Respondent Experience Variable (Y) on a scale at the Central Java Region level

Variable	P-Value	Correlation	Sig.
Dimension	0.010	0.982	Significant
E1 - Learning style	0.000	0.746	Significant
E2 - Characteristic of learning	0.020	0.963	Significant
E3 - Time and Place	0.000	0.920	Significant
E4 - Course Characteristic	0.000	0.746	Significant
E5 - Course Material	0.013	-0.185	Significant
Result	0.000	0.963	Significant
Cronbach - α	**0.929**		

Compared to the test data of 540 respondents, the results of the validity and reliability tests in a larger sample size of 1200 respondents demonstrate that the overall results are deemed significant and reliable in accordance with the guidelines outlined at the start of this sub-chapter. This proves that when the required data is lacking or has little variability and little power to detect differences, it will affect other variables. For example, the missing variable may be a mediator, explaining the mechanism behind the relationship between time/place of study and the dependent variable. This implies that the dataset can proceed to the categorization step of the analytical procedure.

The Q-Q plot findings in figure 9(a) demonstrate that every variable is near the line. This suggests that every variable has a normal distribution. The variables are dispersed from the main line, as seen in figure 9(b). This graph compares the regression model's predicted values with the residual values, or the difference between the actual and expected values. If our model is perfect, the data points on this graph will be randomly distributed around the zero-horizontal line. Then from figure 9(c) a line appears like a mountain with the highest point at 0, which means that the standardized residual is normally distributed. Overall, the validity and reliability results show that most variables have significant differences when compared based on related variables. This means that the division based on inter-variables has a significant effect on the average value of these variables.



(a) (b) (c)

Figure 9. Plot results on validity and reliability tests of all variables

4.2. Data Classification

The first classification result is the TEMUS grouping between Lecturers and Students from the 3M aspect. For measurement, we look at the test data in one of the selected areas as mentioned in sub-chapter 4.1. First, we look at the following figure 10 for classification based on the 3M aspect:

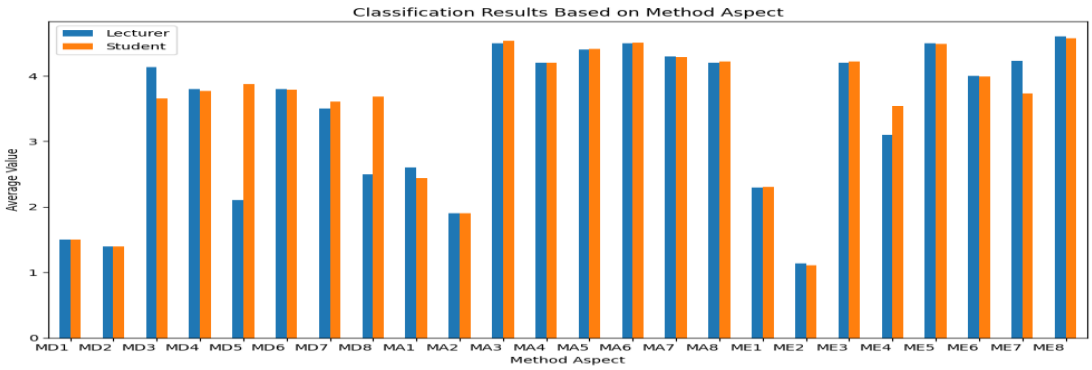


Figure 10. Classification of method aspects in Lecturer and Student

According to the method aspect categorization, three of the eight indicators MD3, MD5, and MD8 seem to be unbalanced between lecturers and students. This suggests that the indicators need to be developed or at the very least adjusted to the course content. It is believed that all indicators for the material element are balanced between students and lecturers. Indicators ME4 and ME7, which presuppose that the medium used in learning must be modified or at the very least standardized, are the only indicators in the media element that do not reflect the balance between lecturers and students. The following are the results of the course classification. The most prominent courses in the application of their dimensions will be determined by the classification of the course. Based on the characteristics covered, these courses are then classified into three categories, especially 3M. The author uses the cluster technique so that it can be seen comprehensively. The classification findings are as figure 11 follows:

