

# Intelligent Personalized Learning Management Model using the Case-Based Reasoning Techniques

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## Abstract

The application of Information and Communication Technologies in education and the impact of the Internet have fostered online learning, breaking many limiting barriers of traditional education such as space, time, quantity, and cover-age. However, the new proposals affect the quality of educational services, such as linear access to content, standardized teaching structures and methods that are not flexible to the users' learning style. In this context, an Intelligent Model for Personalized Learning Management is implemented in a Virtual Simulation Environment based on Instances of Learning Objects, with the aim of identifying the best learning style of a student to provide them with the best learning object, using a similarity function through Weighted Multidimensional Euclidean Distance. The proposal is validated through a cross validation and experimentation on the MIGAP platform (Intelligent Model of Personalized Learning Management), for the development of courses on Newtonian Mechanics. The results show that the proposed model has a classification efficiency of 100%; above the following models: Simple Logistic with 99.50%, Naive Bayes with 97.98%, Tree J48 with 96.98%, and Neural Networks with 94.97% of success. The application of this model in other areas of knowledge will allow the identification of the best learning style, with the purpose of enabling educational resources, activities, and services to be flexible to the student's learning style, improving the quality of educational services.

## Keywords

Model, System, Management, Learning, Learning Style, Case-Based Reason.

## 1. Introduction

Students have different rhythms and learning styles according to their educational needs [1]. Providing standardized instruction limits the ability to adapt content and teaching methods to individual student characteristics [2]. This can hinder their understanding and retention of information, and can lead to lack of motivation and engagement as standardized teaching tends to focus on the transmission of information and memorization of data, this limits opportunities to foster creativity, critical thinking and problem solving [3]. Students do not have the opportunity to explore different approaches, pose challenging questions, or develop critical thinking skills that are essential in today's world. In today's world, skills such as critical thinking, problem solving, collaboration and creativity are required to succeed. However, standardized teaching focuses primarily on the transmission of theoretical knowledge and does not provide opportunities to develop these twenty-first century skills. This can leave students ill-prepared to face real-world challenges and limit their ability to adapt and thrive in changing environments [4]. When students experience standardized teaching, they are more likely to feel unmotivated and disengaged from the learning process. Lack of variety, personalization and relevance may

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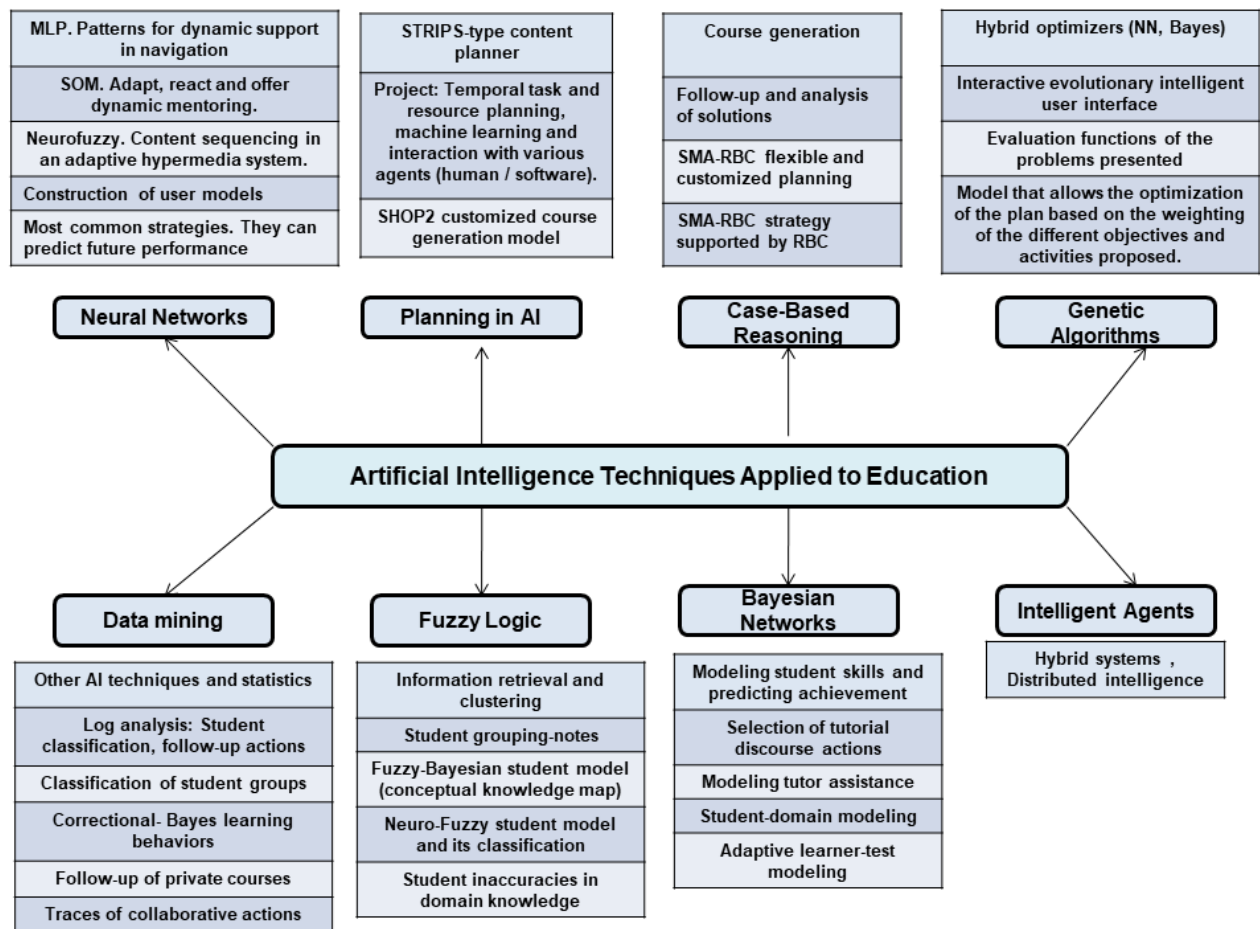
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cause them to perceive learning as boring, which negatively affects their engagement and willingness to actively participate.

