Personalized learning with learning style using fuzzy for university students performance

Endina Putri Purwandari[1], Endang Widi Winarni[2], Siti Soraya Abdul Rahman[3], Jafar Nashrudin Al Azam[4]
[1]Department of Information System, Faculty of Engineering, University of Bengkulu, Bengkulu, Indonesia
[2]Department of Primary Education, Faculty of Education and Educational Sciences, University of Bengkulu, Bengkulu, Indonesia
[3]Department of Artificial Intelligence, Faculty of Computer Science and Information Technology, Universiti Malaya, Kuala Lumpur, Malaysia
[4]Computer Systems Analyst, Ministry of Religious Affairs, Bengkulu, Indonesia

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ABSTRACT

The main challenges of traditional learning systems are time-space constraints and teacher-centeredness. The emergence of information technology has given rise to e-learning systems characterized by teacher-centred strategy components and one-size-fits-all strategies. Furthermore, the concept of personalization is presented through learning technology that provides educational content to the students learning style. This research develops a personalized system that aligns teaching strategies with students' learning styles using the Myers-Briggs Type Indicator (MBTI). The emphasis is on adaptive and revising teaching strategies to improve student learning performance. The system is developed to create student profiles to determine their learning styles based on the MBTI and fuzzy. The system was tested with undergraduate students at the information systems department in University of Bengkulu. Research shows that students in the experimental group have higher post-test scores, greater learning achievement and performance than the control group. Fuzzy clustering-based personalized e-learning could improve university student performance. The use of personalized online learning significantly affects learning management system (LMS) integration, lecturers, and curriculum development.

Corresponding Author:

Endina Putri Purwandari
Department of Information System, Faculty of Engineering, University of Bengkulu
Bengkulu 38371, Indonesia
Email: endinaputri@unib.ac.id

1. INTRODUCTION

E-learning has become an alternative learning method, and internet technology has been used to enhance student learning [1]. This learning method is more adaptive than conventional learning. Traditional learning provides a one-size-fits-all approach that tends only to support one educational model. Because in a typical classroom situation, a teacher must handle several students simultaneously. This situation forces students to experience the same learning scenario without considering their needs, characteristics, or preferences. Class productivity increases once teachers learn to provide the detailed and structured teaching that students need.

The successful examples of e-commerce systems can inspire and help us build personalized e-learning systems and provide learners with a new way to break away from the more traditional education model. Responding to individual needs, personalization in education not only facilitates students to learn better by using various means to create various learning experiences but also the needs of teachers in preparing and designing varied teaching or learning packages [2]. Nevertheless, a critical factor is frequently disregarded when establishing a personalized e-learning system. This issue concerns the whole person's understanding of the main psychological resources influencing an individual's desire and intention to learn online. The development of personalized learning has focused more on technology than on important issues centered on learners. Every learner owns a unique learning style that enables them to learn more effectively. Neglecting this style can result in online learning solutions that are unstable or ineffectual [3]. It is generally accepted that the majority of individuals prefer visual media, interaction, or the acquisition and processing of stimuli or information. Therefore, in order to learn more effectively and efficiently, learners must be knowledgeable of their styles, which makes it easy for them to regulate their learning style [4]. This information will allow learners to optimize their learning strategies and utilize their resources. The degree of learning style was related to academic performance and students' evaluations [5]. Furthermore, an individual's personality preferences influence how they participate more actively in learning and assume responsibility for decision-making and self-regulation. It can determine a learner's preferences and tailor teaching to that person's strengths and preferences. The achievement and enjoyment of students can be enhanced by customizing the teaching process to accommodate the learning styles of various student groups.

The learning process must be supported by the mobilization of resources to ensure that it is not only tailored to the preferences of a select few but also to the needs of all learners. While numerous studies have evaluated the efficacy of personality-based teaching strategies, it remains difficult to establish a definitive understanding of their relationship. Four common learning style models, visual, aural, read/write, kinesthetic (VARK), Kolb, Honey and Mumford, and Felder-Silverman learning style model (FSLSM). The Kolb learning style inventory and the FSLSM are the primary instruments utilized in the majority of these investigations [6]. For example, researchers have tried to make e-learning systems more personalized by tailoring the lessons to each student's likes and dislikes [7], their educational background and previous experiences, and their personalization of learning material [8]–[10]. Classification of learning styles can also be done using a deep belief network (DBN)-based approach for large-scale online education to identify students' learning styles and classify them using the learning style standard index [11]. VARK learning styles can also be used as a basis for personalizing learning styles by measuring affective factors and engagement behaviors such as skills, participation/interaction, performance, and emotional [4]. Further research identified, based on FSLSM, machine learning techniques that consider the combination of lecture material access frequency and total time spent by students on each lecture activity in Moodle [12]. FSLSM can also be used to create validated student profiles and supports intelligent mobile learning systems that adapt to students responsively [13]. Furthermore, a personal adaptive e-learning system called adaptive provides identification of learners based on their learning style and level of knowledge with specific differences between learners in terms of time, online interaction, and learning duration [14]. Most studies have focused on the personalization of educational materials in order to establish a framework, and few have focused on teaching strategies. It is essential to establish a personalized system that dynamically adjusts to learners' learning preferences and intelligently recommends web-based activities that integrate the first and second aspects [15]. Therefore, the issue is not the development of e-learning materials (what we teach) but rather the identification and application of available information in a custom manner (how we teach) [16]. In this respect, our work is novel and very different from prior attempts in this field.