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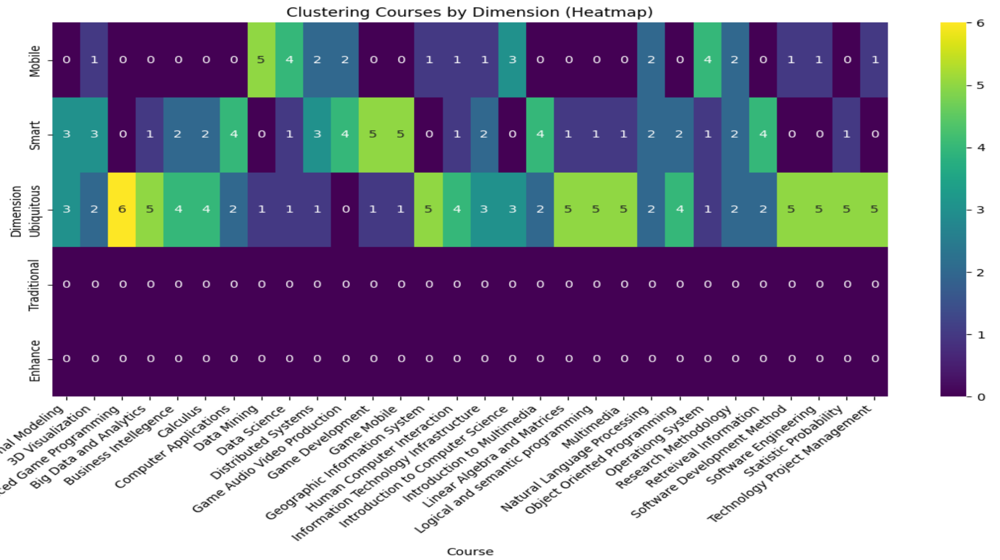

Figure 11. Classification of courses against TEMUS dimensions

Overall, more Ubiquitous, Smart, and Mobile Dimensions are used in the courses that implement TEMUS, according to the results of the classification based on courses in figure 11. Of the thirty courses in the data, fifteen use the smart dimension, twenty-eight use the ubiquitous dimension, and twenty-three use the smart dimension. No courses utilize the traditional or enhanced dimensions. Furthermore, it seems that a number of courses employ dual or mixed dimensions. The author provides the course plot in figure 12 as follows for further information:

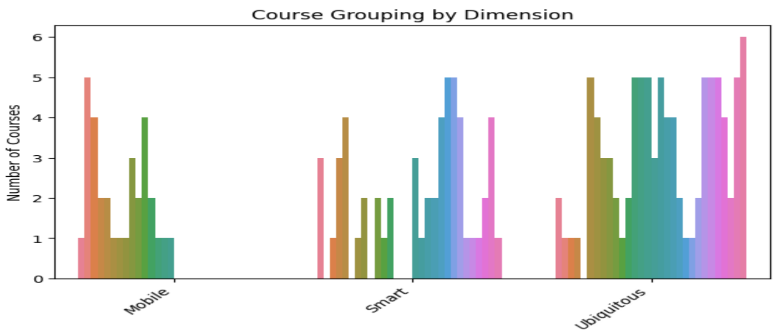

Figure 12. Plotting courses based on the dimensions used

Similar classification also occurs in the Department section. Figure 13 below will explain 3 departments that contribute to the dataset can also be classified in the implementation of the learning dimensions used.

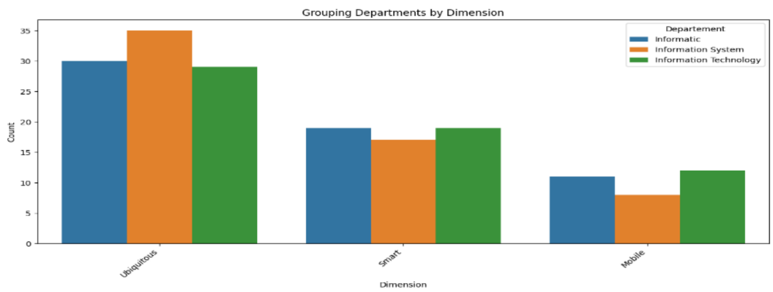

Figure 13. Plotting department based on the dimensions used

Following classification, all current departments based on the information provided by lecturers and students also did what their academic community had done. The ubiquitous dimension is the most prevalent in terms of implementation. This indicates that the current academic setting has changed to adopt the ubiquitous learning approach. The concept is characterized by easy access to learning resources, flexibility in terms of time and location, and materials that are readily available everywhere.