Artificial Intelligence (AI) applied to education is a growing field of interest, where the main goal is to contribute to the formulation and application of techniques to the development of systems that support the processes of computer-assisted teaching and learning with the purpose of building more intelligent systems [5]. The word "intelligent" used in these systems is primarily determined by their ability to continuously adapt to the learning and knowledge characteristics of the different users [6].

In the field of Artificial Intelligence applied to education, research is focused on the development of systems for education, based on aspects of knowledge [7]. Figure 1, shows the main AI techniques applied to education.



**Figure 1:** Main AI techniques applied to education. Adapted from [7]

According to [8] they elaborated a course in five lessons with a basic level of complexity to explain concepts on programming fundamentals. According to the MODESEC methodology, the student can make changes to recommendations made by the system and in this case, it will be qualified as an inappropriate recommendation. If the number of changes needed to adjust a pedagogical strategy according to the student's profile is high, the level of personalization will be low. The authors did not evaluate academic performance in this subject, but rather the relevance of a strategy recommended by the system.

In the research developed by [9], the authors compared between final grades of two sections of a programming course. One section was taught traditionally and the other was adapted to match the student's learning style with the teacher's teaching style. In this case, the experimental results showed a large contrast between the final grades of students in both sections.

Also, [10] demonstrated that the modules realized can help teachers to distribute the material suitable to students' learning styles helping students to study more effectively according to their preferences. The components of the model include: a multimedia library, a repository of learning objects, a student model (case), an instructional model, an adaptive engine and a user interface.

Finally, [11] provide in their study, an approach that detects the learning style of students in order to provide adaptive courses in Moodle and includes a novel tool that is the evaluation of student interaction with different resources. For this research, two groups of students were formed: the experimental and the control group. The former had access to a Moodle course that automatically detected their learning styles and had an adaptive mechanism, while the latter had access to a standard version of a Moodle course. They showed that the adaptive course group had a better performance and a higher motivation for the development of the subject.

Learning styles are the cognitive, affective, and physiological traits that serve as relatively stable indicators of how learners perceive interactions and respond to their learning environments [12]. It can be concluded that each person has his or her own learning "fingerprint". Each person develops and enhances a certain strategy (some learn from reading, others by practicing, some from group work, others from isolated work), however, we all possess in different percentages some trait of the different learning styles.

The following models focus on the learning process, which is why they are analyzed in the research conducted. Honey's model, based on Kolb's model [13], specifies 4 learning styles shown in Table 1: active, reflective, theoretical and pragmatic.

**Table 1**  
**Characteristics of each learning style [13]**

<b>Learning Styles</b>	<b>Main Features</b>
<b>Active</b>	Entertainer, Improviser, Discoverer, Risk-taker, Spontaneous
<b>Reflective</b>	Weighed, Conscientious, Responsive, Analytical, Thorough, Comprehensive
<b>Theoretical</b>	Methodical, Logical, Objective, Critical, Structured
<b>Pragmatic</b>	Experiential, Practical, Straightforward, Effective, Realistic

## 2. Methodology

The main objective of the present research is to develop dynamic methods for the search and identification of the best learning style of a student in order to provide resources and activities according to this learning style. These methods are applied in real time, using a technique of Artificial Intelligence called Case Based Reasoning (CBR); through the similarity function, using the Weighted Multidimensional Euclidean Distance. CBR will provide a method for customizing the best learning strategy. The efficiency in terms of learning style selection via CBR is compared with the results obtained by other learning style selection algorithms such as: Neural Networks, Naive Bayes, Tree J48 and Simple Logistic. In this context, the MIGAP (Intelligent Model of Personalized Learning Management) platform is designed and implemented to present learning contents, which are adapted to the best learning style according to the model of [13].