Studies have shown that adjusting individual learning styles through teaching design is important in achieving learning outcomes. The study showed that the teaching method for the selected learning style improves individual performance significantly. Until now, many studies have been conducted on learning styles. There have been numerous models proposed for the identification and measurement of learning styles, including the Kolb questionnaire [17], Honey and Mumford questionnaire [18], VARK [19], the Myers-Briggs type indicator (MBTI) [20], and FSLSM questionnaire [21]. The MBTI provides a social context that Kolb lacks. It has dimensioned that Kolb lacks, such as explaining why students are highly engaged during small-group discussions but quiet during large-group presentations. VARK only provides a method of presenting material, but does not explain why students lose interest in the presentation. The MBTI can uncover these causes because it explores internal cognitive aspects, not just sensory input, in VARK. Furthermore, the MBTI has a greater capacity for personalization than FSLSM. The MBTI can detect technical aspects that FSLSM lacks, such as providing teacher feedback suggestions to increase self-confidence in students with the feeling type. Unlike other personality preference identification models that focus on performance metrics or behavioral data. The MBTI has the advantage of ensuring that personalization is based not only on past performance but also on intrinsic cognitive traits, thus promoting a more engaging and effective learning experience. Furthermore, the MBTI offers deeper insights into how learners process information, make decisions, and engage with educational content. It also provides a structured framework that aligns learning experiences with cognitive preferences. MBTI learning-style prediction has emerged as a valuable tool for tailoring learning content to individual preferences and learning styles. Other research has utilized deep learning approaches and learner profile ontology (LPO) to predict learning styles using the MBTI to improve personalization and recommendation processes [22]. This study differs from prior studies by employing the MBTI model to classify students' learning styles using fuzzy C-means (FCM).

2. METHOD

The MBTI, developed by Katharine Briggs and Isabel Myers, is based on the work of C.G. Jung, a psychiatrist who conducted extensive research on human behavior. The MBTI is a tool that helps individuals understand their own behavior and identity. It specifies personality traits that have been documented and studied in numerous studies [23]. Table 1 illustrates how the MBTI categorizes an individual's preferences into four scales. The various combinations of preferences produce sixteen personality types symbolized by four letters. Each individual has a dominant personality preference that becomes their comfort and strength in learning. If the learner is an introvert, then this guidance preference is usually used in a closed and more personal way [24]. The dominant process (first process) is the most relied-on, conscious, and developed process. Auxiliary process (second process)—the preference further relied on to support and balance the dominant process. Designing and developing sixteen teaching styles for the same course can be a complex task for educational designers, as it requires meeting learners' needs. Myers divides the grouping into four dominant pattern types.

Table 2 illustrates our proposed classification of learners based on dominant preferences for each MBTI type. For example, S indicates all learners are in the ISTJ, ISFJ, ESP, or ESTP categories. For instance, INFJ stands for introvert, intuition, feeling, and judging. This indicates that one's preferences are more dominant than others. The MBTI assessment of the dominant preference pattern in an individual. The presence of I is greater than E, the presence of N is higher than S, the presence of F is higher than T, and the presence of J is higher than P. This classification is used to assess the suitability of the class's teaching and learning styles.

The proposed personalization system is web-based and developed using PHP and MySQL. This system is intended to serve as a personalized learning management system (LMS) for a variety of subjects and disciplines. This personalized system includes three main models, namely the domain model, the pedagogical model, and the learner model [25]–[27].

i) Domain model contains knowledge about curriculum structure and conceptual concepts. A tree of learning elements or concepts is provided by each course [28]. One unit of knowledge is contained within a learning unit. It exhibits a variety of learning objects, including external illustrations such as glossaries, examples, questions, activities, and presentations. The domain in this study is Java programming, with five learning concept units, namely data types, programming operators, classes and objects, looping, and branching.
ii) Learner model contains relevant resources about learning style personalization, representing learner characteristics to customize learning content [29]. All user-related data, including user profiles and personal information preferences, is stored in this component. This allows the system to provide specific instructions based on each student's learning style or group of students.
iii) The pedagogical model consists of two parts [30]. The first part is the personalization engine, which contains the system rules and forms for determining student personalization. Second, the strategy model is to determine whether the resources provided are appropriate for specific learning styles. The pedagogical model is a representation of the teacher's understanding of the most effective methods for teaching each concept. Teachers can implement distinct methodologies to instruct the same concept. When selecting learning objectives for learners and establishing learning outcomes, this cognitive knowledge assists lecturer in making informed decisions.

The introductory Java programming class in the Department of Information System at the University of Bengkulu, Indonesia, has thoroughly implemented and tested the personalization system to facilitate student learning. The personalization system recommends useful and interesting materials according to preferences. The system also implements the three main models: domain, pedagogical, and learner.