In general, it can be determined by the classification that is generated. Additionally, machine learning can be used to quantify the degree of fit between the lecturer and the student in the TEMUS dimension. This is the formula (3) that is utilized:

$$match\% = \left(\frac{Nl}{Nl + Ns}\right) * 100 \quad (3)$$

Description: Nl : Number of Lecture; Ns : Number of Student; $match\%$: Average Score

From this formula, the percentage of compatibility findings are given in table 8 below:

Table 8. Percentage value of match between Lecture and Student on TEMUS Dimensions

Dimension	Lecture	Student
	Percentage Match	
Traditional	0.00	
Enhance	2.17	
Mobile	7.69	
Smart	12.5	
Ubiquitous	18.75	

4.3. Test results using machine learning on TEMUS classification

Method, Material, and Media are the three characteristics of the correctly gathered data that serve as indicators of the classification variables in this examination of the classification results. A code attribute for each of these indications has undergone validity and reliability testing. Four machine learning algorithms—Random Forest, Decision Tree, Support Vector Machine, and k-Nearest Neighbor—will be used to conduct statistical testing on this model. Aspects such as Method (MD1 to MD8) as X against the Dimension result column as Y, Material (MA1 to MA8) as X against the Dimension result column as Y, and Media (ME1 to ME8) as X against the Dimension result column as Y will all be included in the classification result test. All of the Central Java Province's universities, including the three that served as research samples, were included in the data that the author utilized to measure this classification model. The values between the following will be used to interpret this classification measurement:

MSE (Mean Square Error) value. This very low MSE value indicates that the average squared difference between the model's predicted value and the actual value is very small. This means that the model is very accurate in predicting the data after it is converted into numeric values. R Square (R2) Value. The R-squared value approaching 1 indicates that the model is able to explain almost all of the variability in the data. This means that the model fits the data very well and is able to capture strong patterns in it. Accuracy Value. An Accuracy Value that has a large percentage means that the model has successfully classified a large percentage of the data correctly. A very high percentage value will indicate very good performance, especially for classification problems. Recall Value. A high recall indicates that the model is very good at identifying all positive examples (for example, identifying all cases of learning achievement effectiveness). Precision Value. A high precision indicates that most of the model's positive predictions are truly positive. This means that the designed model rarely gives false positive predictions. F1 Score Value. F1-score provides a balance between precision and recall. A high F1-score value indicates that the model has good performance in both aspects. The following are the measurement results using the Random Forest, Decision Tree, Support Vector Machine, and k-Nearest Neighbor algorithms. For the first result, namely the measurement of the Method aspect, starting from the MD 5 variable to MD8. First, we look at the results in terms of the method as seen in table 9 and figure 14 below:

Table 9. The results of the classification measurement on the Method (MD) aspect

Index	MSE	R Square	Accuracy	Recall	Precision	F1 Score
Random Forest	0.20	0.99	0.90	0.90	0.91	0.90
SVM	0.14	0.99	0.91	0.91	0.91	0.91

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Decision Tree	0.21	0.99	0.91	0.91	0.92	0.90
k-Nearest Neighbor	0.33	0.98	0.86	0.86	0.86	0.86