### 2.1. Artificial Intelligence Technique applied to the proposal

The Artificial Intelligence technique applied is Case Based Reasoning, which in the first instance detects the learning style of the student to determine the best learning strategy that best suits this learning style. CBR is the process of solving new problems based on the solutions of previous problems.

### 2.1.1. Case-Based Reasoning

Case-Based Reasoning (CBR) is a body of concepts and techniques that address issues related to knowledge representation, reasoning and learning from experience [14]. Similarity is the concept that plays a fundamental role in Case Based.

### 2.1.2. Case definition

Also known as instance, object or example. It can be defined as a piece of contextualized knowledge that represents a meaningful experience.

### 2.1.3. CBR Stages

The main stages are four: Retrieval, Reuse, Review and Retention. These four stages involve basic tasks such as: case clustering and classification, case selection and generation, case learning and indexing, case similarity measurement, case retrieval and inference, reasoning, adaptation rules and data mining.

### 2.1.4. CBR life cycle

The life cycle for troubleshooting using a CBR system consists of four states.

- Retrieval of similar cases from an experience base.
- Reuse of cases by copying or integrating solutions from the retrieved cases.
- Revision or adaptation of the retrieved solution(s) to solve the new problem.
- Retention of a new solution, once it has been confirmed or validated.

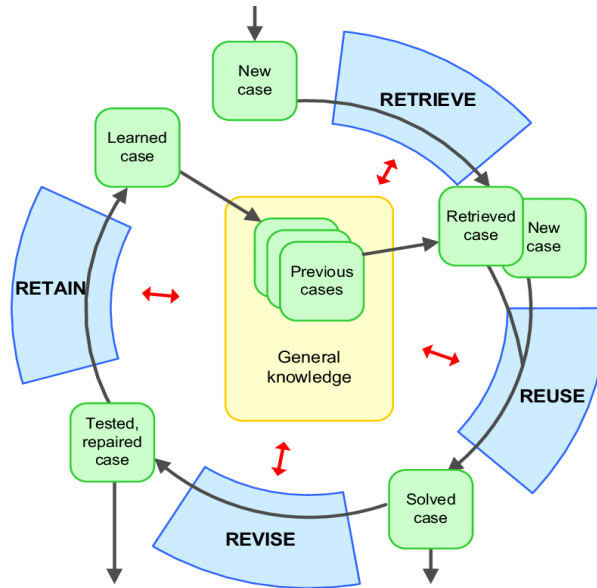


Figure 2: CBR life cycle [14]

## 2.2. Weighted Euclidean Distance

Based on the location of objects in Euclidean space, an ordered set of real numbers representing the shortest distances between objects is retrieved. Formally the Euclidean distance between the cases is expressed as follows. Where we denote  $CB = \{e_1; e_2; \dots e_N\}$  the library of  $N$  cases, representing the learning styles database [15].

Each case in this library is represented by an index of its corresponding feature, and each case is associated with an identification tag.

The weighted metric distance can be defined as:

$$d_{pq}^{(w)} = d^{(w)}(e_p, e_q) = \left[ \sum_{j=1}^n w_j^2 (x_{pj} - x_{qj})^2 \right]^{\frac{1}{2}} = \left( \sum_{j=1}^n w_j^2 x_j^2 \right)^{\frac{1}{2}} \quad (1)$$

Where  $x_j^2 = (x_{pj} - x_{qj})^2$ . When all weights are equal to 1, the previously defined weighted metric distance degenerates to the Euclidean measure  $d_{pq}^{(1)}$ . This means that it is denoted by  $d_{pq}$ . The distance between two cases  $e_p$  and  $e_q$  is calculated by

$$d_{pq}^w = \sqrt{\sum_{j=1}^n w_j^2 \rho_j^2 (e_{pj}, e_{qj})} \quad (2)$$

### 2.3. Architecture of the proposed model

The architecture of the proposed model has three main components: a user interface, an inference engine and a case base. The case base contains the descriptions of previously solved problems in the form of features (predictors and objectives). Each case may describe a particular episode or a generalization of a set of related episodes. The inference engine is the reasoning engine of the system, which compares the inserted problem with those stored in the case base and as a result infers an answer with the highest degree of similarity to the one sought. The user interface allows communication between the system and the user, giving the possibility to interact with the case base, pose new problems and consult the inferred results.

The model incorporates to the classical architecture of an Intelligent Tutor System, a learning object (content) selection process, influenced by the teaching strategies of the learner's learning styles. These teaching strategies will be the link of the learning objects through the teaching-learning strategies applied to the design of the course contents.