Table 1. MBTI preferences

Preferences	Definition
Extrovert (E) or introvert (I)	Where a person prefers to focus their attention
Sensing (S) or intuition (N)	The way a person prefers to take in information
Thinking (T) or feeling (F)	How a person deals with the external world
Judging (J) or perceiving (P)	Where a person prefers to focus their attention

Table 2. Learner preferences based on MBTI [24]

Types	Dominant preferences	Myers Briggs
Sensing	S	ISTJ, ISFJ, ESTP, and ESFP
Intuitive	N	INFJ, INTJ, ENFP, and ENTIP
Feeling	F	ISTP, INFP, ESFJ, and ENFJ
Thinking	T	ISTP, INTP, ESTJ, and ENTJ

Figure 1 shows the system architecture and framework of personalized system. The module begins with a new learner registering using a registration form for initial personal profile information. Each profile stores personal information provided by the learner, namely name, age, and other personal attributes. After registration, the system offers an initial questionnaire to detect and store learning styles in the student model. Learners must answer the MBTI psychological questionnaire with 60 questions to determine their learning styles. The student model stores four learning styles, and the questionnaire results suggest that one of these styles is preferred. When students log in, a learning session begins based on the learning style recommendations and educational experiences. The learning style recommendations include a knowledge test and quiz for each lesson. The quiz significantly impacted the measurement of the student's academic performance [31]. The examination includes a variety of code-solving assignments and multiple-choice questions. Each preference is given a different learning strategy, namely:

i) S: this type of student significantly depends on all five senses to receive knowledge. They are fond of concrete structure, organization, and data. They are adept at memorization, typically realistic, and relatively conventional. They frequently encounter challenges with theoretical concepts. Sensory students should use the application-theory-application approach [32]. The teacher begins by presenting an application, and then students analyze and solve the problem without utilizing the course theory. The lecturer initiates the process by presenting an application, and students subsequently analyze and resolve the issue without relying on the course theory.

ii) I: intuitive learners perceive the world through intuition and require knowledge of the theory before committing to a fact. Intuitive students are given the learning sequence theory-application-theory [32]. The teacher starts by presenting the theory, and then learners analyze and resolve the issue using the theory of knowledge. The lecturer reinforces the student's analysis by re-presenting the theory to expedite learning.

iii) F: learner follows their heart more than logic. They feel appreciated when they can help others. This type of learning pattern uses the theory-application-problem solving approach with the addition of a collaborative discussion environment. Feeling-type learners might like doing activities in groups and working in small groups where they can talk to other people more. Furthermore, problem solving activities and case studies are carried out in a collaborative environment.

iv) T: learners with this type think more emphasizing logic and objectivity in their reasoning. They prioritize truth over wisdom, adhere to their logic rather than their emotions, and demonstrate proficiency in inductive thinking, logical decision-making, investigations, and planned tasks. This type of learning pattern uses the theory-application-problem solving approach. The teacher begins by presenting the theory, and then students analyze and complete practical exercise applications using course knowledge. Next, the teacher presents logic-based problem-solving questions.

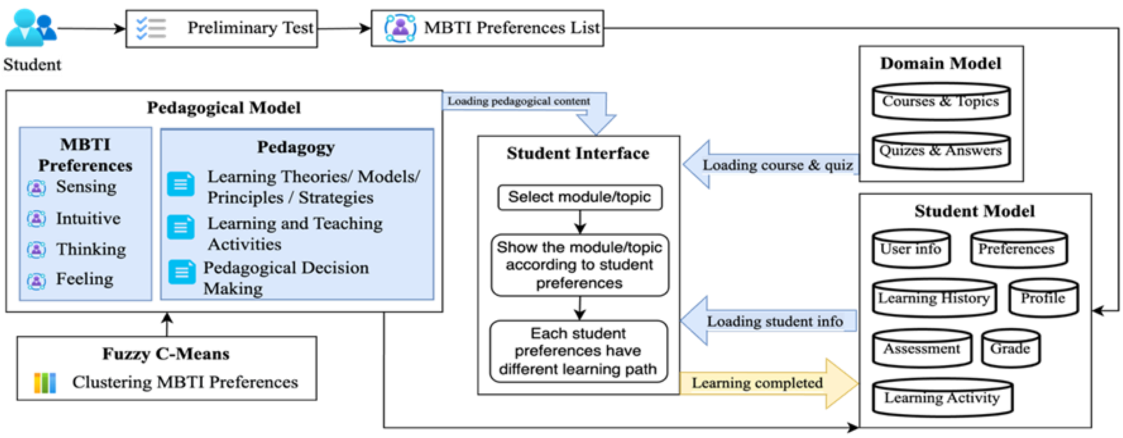

Figure 1. Personalized system framework

Thus, the implementation of an MBTI-based personalized learning system provides a new dimension in education. This implies the creation of four differentiated content based on sensory, intuitive, thinking, and feeling preferences. This personalized system helps teachers monitor the progress of each individual's abilities. This reduces the complexity of providing differentiated instruction and conducting learning assessments simultaneously. The technological support of this personalized system helps teachers and students automatically experience diverse learning experiences.

