A proposed architectural learner model for a personalized learning environment

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Abstract
Nowadays, the need for e-learning is amplified, especially after the Covid-19 pandemic. E-learning platforms present a solution for the continuity of the learning process. Learners are using different platforms and tools for learning. For this, it is necessary to model the learner for the personalization of the learning environment according to his needs, and characteristics, which will allow having a more effective and efficient environment. The existing literature maintains that the learner model represents the basis and the key to adaption. To achieve this goal, we propose a new adaptation aspect of the learner model by integrating relevant information such as learning style, domain-related data, assessment-related data, and affective data. It has advantages in terms of precision as it solves the problem of management uncertainty of some parameters. Our approach suggests that the combination of stereotype method, fuzzy logic, and similarity techniques is an appropriate approach for initializing and updating the learner model for learning personalization.

Keywords Personalization · Learner model · Stereotypes · Adaptive environment · Learner characteristics

1 Introduction

A learning system is an environment accessed by thousands of learners around the world, certainly with different profiles. Providing the same learning and teaching circumstances to all learners can be pedagogically inefficient (Chrysafiadi & Virvou, 2013).
The environment must be able to generate adapted learning paths, follow learning activities, adjust misconceptions, interpret results, and deduce the needs, preferences, and learning characteristics of each learner to provide a personalized and adapted experience that helps the learner achieve his/her goals. The concept of personalization has converted the traditional "one size fits all" approach to a "one size for each learner" approach. In other words, a learning system must provide personalization according to each learner’s preferences, learning styles, objectives, expectations, and specific skill levels.

Personalization in education requires both knowledge of the learner and the conception of significant learning tasks (Papanikolaou et al., 2003). The generation of an environment that promises to respond to the different needs of the learners is a difficult task considering that learners differ not only in their needs but also in their learning characteristics. In this sense, information about the learner is needed, and the easiest way is to extract it from the data stored in his model. The learner model is one of the distinctive components of an adaptive environment (Brusilovsky & Millán, 2007). It reflects the image of the learner in the learning environment.

Learner modeling has extended to many of today’s so-called personalized and adaptive educational systems such as adaptive educational hypermedia systems, semantic web-based educational systems, and intelligent tutoring systems (ITS) (Kaya & Altun, 2011). Brusilovsky in (Brusilovsky & Millán, 2007) mentioned that learner modeling and adaptation have a mutual connection in the way that the degree of adaptability of the system depends on the information extracted and stored in the learner model. The impression of isolation of the learner and lack of interaction in the learning environment can be solved by learner modeling. This will help the course instructor to discern and detect the change in the learner’s behavior and intervene to adjust the environment according to the learner’s requirements to regain the motivation and attention of the learner.

Consequently, the objective of our paper is to develop a learner modeling architecture and the way that is used to provide an adaptive learning process. This has been accomplished by determining the appropriate learner characteristics and by combining the learner modeling approaches and the logic technique. In addition, the paper also presents the methods used in a significant number of learner modeling and adaptive learning works.

The remaining part of this paper is divided into five sections. The second section explains related works. The third section describes the proposed architecture of the learner model. The fourth section presents a comparative study of the methods used in the literature and those used in our model. Finally, the last section concludes the work with future perspectives.

2 Related works

Personalizing learning is a very delicate task. The learner model is the pivot of any adaptive learning environment, which permits the improvement of the learning process. Therefore, learner modeling has always been one of the most important research in the field of learning personalization because of its impact. Different
learner models have been proposed, with different characteristics and modeling techniques. Authors have often focused on the learner’s level of knowledge as the main learning objective. Thus, the interest in modeling other characteristics such as learning style, motivation, and affective aspects continues to expand (Chrysafiadi & Virvou, 2013; Abyaa et al., 2019). Others propose to integrate the diplomas obtained by the learner to adapt the recommendations (Jeghal et al., 2013).

Many authors have used hybrid techniques for modeling learner characteristics (Tsiriga & Virvou, 2002, 2003; Surjono & Maltby, 2003; Tourtoglou & Virvou, 2008, 2012; Castillo et al., 2006; Hernández et al., 2017; Adel et al., 2016; Pelánek et al., 2017; Tlili et al., 2017) and machine learning techniques remain one of the most used techniques (Abyaa et al., 2019). Clement et al. (2011) proposed a learner modeling mechanism based on ontologies and diagnostic rules. The model, which was implemented and integrated into the MAEVIF platform, has allowed the system to make tutoring decisions and to provide more adequate feedback at each moment. In (Jeremić et al., 2012), the authors combined two modeling techniques, stereotype, and overlay, focusing on cognitive characteristics for the conception of a student model in a DEPTHS (Design Pattern Teaching Help System). To update the model, fuzzy rules are applied during the learning process to ensure the efficiency and accuracy of the model. (Gaudioso et al., 2012) have developed a web-based learning system for teaching physics in secondary level education. They use an overlay technique to help teachers to monitor and understand the behavior of learners, especially in a problem situation. The model also proposes the recommendation of suitable learning resources.