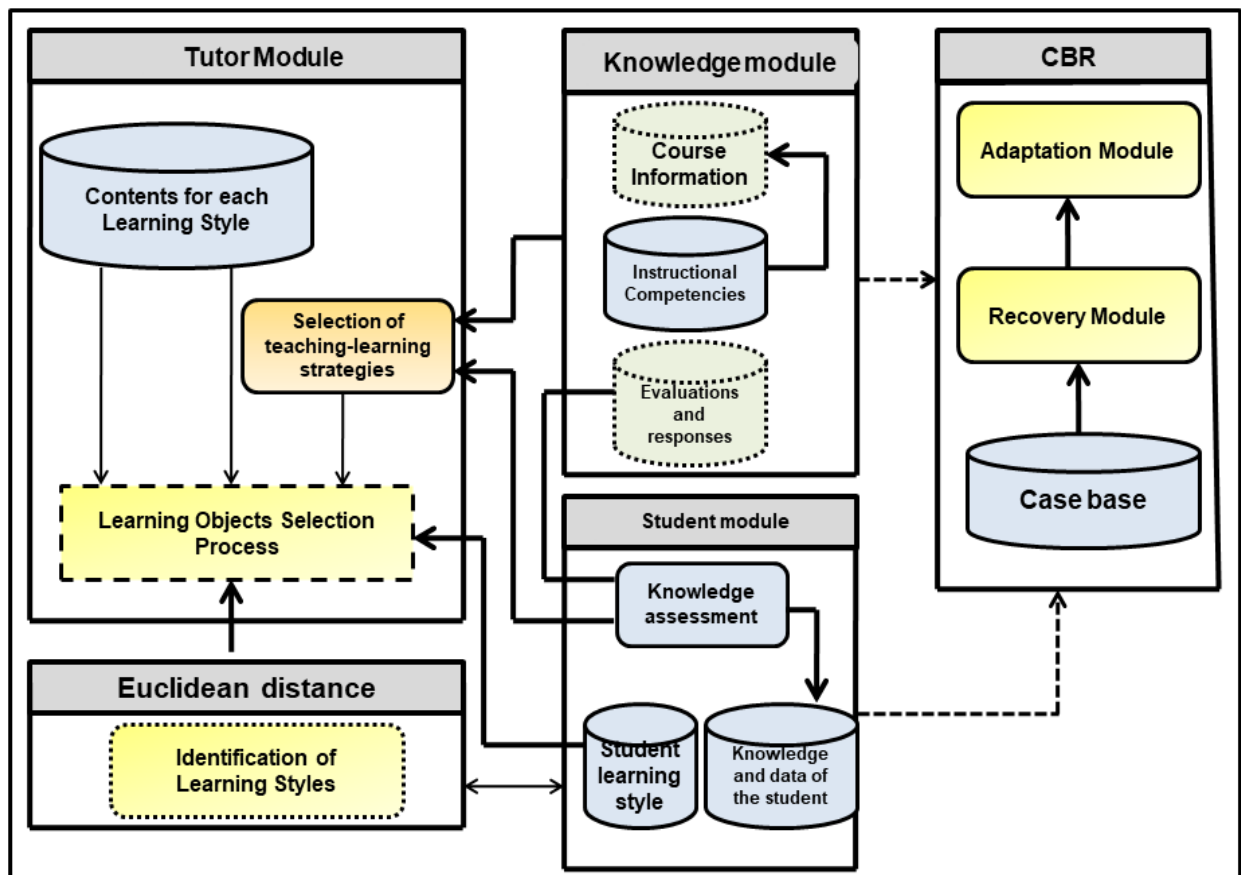


Figure 3: General architecture of the proposed model

The general structure of the proposed model: Intelligent Personalized Learning Management System considers students' learning styles, integrating Case-Based Reasoning, for the selection of teaching-learning strategies and for the identification of the learning style with greater emphasis. The architecture proposes innovations in the representation of the tutor module and the knowledge module. In particular, the tutor module incorporates the CBR technique, which will be in charge of choosing the contents considering the teaching strategies that favor the student's learning styles.