3. FUZZY C-MEANS CLUSTERING

An individual’s learning approach may differ based on the task or educational material. It is crucial to estimate the dynamic learning approach during the learning process. One method for identifying the optimal cluster in a vector space is fuzzy clustering, which uses the Euclidean distance metric. Fuzzy clustering is particularly beneficial for the identification of fuzzy principles in fuzzy modelling [33]. FCM is one of the numerous data clustering algorithms. FCM is a data clustering technique that determines whether each data point belongs to a cluster based on its membership degree [34]. The FCM algorithm eliminates the binary boundaries in MBTI, such as introvert or extrovert, which can be inaccurate because students may fall in the middle of spectrum. Students are no longer required to fit into one preference; instead, the FCM assigns degrees of membership, such as 0.6 for T and 0.4 for F. This overcomes the MBTI's psychometric limitations mathematically by transforming it into gradational data. Furthermore, the FCM can handle small changes in scores without drastically altering classification results, unlike a binary system. The system can detect when a student remains in a fuzzy area, making personalized learning applications more stable against fluctuations. Fuzzy logic overcomes the MBTI shortcomings by transforming a binary instrument into a more dynamic and relevant model for personalized learning.

Clustering with FCM can group and adjust learning styles with teaching strategies [35]. After students follow the learning strategy, they are grouped into three groups based on the learning outcomes that have been obtained. These three cluster groups have good, moderate, and poor learning outcomes. Grouping is based on 5 fuzzy input variables: pretest value, posttest value, pretest time, posttest time, and material time. The initial stage in FCM procedure begins with the representation of sample data in a matrix X with dimensions $n \times p$. This matrix organizes information, where n represents the number of student data samples, while p indicates the number of input variables analyzed. Technically, each element x_{ij} in the matrix reflects specific value of i sample on j variable. These variables include performance and duration parameters, namely pretest scores, posttest scores, pretest duration, posttest duration, and interaction time with the learning material.

Once the data representation in the decision matrix is formed, the system establishes fundamental control parameters to guide the optimization process. These parameters include the number of clusters (c), the weighting rank (w), and the stopping criteria, which include the maximum number of iterations ($MaxIter$)) and the error threshold (ε). Furthermore, the initial objective function (P_0) and the initial iteration index (t) are defined as computational reference points. The next step is to form the initial partition matrix U by generating random membership values μ_{ik}. These membership values represent the initial degree of association from each data item with the available clusters. Random number generation is performed using a special function to ensure that a student's total membership degree across all clusters is exactly 1.

After initialization, the algorithm determines the cluster centers, which serve as the prototypical representatives for each group. This calculation is performed by computing the weighted average of the data points, where the weights correspond to the membership degrees raised to the power of the weighting rank (w). Formally, the center of each cluster k for every variable j, denoted as v_{kj}, is calculated by dividing the sum of weighted data values by the total sum of membership powers for that specific cluster. This process results in the construction of cluster center matrix V, an array of size $c \times p$ that defines the coordinates of each centroid in the multidimensional variable space.

In the next phase, the objective function P_t is calculated to evaluate the grouping's effectiveness at iteration t. The calculation begins by determining the Euclidean distance between each data object i and its respective cluster center k. This distance is squared and then multiplied by the random number's power result, which represents the initial membership degree. These weighted values are subsequently summed across all indicators and clusters to yield the total objective function value.

The system then utilizes the modification of partition matrix to update the membership degrees μ_{ik}. This involves raising the difference between the indicator and the cluster center to a specific power for each cluster. Through this iterative process, the algorithm continuously refines the membership values until the convergence criteria are met—specifically when the change in the objective function between iterations falls under the threshold (ε) or the maximum number of iterations is reached.

The final result is determined at the defuzzification stage to obtain the final membership matrix. If two cluster centers or centroids are known, namely the INTJ cluster center with $v_1 = [0.9, 0.9, 0.9, 0.9]$ tends

INTJ, and the ESFP cluster center with $v_2 = [0.1, 0.1, 0.1, 0.1]$ has the opposite tendency. A student with a score of [0.8, 0.7, 0.8, 0.6] is likely to be an INTJ. Then, we do the calculation to find out the position of student from the two cluster centers. The distance to INTJ with $d_1 = 0.387$ and the distance to ESFP with $d_2 = 1.261$. Furthermore, the calculation of the fuzzy layer degree for the two clusters with scores 0.91 for the INTJ cluster and 0.09 for the ESFP cluster. Based on this, the student has a high certainty of 1.0 in the INTJ cluster. The system will implement the INTJ strategy of providing in-depth information independently and displaying activity details according to N rules.

In the FCM stage, the number of clusters was selected with a cluster value ($c = 3$). Although the MBTI has 16 possible types and 4 dominant learning styles, learning outcomes tend to cluster into three levels of competence: good, moderate, and poor. Based on the Elbow method [36], adding clusters above 3 does not result in a significant decrease in the objective function (P_t). Therefore, the cluster value ($c = 3$) is the optimal balance point between complexity and accuracy. The selection of the weighting rank ($w = 2$) has shown the most stable distribution of membership degrees (μ_{ik}) for the five input variables. The silhouette score index metric is used to ensure that each student is in the right cluster. A score close to 1 indicates that the distance between the student and their own cluster center is much smaller than the distance to the center of other clusters. Furthermore, the selection of cluster $c = 3$ was validated using the silhouette index, which confirmed that students were optimally grouped into high, moderate, and low learning outcome categories without significant overlap. This quantitative validation ensures that subsequent instructional interventions, such as for the INTJ profile, are based on high-quality cluster partitioning.