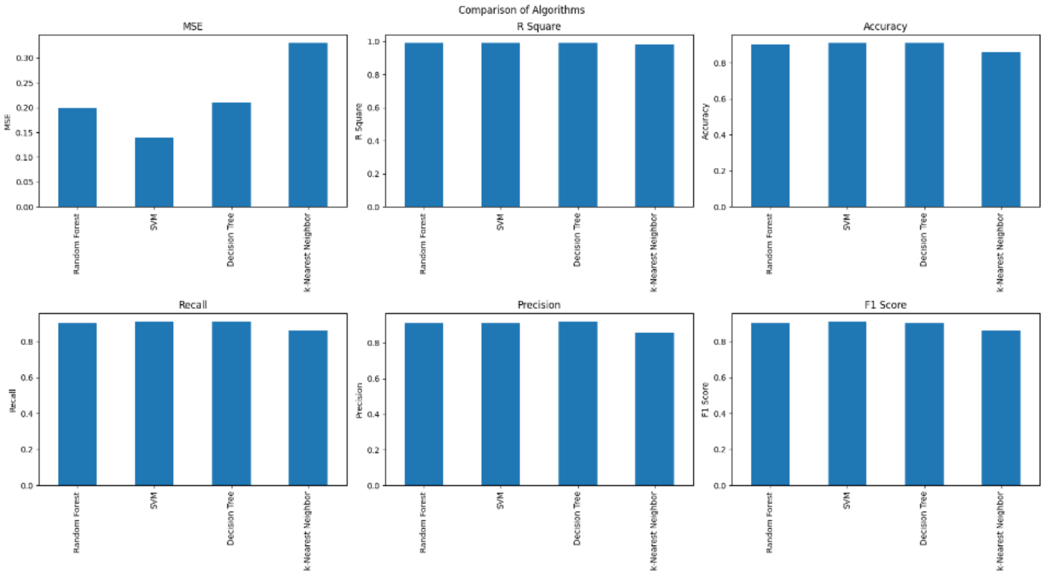

Figure 14. Comparison of measurement results of the classification method (MD)

The next step is to assess the material as know table 10 and figure 15 classification against the TEMUS dimension, and the outcomes are as follows:

Table 10. The results of the classification measurement on the Material (MA) aspect

Index	MSE	R Square	Accuracy	Recall	Precision	F1 Score
Random Forest	0.26	0.96	0.86	0.86	0.87	0.85
SVM	0.14	0.98	0.87	0.87	0.87	0.86
Decision Tree	0.46	0.94	0.84	0.84	0.84	0.83
k-Nearest Neighbor	0.36	0.95	0.80	0.80	0.80	0.79

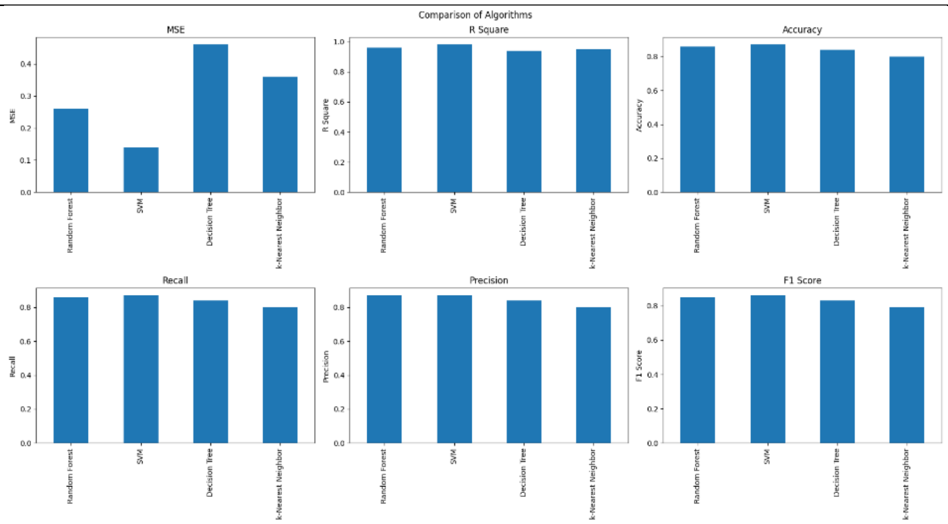

Figure 15. Comparison of measurement results of the classification method (MA)

Lastly, table 11 and figure 16 show the results of the classification measurement on the Media aspect against the TEMUS dimension. The following are the results obtained:

Table 11. The results of the classification measurement on the Media (ME) aspect

Index	MSE	R Square	Accuracy	Recall	Precision	F1 Score
Random Forest	0.14	0.99	0.90	0.90	0.91	0.90
SVM	0.14	0.99	0.89	0.89	0.90	0.89
Decision Tree	0.60	0.94	0.89	0.89	0.89	0.89
k-Nearest Neighbor	0.31	0.97	0.75	0.75	0.77	0.74