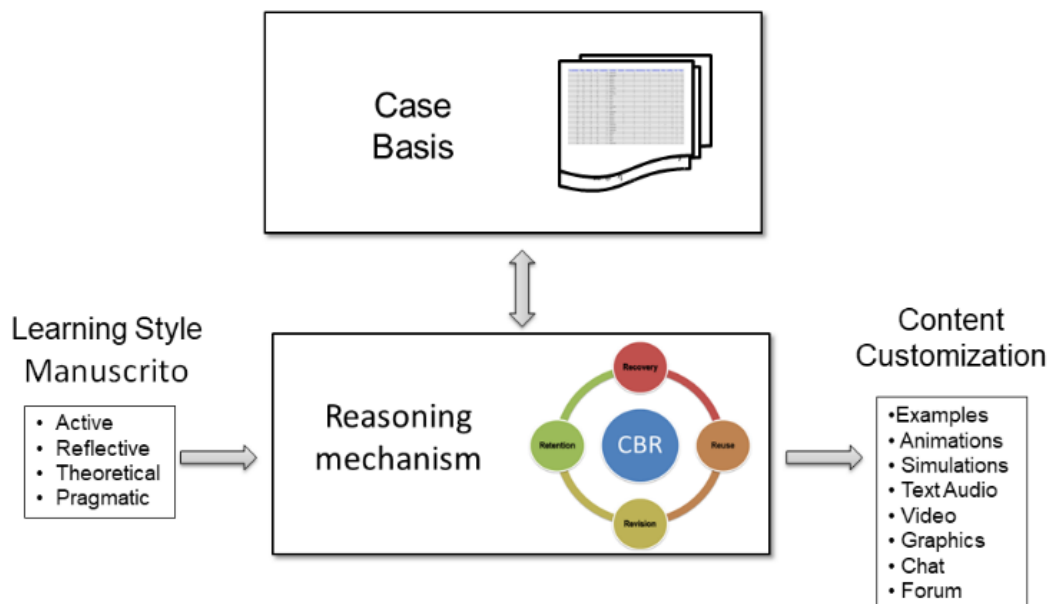
The knowledge module is influenced by the teaching strategies of the student's learning styles. These teaching strategies will be the link of the learning objects through the teaching-learning strategies applied to the design of the content area.

The following is a description of the modifications made to the modules of the general architecture of the Intelligent Tutorial System:

**Tutor Module:** The tutor module incorporates the teaching-learning strategies considered in the design of the topics of the different courses, as well as the redefinition of the teaching strategies according to the student's learning style. It also incorporates a process to adapt the contents to be presented to the student's learning style:

- Identify learning styles.
- Select the topics to be shown to the student, linking their learning style with the teaching strategies used in the creation of the topics and thus favoring their learning.
- In the knowledge module, a database is added to store the subject competencies. As well as the use of some metadata in the course contents to characterize the competencies that are sought to be developed.
- The interface module will show the learning objects chosen by the tutor module selection process.

The Case-Based Reasoning module is added, which is an approach that approaches new problems by taking as a reference similar problem solved in the past. So similar problems have similar solutions.



**Figure 4:** Tutor module

The case base is confirmed by the results of the test [13] carried out on 199 students, where the predominant learning style and the preferences regarding the material used to understand a certain content can be appreciated. Figure 4, shows the case base used.

## 2.4. Knowledge module and student

As a first step, learning objects (LOs) are created and imported into the LMS. LOs are defined as any entity, digital or non-digital, that can be used, reused or referenced during technology-supported learning. The OA are designed and implemented using various programs, integrating didactic materials (text, video, images, sound, simulations, etc.) into these programs. Once the OA are imported into the knowledge module, the process begins by determining the learning style of the student and the personalization of learning content.

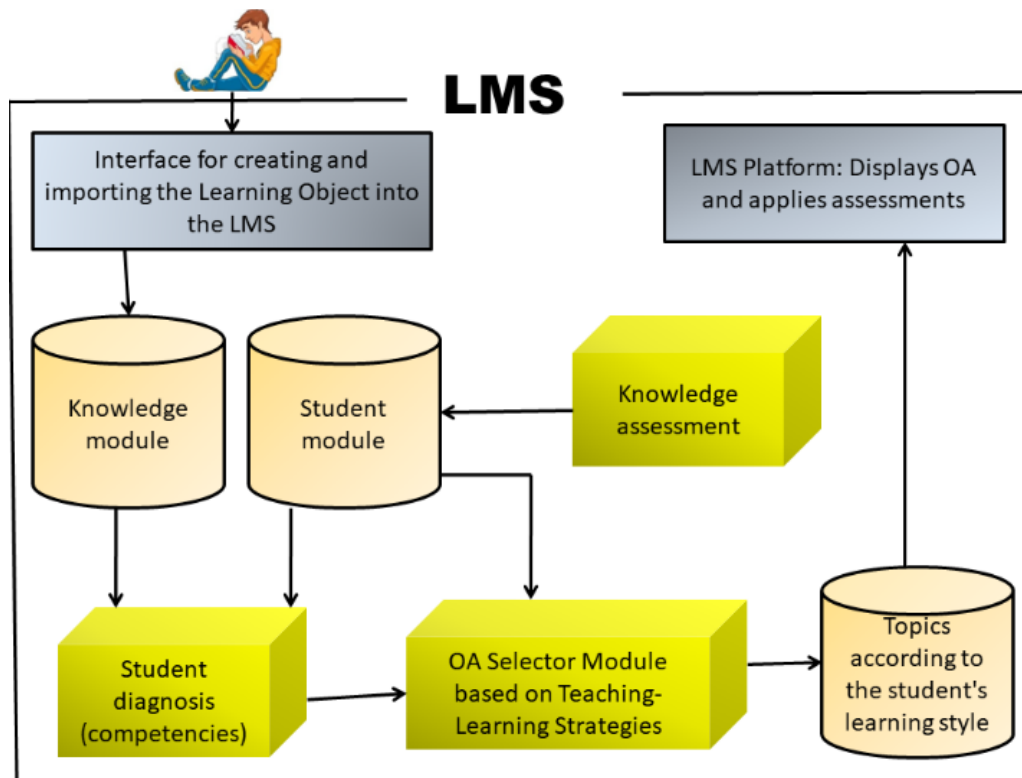
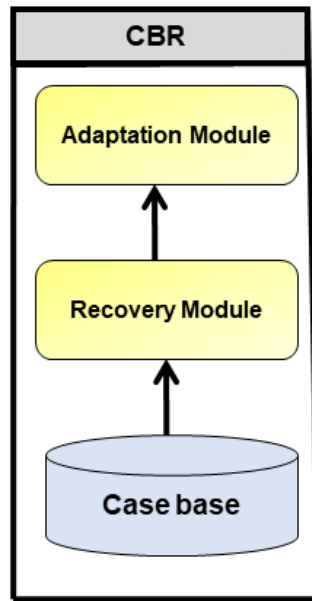