4. RESULTS AND DISCUSSION

The experiments were conducted to assess students' understanding after the learning process and the system's effectiveness. The experiment was performed on the basic Java programming course with five units: data types, variable names, class names, arrays, and operators. A total of 72 Department of Information Systems students were recruited for this experiment, with 36 students enrolled in the experimental class and 36 in the control class. The control group employed a conventional teaching approach, whereas the experimental group implemented our proposed framework. Both treatment groups examined the identical five learning units.

The system has implemented four variants of the course materials to create a personalized learning environment for students with varying learning styles. The MBTI learning type test is administered to students upon their entry into the system. The student model calculates and stores 60 questions that represent learning approaches and preferences. This questionnaire maps these questions. The experimental class's MBTI questionnaire results are illustrated in Figure 2.

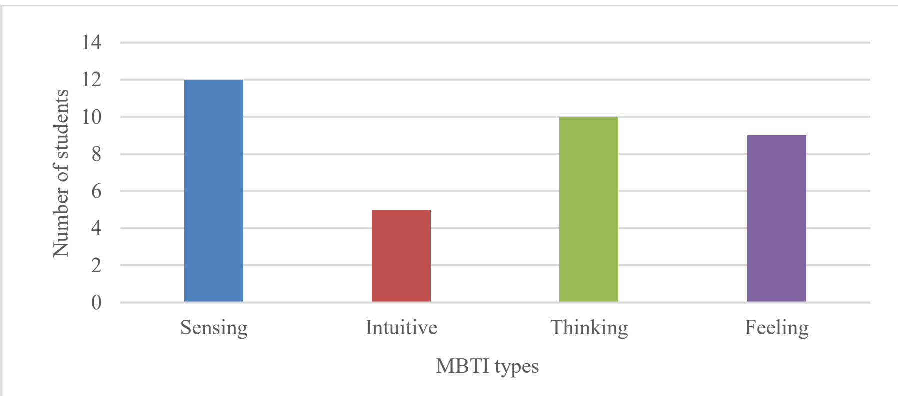

Figure 2. MBTI questionnaire results

Based on the MBTI learning style values, students in the experimental class are grouped into 3 clusters: good, sufficient, and lacking. The parameters used in the clustering process using FCM are:

i) Determining the initial value by determining the criteria, number of clusters, rank, maximum iteration, error, initial objective function, and initial iteration.
   – Number of clusters ($c = 3$), with groups divided into 3: poor, moderate, and good.
   – Number of criteria ($j = 5$), pretest value, posttest value, pretest time, posttest time, and material time.

- Rank ($w = 2$), which means that every random value used in each calculation will be raised to the power of 2.
- Maximum iterations ($MaxIter = 30$), that run with a maximum of 30 to get the best cluster results.
- Smallest error ($\varepsilon = 0.001$). This system will calculate and fix the data membership degree value at each iteration. The iteration will only stop when two conditions are reached, namely when the iteration has reached the maximum value (30 iterations) or the difference in objective function value (t) with previous iterations ($t - 1$) smaller than the specified error value (0.001).
- Initial objective function ($P_o = 0$) and initial iterations ($t = 0$). The iteration starts from 0, making it easier to check each iteration's initial value and calculation value. However, in the first iteration, the objective function value does not have a comparative value with the previous iteration, so the value is set P_o (0) as a comparison at the beginning.

ii) Generate random numbers. There are 3 clusters, namely low, middle, and high, so three random numbers will be generated in each data represented by the variables ui1, ui2, and ui3. Examples of random numbers from sample students can be seen in Table 3.

Table 3. The random number

Student	Random number		
	Low (C1)	Middle (C2)	High (C3)
S1	0.52	0.21	0.27
S2	0.42	0.28	0.3
S3	0.46	0.27	0.27
S4	0.33	0.3	0.37
S5	0.44	0.29	0.27

iii) Calculate the cluster center of each indicator in the three clusters. Calculation by multiplying the power of random numbers by each indicator in the three clusters. The results of each indicator will be added up and then divided by the number of powers of random numbers for each cluster. In Table 3, variables ui1, ui2, and ui3 display random numbers representing each cluster. X1, X2, X3, X4 and X5 show indicators, where X1 represents pretest, X2 represents posttest, X3 represents pretest time, X4 represents material time, and X5 represents posttest time. Examples of cluster center results are in Table 4. V-C1 is the center of cluster 1 (6.131, 6.656, 8.031, 8.324, 6.281), V-C2 is the center of cluster 2 (5.964, 6.411, 7.367, 8.474, 6.051), and V-C3 is the center of cluster 3 (6.018, 6.497, 7.040, 7.872, 6.007).

iv) Calculating the objective function. The objective function is calculated by calculating the difference between the indicator and its cluster center, then raising it to the power of 2. Then, the value of each power result for all indicators is added up. This applies to each cluster. After getting the total value for each cluster, the next step is to multiply it by the power result of the random number (initial membership degree). The objective function at iteration 1 is 2073.123.

v) Calculating the change in the partition matrix (new membership degree) is done by raising the power of the difference value of the indicator to the cluster center to the power of 2. This is done when calculating the objective function. The difference in the change in the partition matrix, the power value is raised again to the power of $-1/(w - 1)$ for each cluster. Next, the power value is added to the other clusters in Table 4.