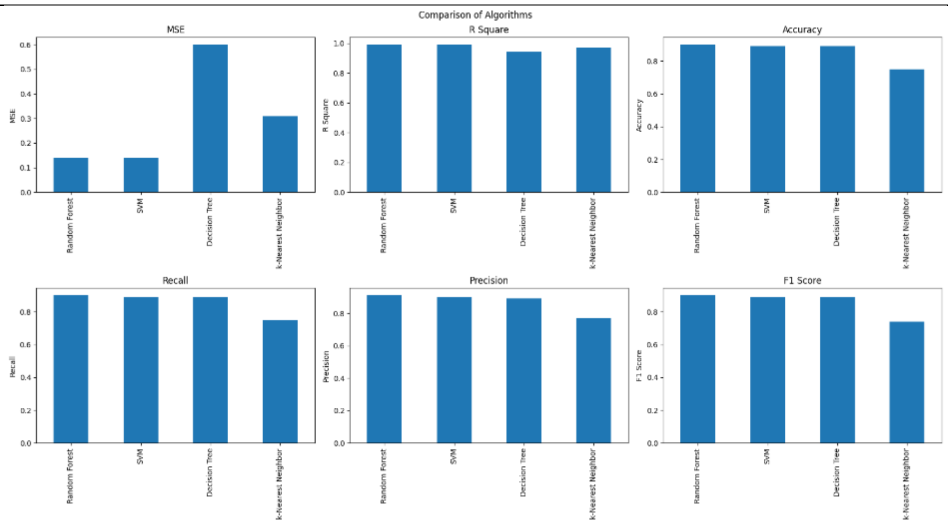

Figure 16. Comparison of measurement results of the classification method (ME)

Based on the results of the classification comparison contained in table 9, table 10, and table 11, we can see quite clear differences in the results of the MSE, R-Square, Accuracy, Recall, Precision, and F1-Score values. To be able to see the differences, the author will present significant differences in the 4 algorithms used in the classification performance test, the following differences can be seen in table 12 below:

Table 12. Results of comparative measurements of 3M indicator models.

Indicator	Model	MSE	R Square	Accuracy	Recall	Precision	F1 Score
Method	SVM	0.14	0.99	0.91	0.91	0.91	0.91
Material	SVM	0.14	0.98	0.87	0.87	0.87	0.86
Media	Random Forest	0.14	0.99	0.90	0.90	0.91	0.90

There are variations in the models that are employed for the three indicators Method, Material, and Media as explained in table 12. It is crucial to select the model that best fits the data's properties and the analysis's goal. Variations in the classification outcomes for every indication are normal and can be attributed to a number of reasons. To deliver the best result, we will attempt to examine the measurement of the 3M indicators, which are Method, Material, and Media in their whole. Table 13 and figure 17 below show the findings for the overall measurement while still utilizing the four algorithm models:

Table 13. Results of measuring the 3M indicators as a whole against the TEMUS Dimension

Index	MSE	R Square	Accuracy	Recall	Precision	F1 Score
Random Forest	0.46	0.99	0.86	0.86	0.87	0.84
SVM	0.73	0.99	0.59	0.59	0.52	0.53
Decision Tree	0.60	0.99	0.87	0.87	0.87	0.86
k-Nearest Neighbor	0.49	0.99	0.80	0.80	0.80	0.78