Figure 5: Knowledge module and student module

## 2.5. Case-Based Reasoning Module

In the CBR module, a case similar to the new one is retrieved and the solution of the retrieved problem is proposed as a potential solution to the new problem. This is derived from an adaptation process in which the old solution is adapted to the new situation. These systems define a series of steps and components that interact in a cycle of reasoning. From a new problem, cases similar to the one introduced are recovered, which subsequently go through a process of adaptation, achieving an answer in accordance with the situation presented. Then, if necessary and after review, the system decides whether or not to learn the given solution. The above is considered the case-based reasoning cycle as shown in Figure 6.



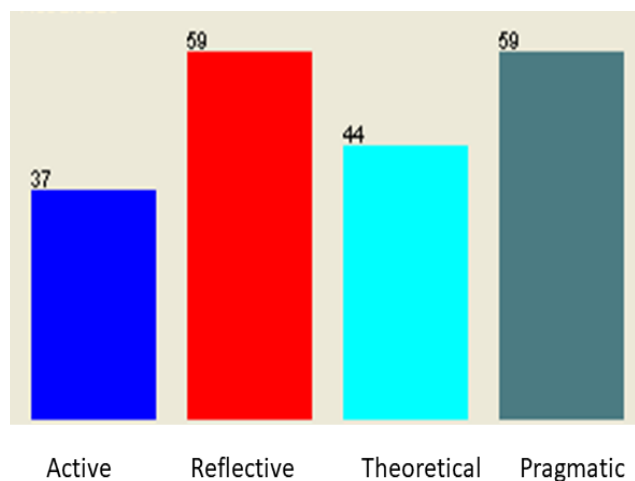
**Figure 6:** CBR module

## 2.6. Validation of proposed model

In the experimentation carried out, the database is made up of 199 students, which according to their learning styles are entered into the Case-Based Reasoning mechanism, prior to a case indexing process, which retrieves cases using the Euclidean distance in  $n$  dimensions as a measure of similarity. Once the evaluation process is concluded, the winner is reviewed, returning the personalized content according to the learning style entered, and if this case is significant, it is retained, as shown in Figure 4. ([See case base here](#))

To carry out the experimentation, we experimented with the [MIGAP](#) platform in order to determine the predominant learning style; the frequencies of the learning styles detected in each of the students in each course were analyzed to determine whether they influenced the students' performance.

Figure 7 shows that 37 students possess the active learning style, 59 students possess the reflective learning style, 44 students possess the theoretical learning style, and 59 students possess the pragmatic learning style.



**Figure 7:** Learning styles detected



## Results

To evaluate the results of the proposal with other algorithms, the cross-validation technique is used to evaluate the results of a statistical analysis and ensure that they are independent of the partition between training and test data. It consists of repeating and calculating the arithmetic mean obtained from the evaluation measures on different partitions. It is used in environments where the main objective is prediction and you want to estimate how accurate the model will be in practice. It is a technique widely used in artificial intelligence projects to validate generated models.

Table 2 shows the results obtained by applying CBR where the percentage of success is 100% and an error percentage of 0%, using a search by similarity through the Weighted Euclidean Distance. Having as input data the learning styles obtained through the test of [13] and the preferences of teaching strategies obtained through a survey.