Table 4. Change matrix

Data	P1-1	P1-2	P1-3	P1+P2+P3
S1	0.0398	0.0300	0.0281	0.0979
S2	0.0081	0.0075	0.0068	0.0224
S3	0.0279	0.0287	0.0252	0.0818
S4	0.0113	0.0108	0.0121	0.0341
S5	0.0161	0.0136	0.0132	0.0429

The new partition matrix value is obtained by dividing the rank value of cluster x by the sum of the rank values of all existing clusters. Thus, the latest membership degree value will be obtained, the sum of which is equal to 1. Furthermore, the results are checked on each cluster. The highest membership value determines cluster assignment, as shown in Table 5.

Table 5. Cluster for the 1st iteration

Data	Random number		
	Cluster 1	Cluster 2	Cluster 3
S1	0.4068	0.3063	0.2869
S2	0.3613	0.3365	0.3022
S3	0.3408	0.3512	0.3080
S4	0.3308	0.3151	0.3541
S5	0.3756	0.3169	0.3075

vi) Performing a stop condition check to fix the value of the degree of data membership in a particular cluster. The initial objective function value (P0) is defined in the first iteration as 0. So | Pt (current objective function)–Pt-1 (initial or previous objective function) | =2073.123–0=2073.123, meaning | Pt (current objective function)–Pt-1 (initial or previous objective function) | > ε. This is because the applied error value is 0.001. Furthermore, another check is carried out for the MaxIter. At the initial value, the desired MaxIter is set at 30, so the calculation will continue to the 2nd iteration to recalculate the cluster center value.

vii) Data enters a cluster if the value of the last partition change matrix (ui11, ui22, ui33) representing clusters 1, 2, and 3 is higher than the others. For example, in data S1, ui22, with a value of 0.8563, is higher than ui11, which is 0.1008 and ui33, which is 0.0429, so it can be concluded that data S1 enters cluster 2. From the experiment using the sample data above, the cluster results at each iteration differ. It can be seen in the last iteration that there are 6 data entries in cluster 2, 2 data entries in cluster 1, and 2 data entries in cluster 3. This reflects the iterative refinement of cluster centers in FCM until it reaches the right result, so that the clustering result at the last iteration is considered the most appropriate. Based on the FCM clustering results, 3 clusters are formed, as shown in Table 6.

Table 6. Cluster center results

	Center cluster					Total	Cluster
C1	7.585	8.117	11.074	19.018	8.645	54.439	High
C2	7.357	7.997	8.700	6.198	7.074	37.326	Mid
C3	0.672	0.758	0.723	0.822	0.576	3.551	Low

Based on the formed cluster center, cluster 1 can be produced as a good scale, cluster 2 as a medium scale and cluster 3 as a lower scale. The results of fuzzy clusters depend on the amount of data, groups, or learning styles clustered, and they are identified as new entities to be re-implemented in algorithms that make their output different. The cluster results for each MBTI learning style (see Figure 3) show that the majority have a sensory learning style (11 students), followed by feeling and thinking (10 students), and the least intuitive (5 students). Of the four learning styles, the ones that successfully achieved a high level of thinking were thinking and feeling, with 3 students.

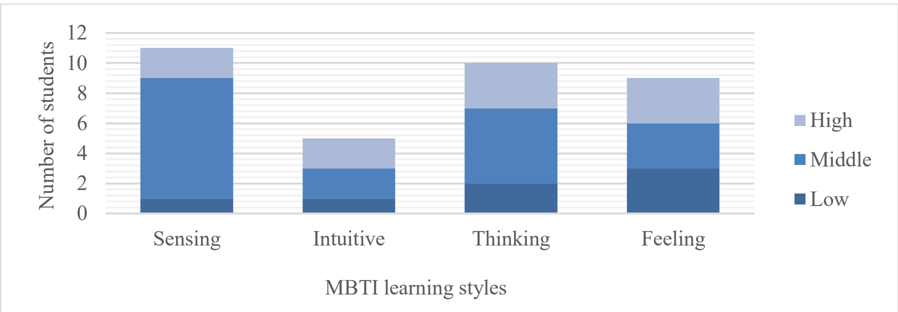

Figure 3. Learning style clustering with FCM

During the eight-week experiment, students studied the learning materials using one of the learning styles. This research emphasizes content-based personalization strategies. Each MBTI learning style receives different learning content tailored to its learning style. Table 7 shows the statistics of interaction by learning styles group in the experimental class:

i) Students with a S style is given material delivered sequentially, starting with application, theory, and application. They had the lowest pretest scores and required the longest time to complete the pretest and posttest, read the course material, and then achieve a good posttest score. This learning style's strengths include processing information with a focus on concrete, detailed, and tangible facts, engaging all five senses in the learning experience. However, sensing students require additional time to understand abstract concepts and struggle to grasp lengthy information and broad ideas [37].
ii) Students with the N style is given material delivered sequentially, starting with theory, application, and theory. They had: the lowest pretest and posttest scores; and the shortest learning time, pretest, and posttest time compared to other learning styles. N students tend to focus more on the big picture and abstract thinking, often overlooking details in the learning process [38].
iii) Students with a thinking learning style are given material delivered sequentially, starting with theory, then application, and finally problem solving. They had: the highest pretest and posttest scores; and moderate reading time, pretest, and posttest time. This T style's strengths include logical, in-depth thinking and more efficient time management, resulting in effective results [39]. However, this learning style cannot develop effectively if the material presented lacks a clear, factual structure.
iv) Students with the F are given material delivered randomly, starting with theory, application, and problem solving. They have: moderate pretest and posttest scores; and moderate reading time, pretest, and posttest time. This type can learn meaningfully and understand the material, so it is best to balance emotion and logic when making learning decisions.

Table 7. Statistics of students’ interactions

Learning styles	N	Pretest score	Posttest score	Time spent on pretest	Time spent on course	Time spent on posttest
S	11	6.22	7.17	11.50	11.08	9.45
N	5	6.53	6.73	5.40	4.97	2.83
T	10	7.97	8.38	6.90	9.23	7.00
F	10	7.03	7.53	9.73	10.92	6.67

Generally, in the MBTI theory, no learning style is truly superior to another. Each learning style has strengths and weaknesses depending on the material being studied. However, in Table 7, the T style group showed a significant improvement in the interaction statistics. This learning style relies on logic, objective analysis, and cause-and-effect relationships, achieving the highest scores on both the pretest and posttest. Therefore, the T style demonstrated the most beneficial performance. This is supported by instructional strategies that can provide in-depth information independently, and by learning interventions aligned with the learning patterns of students of this type. Meanwhile, the S style requires the longest learning time because it is very thorough, using concrete data and technical procedures that take more time to understand. Although this study focused on quantitative behavioral data, the T group showed the greatest benefits, as evidenced by high certainty scores and significant improvements.

Although this study did not use a satisfaction questionnaire, student engagement can be analyzed through behavioral variables stored in the system, such as the five input variables. Students with high closeness to the cluster center demonstrated more stable test-taking patterns for both the pretest and posttest. This indicates cognitive satisfaction and focus when learning personalized material. Student engagement was objectively captured through material interaction time and test duration, as fuzzy input variables.

Student learning motivation can be represented through five input variables: pretest score, posttest score, time spent on course, pretest, and posttest. Students with high motivation tend to spend more time exploring and reading the material. Furthermore, based on the duration of the pretest and posttest, students who complete the material quickly but achieve high scores indicate high motivation to learn. A significant increase from the pretest score to the posttest score also indicates high motivation to learn. Personalized learning strategies can also increase students' motivation to learn.

Implementing a personalization strategy through the four learning styles, combined with application, theory, and problem solving, does not create an additional burden for teachers. Support for teachers in implementing this personalization is provided through systemic and instructional support. First, FCM provides systemic support through a personalization system that automatically groups students and provides recommendations based on learning styles. Teachers automatically receive recommendation information from the system without needing to calculate scores for each student. Second, instructional support is provided through reusable learning objects (RLOs). Through RLOs, existing materials can be reused by rearranging them according to each student's learning style. FCM can help teachers scale their teaching in handling large classes with four different learning styles. Personalized learning, supported by an e-learning system, makes learning activities easier than manual learning in the real world. Implementation in the real-world classroom involves rotating activities using different stations. For example, the first station is for theory through understanding the material, the second station is for application through experimenting with program coding, and the third station is for problem solving through discussion, exploration, questions, and answering ideas among peers. In the real world, teachers are overwhelmed by the need to facilitate each station intensively. Meanwhile, with the help of a personalized learning system, teachers only need to facilitate one station intensively, while the other stations run automatically.

Students' learning success was measured using a posttest related to the learning materials presented. The results were analyzed using a two-tailed and independent t-test following the research design conducted to determine the differences in achievement between the two groups. The Kolmogorov-Smirnov test was also used to examine the distribution of the collected data. The analysis of the dependent variable post-test scores was used as an indicator to represent students' learning efficiency.

Table 8 shows that the independent t-test results for pretest scores have sigma value above the threshold (Sig. >0.05). This indicates that both the control and experimental classes have equal initial abilities as there is no significant difference between the two classes. All student groups started from the same point, which is statistically identical. The experimental group had substantially higher post-test scores than the control group, with a significant difference in learning achievement and performance (Sig. <0.05). This reinforces our hypothesis that learning achievement can be enhanced through the implementation of personalized teaching approaches based on student profiles. Furthermore, this system tailored to learners' individual needs and preferences, can improve students' motivation and engagement [40]. The results show that learning styles benefit students by improving learning efficacy and efficiency.