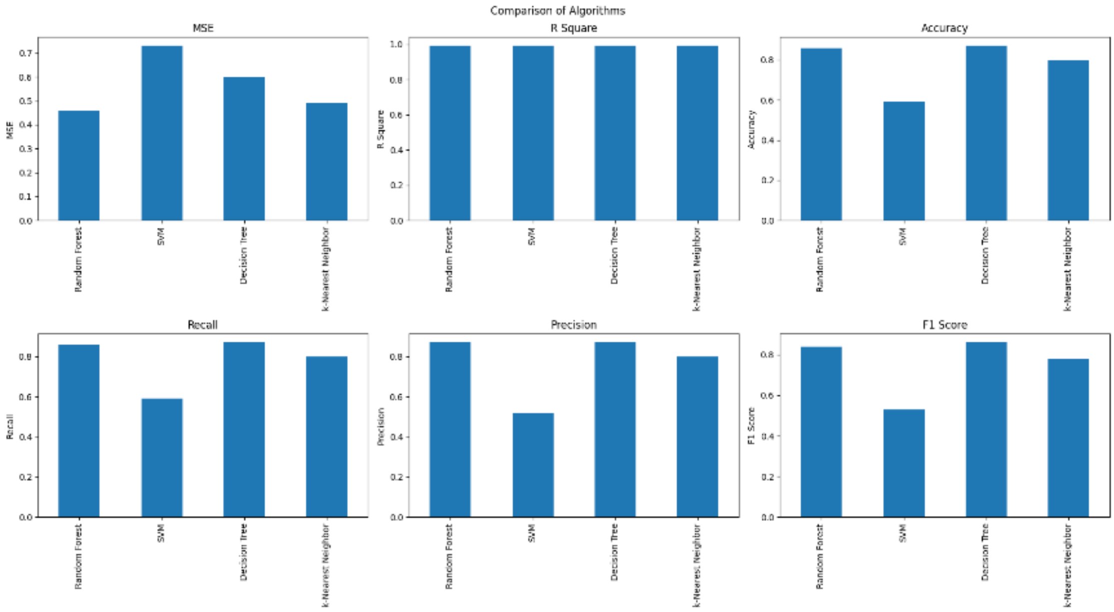

Figure 17. The results of the visualization of the 3M indicators as a whole against the TEMUS Dimension

Based on the results of a comprehensive evaluation of the 3M indicators, Random Forest and Decision Tree are the best models for the dataset used. Both models have excellent performance in terms of classification and are quite good at predicting numerical values. Comparing each indicator separately, as shown in table 9, table 10, and table 11, however, shows that the Random Forest model performs best in the Media aspect and second in the Method and Material aspects, behind SVM. On the other hand, the Decision Tree model ranks third among the three Method, Material, and Media dimensions. Measurement of all of that the author reviews from the MSE value. MSE is a very important metric in evaluating the performance of prediction models, including machine learning models. The main reason why it is necessary to pay attention to MSE is because MSE provides a concrete number that shows the average square of the difference between the model's predicted value and the actual value. This number provides a clear picture of how much the model's error is in making predictions. The smaller the MSE value, the better the model is at predicting. Based on the results of all explorations, it is concluded that in interpreting the analysis of the results of the classification measurement in this research model, it is more optimal if using the Random Forest model.

4.4. Discussion

Education research has benefited greatly from a number of self-learning assessment models, including competency-based evaluation, authentic evaluation, formative evaluation, technology-based evaluation, collaborative evaluation, project-based evaluation, and portfolio-based evaluation. Among the qualities of the assessment itself, we are aware of the following: formative, holistic, authentic, and technology-enhanced. These qualities also aid in the creation of evaluation models. The general features are not an issue after careful observation. When the evaluation features incorporate technology, like in Technology-Enhance, an issue occurs. It might be argued that the problems that have emerged in the features of Technology Enhance are significant; some of these issues include (1) A digital divide exists. Access to technology varies among students. The evaluation process may become unjust as a result. (2) Leads to a dependence on technology. Students who rely too much on technology may find it challenging to cope without electronics or internet access. (3) Problems with data security. To prevent misuse, student data privacy must be appropriately protected. (4) Cost issues. The use of technology in evaluation requires a significant investment, especially for hardware and software. (5) Reasons why people don't interact with each other. Even while technology might boost productivity, face-to-face communication between educators and students is still crucial for giving more detailed and individualized feedback. (6) Standardization that is not uniform. To guarantee quality and dependability, there must be a clear standard for the creation and application of technology-based assessment instruments. (7) Issues with human resource competencies, particularly in the field of education. To create and oversee successful assessments, educators must possess sufficient technological proficiency.

Seeing the problems that arise in the characteristics of this Enhanced Technology is actually not an absolute benchmark for learning effectiveness, but rather for efficiency. In fact, efficient learning is not necessarily considered effective. So there needs to be an adjustment to this problem. Therefore, this study provides innovation in the form of 5 new dimensions in the learning cycle that is carried out. In addition, simplifying aspects can help focus on personal learning styles and academic performance. If referring to similar research, there are similarities in the objectives, namely measuring learning effectiveness. The use of data is also the same, namely using a questionnaire. The difference is in modeling using dimensions to measure effectiveness. The following table 14 is the role of results in contributing to the development of sustainable research in the field of educational information systems:

Table 14. Research contributions to the development of the model

Resource	Topic Focus	Domain	Contribution
[27], [28], [29], [30]	Focus on target Method.	Basic aspects of learning	Learning Evaluation
[31]	Focus on target Material.	Technology perspective	Development of Evaluation Model
[30], [32]	Focus on target Media.	Technology perspective	Learning Evaluation
[33]	Focus on target Method.	Dimensional usage	Development of Evaluation Model
[34], [35]	Focus on target Method.	Technology perspective	Development of Evaluation Model
Irfan et.al., 2024 (Currently)	Focus on target Method, Material, and Media	Dimensional usage	Development of Evaluation Model