**Table 2**  
**Confusion Matrix applying CBR**

Learning style	Active	Reflective	Theoretical	Pragmatic	Data	Hits	Errors
Active	51	0	0	0	51	51	0
Reflective	0	48	0	0	48	48	0
Theoretical	0	0	53	0	53	53	0
Pragmatic	0	0	0	47	47	47	0
						199	0
Percentage of hits and misses						100.0%	0.00 %

Table 3 shows the results obtained through the Simple Logistic algorithm with a success rate of 98.99%. The Simple Logistic algorithm was the second best in the list; this is because, although it managed to correctly classify a large number of positive instances, it also misclassified negative instances with an average of 0.003.

**Table 3**  
**Confusion Matrix applying the Simple Logistic Algorithm**

Learning style	Active	Reflective	Theoretical	Pragmatic	Data	Hits	Errors
Active	37	0	0	0	37	37	0
Reflective	0	58	1	0	59	58	1
Theoretical	0	0	44	0	44	44	0
Pragmatic	0	0	0	59	59	59	0
						198	1
Percentage of hits and misses						99.50%	0.50 %

Table 4 shows the results obtained through the Naive Bayes classifier with a 97.98% success rate. This is a supervised classification and prediction technique that builds models that predict the probability of possible outcomes. It is a supervised technique because it needs to have classified examples for it to work.

**Table 4**  
**Confusion Matrix applying Naive Bayes Algorithm**

Learning style	Active	Reflective	Theoretical	Pragmatic	Data	Hits	Errors
Active	35	0	0	2	37	35	2
Reflective	0	58	1	0	59	58	1
Theoretical	0	0	44	0	44	44	0
Pragmatic	1	0	0	58	59	58	1
Percentage of hits and misses						195	4
						97.98%	2.01 %

Table 5 shows the results obtained through the Tree J48 classifier with a 96.98% success rate. Decision trees are a widely used learning and classification method, due to the ease of organization and understanding of the knowledge they propose. A decision tree represents a set of constraints or conditions that are organized in a hierarchical manner and that are applied successively from a root to a terminal node or leaf of the tree.

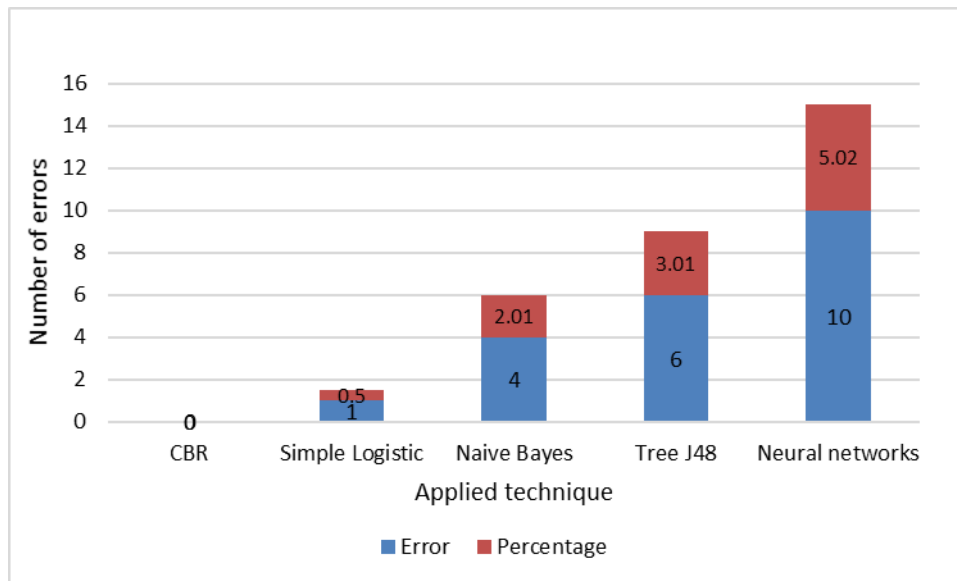
**Table 5**  
**Confusion Matrix applying the Tree Algorithm J48**

Learning style	Active	Reflective	Theoretical	Pragmatic	Data	Hits	Errors
Active	37	0	0	0	37	37	0
Reflective	0	54	4	1	59	54	5
Theoretical	0	1	43	0	44	43	1
Pragmatic	0	0	0	59	59	59	0
Percentage of hits and misses						193	6
						96.48%	3.01%

In table 6, the results obtained through the Neural Networks classifier are presented with an accuracy percentage of 94.97% and an error percentage of 5.02%. Confusion Matrix Applying Neural Networks.

**Table 6**  
**Confusion Matrix Applying Neural Networks**

Learning style	Active	Reflective	Theoretical	Pragmatic	Data	Hits	Errors
Active	35	0	0	2	37	35	2
Reflective	0	55	4	0	59	55	4
Theoretical	0	4	40	0	44	40	4
Pragmatic	0	0	0	59	59	59	0
Percentage of hits and misses						189	10
						94.97%	5.02%



**Figure 8:** Comparison of CBR error rate with other techniques

Figure 8 shows that the highest number of successes in the classification corresponds to the proposed technique of Case-Based Reasoning with 99.50% of successes and 0.5% of error, in contrast to the use of the other techniques used, which has a percentage of successes below the proposal.