Table 8. Result of t-test in the control and experimental group

Group	N	Mean score	Standard deviation	Normality	F	Sig.
Pre-test						
Control	36	6.53	0.99	0.15	0.72	0.396
Experimental	36	6.86	1.29	0.08		
Post-test						
Control	36	7.07	1.04	0.20	8.07	0.006
Experimental	36	8.08	1.50	0.13		

The implementation of personalized online learning has implications for: LMS integration, lecturers, and curriculum design. First, the integration of personalized learning in LMS is highly needed because the system can adjust the content and learning activities to the learning style of each student, and the integration of FCM as AI tool can manage and predict the learning needs of each individual automatically. Second, the personalized system provides a new role for lecturers, not only as developers of course materials. Lecturers also serve as learner designers and data interpreters, as the personalized system displays analytical reports that enable them to adjust teaching strategies. Finally, the personalized system has implications for curriculum design. Traditional curriculum is usually standard and uniform for all students. The curriculum in a personalized system has the following advantages: i) more flexibility that allows different learning paths for each individual, ii) emphasizing clear and measurable learning outcomes and individual competencies rather than just study time or number of meetings, iii) more diverse learning strategies through project-based learning and case-based learning, and iv) adaptive, continuous assessment and evaluation, real-time feedback, and results based on individual performance.

The most popular intelligent techniques have penetrated online learning by offering various roles, such as artificial neural networks, Bayesian networks, fuzzy logic, decision trees, and hidden Markov models [35]. Further research in the field of personalized systems integrated with AI can be developed. Online learning solutions that incorporate AI can be used to automate learning and assessment processes, personalize online courses, provide pertinent materials to the appropriate learners, analyze content to increase learner engagement, and create tailored learning paths. AI has the potential to benefit the education sector, students, and instructors in online learning. By offering a personalized experience, AI has the potential to ensure that all individuals have access to high-quality education.

5. CONCLUSION

Personalized learning is the process by which an e-learning system creates educational experiences tailored to learners' needs, objectives, talents, and interests. A personalized e-learning system that can account for the learner's dynamic personality is suggested. Modules are customized to the individual's personality, and suitable instructional strategies are implemented to facilitate learning. The interaction of T styles in the experimental class had: i) the highest pretest and posttest scores and ii) moderate reading time, pretest, and posttest time. This learning style's strengths include logical, in-depth thinking and more efficient time management, resulting in effective results. The findings indicate that the learning environment will be more enjoyable and improvements will be achieved by positioning learners in proximity to a teaching style that aligns with their preferences. The application of FCM in this study requires technical examination of FCM, such as determining fuzziness parameters. Data normalization is crucial to standardize the calculation of distance between learning styles, a key to successful personalized learning. Furthermore, the implications of this research provide data supporting a personalization system capable of automating student mapping. In practice, teachers shift their roles to become instructional designers by reducing administrative complexity, as learning patterns are embedded in a system that automates the material's form according to each student's learning style. Institutionally, schools implement a LMS integrated with a fuzzy algorithm processing engine to automate student profile management. The strategy for further research development is to combine the results of the FCM algorithm with qualitative observations of teachers (humans) to validate data anomalies that are not captured by the machine.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Endina Putri Purwandari	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Endang Widi Winarni		✓				✓		✓	✓	✓	✓	✓		
Siti Soraya Abdul Rahman		✓				✓		✓	✓	✓	✓	✓		
Jafar Nashrudin Al Azam	✓		✓	✓			✓			✓	✓		✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [EPP], upon reasonable request.

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BIOGRAPHIES OF AUTHORS

Endina Putri Purwandari is a lecturer and researcher at the Department of Information System at the University of Bengkulu. She received his bachelor's degree from the Department of Informatics at University of Bengkulu. She graduated with master's and doctoral degrees from the Faculty of Computer Science, Universitas Indonesia. Her research interests include e-learning, mobile learning, intelligent tutoring systems, information systems, and artificial intelligence in education. She can be contacted at email: endinaputri@unib.ac.id.

Endang Widi Winarni is a professor at Department of Primary Education, Graduate School, University of Bengkulu. She received her Bachelor of Science degree from the Department of Science at the State University of Yogyakarta and her Master of Science Education at the University of Malang. Her research interests are primary education, disaster risk, and science education. She can be contacted at email: endangwidi@unib.ac.id.

Siti Soraya Abdul Rahman is a senior lecturer at the Department of Artificial Intelligence, Faculty of Computer Science and Information Technology at Universiti of Malaya. She was appointed a program leader for adaptive learning environment for problem solving (ALEPS) under the Innovative Technology Research Cluster. She graduated with a bachelor's degree in Information Technology from the University of Glamorgan, United Kingdom, in 1998 and received a master's in Computer Science from the University of Malaya in 2003. She was conferred with a Ph.D. in Cognitive Science from the University of Sussex, United Kingdom, in 2012. Her research interests are data science, cognitive science, artificial intelligence in education, e-learning, and expert systems. She can be contacted at email: siti_soraya@um.edu.my.

Jafar Nashrudin Al Azam is a Computer Systems Analyst at the Ministry of Religious Affairs of North Bengkulu Regency. He received a bachelor degree in Informatics Engineering from the University of Bengkulu. In carrying out my duties, he is responsible for information technology within the office. In addition, he has a strong interest in the development of information technology, particularly in the fields of e-learning and artificial intelligence. He can be contacted at email: technojaf@gmail.com.