Some benefits that can be taken from the results of this study for Lecturers are First, a Deeper Understanding of the Learning Process. Assessing in the 3M aspect, lecturers can gain a deeper understanding of how the methods, materials, and media they use have influenced the learning process. This will help lecturers to identify strengths and weaknesses in their learning practices. Second, More Effective Learning Adjustments. The results of the 3M assessment can be used as a basis for adjusting learning methods, materials, and media to better suit the needs and characteristics of students. Lecturers can identify which dimensions need to be strengthened (for example, the mobile or smart dimension) and how to implement them in learning. Third, the development of Pedagogical Competence. Through the 3M assessment process, teachers can continue to develop their pedagogical competence in designing and implementing innovative and effective learning. In the meantime, the advantages for students consist of: A more engaging educational experience comes first. Students will have a more engaging and pertinent learning experience when teachers modify their teaching strategies, resources, and media in response to the findings of the 3M assessment. Secondly, boosting motivation for learning. Students' motivation to learn will rise when instruction is tailored to their needs and interests. Third, Developing 21st Century Skills. Students can gain 21st century abilities including creativity, teamwork, communication, and critical thinking by taking 3M tests that emphasize mobile, ubiquitous, and smart dimensions. Related to the correlation of the 5 dimensions of TEMUS, there are also benefits from each dimension, including, (1) Traditional: 3M assessment can help identify the extent to which learning still relies on traditional methods or has begun to shift to more modern methods. (2) Enhance: Assessment can measure the extent to which the use of technology has increased the effectiveness of learning. (3) Mobile: Assessment can measure how often and how students use mobile devices in learning. (4) Ubiquitous: Assessment can measure the extent to which learning has been integrated into students' daily lives. (5) Smart: Assessment can measure the extent to which learning has utilized intelligent technology (eg, AI, big data) to personalize learning.

5. Conclusion

According to the research objectives, it has been demonstrated that many variables used as indicators in conducting evaluations are still not focused after reviewing several special evaluation models in learning. This can be achieved by simplifying variables, or what we call aspects, into three parts: Method, Material, and Media. This will help focus on the evaluation that needs to be conducted. Aspect simplification also appears dynamic, making it simply and rapidly adaptable to the circumstances and settings of learning implementation. The evaluation indicators that are now in operation can be approached via this 3M aspect. This work was successful in creating a novel measurement concept in

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dimensional form in addition to effectively simplifying certain features. This dimensional development is more objective and has demonstrated that factors like the learning environment, situations, and gadgets also affect dimensional classification in addition to highlighting individuals. Five cycles of learning implementation—Traditional, Enhance, Mobile, Ubiquitous, and Smart, or TEMUS for short—were successfully designed. The TEMUS Dimension can be used to categorize learning environments, learning models, and learning personalization by simplifying the 3M Aspects, which are evaluations based on Method, Material, and Media. Based on component-side testing and the assembled indications, the test results indicate that the model is valid and dependable, allowing for its use until further development is possible. Additionally, every data exploration result has a high degree of precision and accuracy, with high values and low error rates. According to its function, the model has successfully classified trials by classifying larger samples and research samples, namely those conducted on three research items in a single location. Additionally, the model innovation framework has been effectively assembled and is user-friendly. in order for the model's framework to serve as a tool for dimensional evaluation in the execution of learning. When Lecturers and Students are on the same dimension implementation, then the learning process is declared suitable and effective. If not, then a re-evaluation is needed.

6. Declarations

6.1. Author Contributions

Conceptualization: I.S., T.R.S., B.S., I.T., Z.A.H., A.N.C.P.; Methodology: T.R.S.; Software: I.S.; Validation: I.S., T.R.S., and A.N.C.P.; Formal Analysis: I.S., T.R.S., and A.N.C.P.; Investigation: I.S.; Resources: T.R.S.; Data Curation: T.R.S.; Writing Original Draft Preparation: I.S., T.R.S., and A.N.C.P.; Writing Review and Editing: T.R.S., I.S., and A.N.C.P.; Visualization: I.S. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

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

6.3. Funding

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

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

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

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