It can be seen that the highest number of correctly classified cases corresponds to the CBR, with a mean absolute error of 0%. After comparisons with other classification algorithms, the Simple Logistic algorithm is in second place, the Naive Bayes algorithm in third place, the Tree J48 algorithm in fourth place and the Artificial Neural Networks algorithm in fifth place.

Table 7 shows that the best results of the techniques presented are obtained by the CBR, with an efficiency of 100% vs. 98.99% obtained by the Simple Logistic classifier, followed by the Naive Bayes classifier with an efficiency of 97.98%, then the Tree J48 classifier with an efficiency of 96.98% and finally the Perceptron Multilayer classifier with an efficiency of 94.97%. In addition, a comparison of the error rate of the 0% proposal with the error rate of the other proposals is presented.

**Table 7**

Summary of the selection made through CBR

Class	Data correctly classified	Incorrectly classified data	Accuracy	Instances correctly classified	Accuracy and resilience	Receiver operating characteristic area
<b>Active</b>	1	0	1	1	4	1
<b>Reflective</b>	0.966	0	1	0.966	0.983	1
<b>Theoretical</b>	0.967	0.015	1	0.967	0.978	1
<b>Pragmatic</b>	1	0.014	0.967	1	1	1
<b>Weighted Average</b>	0.99	0.007	0.99	0.99	0.99	1

## Discussion

According to the results obtained, the importance of contrasting learning models and curricular models in terms of personalization should be considered. It is important to remember that a highly technical system with little learning content will discourage students from using it. On the other part, it has been observed that several different approaches have been developed for AI personalization models, mainly developed from a conceptual point of view, and the scope of application remains a very specific current use case and mainly related to the systems and IT domain. This is in line with [16], who argued that systems in this domain will be ubiquitous autonomous systems that use knowledge from recommender systems. On the other hand, the results show a high potential of AI in different learning processes, which is in line with [17], as the learning content can be directly adapted and tailored to the knowledge and domain competencies of the individual learner. Some important data from the reviewed personalization techniques: From a pedagogical perspective, it is necessary to look at intentionality, content development, relationships, and evaluation criteria. From a curriculum standpoint, the principle of uniqueness is evident because the educational environment and the training and dynamics of students cannot be ignored, as the educational discourse is not static but rather constantly changing. It varies and changes according to the outcome. Students can assess the appropriateness of assigned resources and provide feedback on the process as well. Technical tools support and optimize the resource selection process. Students become more aware of their learning processes and styles [18]. While technical elements are important in the adaptation of learning objects, there is no evidence to support the evaluation of specific interventions to improve learning from the data provided by these systems in their use cases. Although technical elements are important in the adaptation of learning objects, there is no evidence to support the evaluation of specific interventions to improve learning based on the data provided by these systems in their use cases. This is also in line with [19], who argue that personalization is more successful when relevant student characteristics are repeatedly measured during the learning process and these data are systematically used to adapt training, a fundamental aspect of artificial intelligence.

The approach of this retrospective reflection will allow the future development of a personalized model that incorporates relevant aspects from different approaches to support learning strategies to improve students' performance [20]. In the field of research, the interface of artificial intelligence and lifelong education is a challenging method of work in teaching and learning.

## Conclusions

The architecture and operation of an Intelligent Model of Personalized Learning Management based on instances of learning objects is developed, the results of which show that the proposed model has an efficiency of 100%; above the following models: Simple Logistic with 99.98%, Naive Bayes with 97.98%, Tree J48 with 96.98%, and Neural Networks with 94.97% of success.

The proposal is validated using the Case-Based Reasoning technique, an efficient and significant behavior is observed in the customization of content according to the students' learning style.

The tests with this prototype allow projecting that the use of this e-Learning technology would directly affect the educational quality of the region. Allowing to optimize some elements of the learning process that are still traditional in our environment.

On the other side, as the structure of the model shows, the most common fields of study are programming fundamentals or fields related to systems engineering, since design instructors are computer science apt. As part of the possibilities of applying AI technologies in the field of education, it is also evident that these technologies are universal. Therefore, no two methods can perform the same task and most studies use different methods to compare results. Finally, this study did not identify studies that included prior knowledge, learning styles, and other non-academic variables that contributed to personalization models in an integrated manner. As a

contribution to future research, it is suggested that learning and curriculum models be considered when developing personalization models. In addition, the methods available in the literature should be compared to assess their strengths and weaknesses. On the other hand, the context of the population on which the model is focused should not be forgotten, which depends not only on the curriculum being taught, but also on the didactic objectives, the resources and the availability of data available to the students.

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