To personalize the learning experience, (Faria et al., 2017) have focused on the importance of the integration of the learner’s emotion, learning style, and personality into the model using the stereotype approach. The proposed architecture consists of four models: learner model, emotional model, application model, and emotional instructional model. Personality data and learning styles were defined by questionnaires embedded in the prototype. The TIPI questionnaire was chosen as the technique whereby the learner identifies his/her personality from the five categories (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism), and for learning style, learners must complete the VARK test. However, focused only on the automatic detection of learning styles through the exploitation of learners’ navigation data in an adaptive learning model (PALM). For the implementation of PALM, the authors applied Fuzzy cognitive maps and fuzzy inference systems a soft computing techniques. The results showed that adaptive learning is a critical factor in improving the effectiveness and efficiency of the learning process. Same as (Sweta & Lalet, 2017; Aryal et al., 2019) proposed an adaptive external recommendation of resources from different MOOCs platforms based on learners’ learning styles and standard video styles used in MOOC videos. While the learner model proposed by (Mawas et al., 2018) includes a multitude of characteristics such as demographic, pedagogical, disability, affective, and multi-sensory characteristics of the learner in the NEWTON project. In another work (Chrysafiadi and Virvou, 2012), the authors considered knowledge as a parameter of learning personalization. Using the overlay approach and the fuzzy logic technique, they modeled the level of knowledge of each concept of
the computer programming domain at each moment of the learner’s interaction with the system. However, (Biswas et al., 2019) modeled learner behavior during the completion of tasks in a learning environment called UrbanSim to predict cognitive skills and problem-solving strategies.

In 2020, (Riyahi & Sohrabi, 2020) developed a hybrid content recommendation approach in-group discussions. It is based on learner rating, content features, and tags as parameters of the user model. This approach consists of three parts, namely collaborative filtering, content-based filtering, and hybrid filtering. In the first part, the users most similar to the active user are determined through the implicit evaluations given by the other users. For the Second part, based on the semantic relevance between the user’s question and the existing posts, similar contents to the query are identified. Also, the problem of sparseness was solved in this part. For the last part, the results of the first and the second part are assembled to recommend the obtained posts considering the number of similar users who have contributed to them. The proposed approach presented a high accuracy compared to others.

In the same year, (Hwang et al., 2020) presented an adaptive learning system. It consists of four modules that are the learner module, the test model, the learning state recording module, and an expert system module that analyzes the affective state and determines the appropriate learning content for each learner based on their affective and cognitive state. The experiment was conducted on a group of fifth-grade mathematics learning students in Taiwan. A set of fuzzy inference rules is used to propose the pre-classified LOs. In addition, to measure the effect of cognitive load on the learning process, a one-way analysis of variance (ANOVA) was applied. The results showed that the performance of learners in the learning system taking into account cognitive and affective factors (experimental group A) surpassed the one analyzing only cognitive performance (experimental group B) and the one using the conventional learning mechanism (control group). Mourad et al. (2020) developed a hybrid rule-based and collaborative recommendation system. The learner profile considers learning outcomes and contextual information. Collaborative filtering is used to predict the learning outcome that will be combined with a set of decision rules to suggest learning materials to a specific learner. As well as, the textual information is extracted during the entrance test, which will allow offering recommendations to new learners. This approach obtained the best prediction result of a final score value of 82.36 via the MSE evaluation metric.

Benmesbah et al. (2021) proposed a personalized learning path, including the development of a learning object model and a learner context model in an online learning environment. For a precise and effective recommendation, the proposed approach not only takes into account the learner’s learning objective, but also his/her level of knowledge, prerequisites, concentration, learning style, available time, and mobility status. To manage this complexity, the authors have separated the contextual dimensions into two steps. The first step is to develop a meaningful sequencing of the concepts, and then the selection from each of those concepts in the concept sequence, an LO that fits the learner model in the second part. To increase search efficiency and find the most suitable learning path for each learner in less time, the authors developed an improved genetic algorithm. Wang et al. (2021) considered both sequential behaviors and general learner preferences for personalized course
recommendations in MOOCs, using Top-N based on TP-GNN (Graph neural network). The experimental results showed the efficiency of the proposed method.

The APPEAL platform proposed by (Sayed et al., 2022) is a personalized platform conceived as a Moodle-based website, including a front-end interface, algorithms, and an API. It aims to ensure efficient learning with less time, improved marks, and learner satisfaction. It considers the learner’s learning style, behavioral aspect, and emotional state. The personalization of learning is shown in the presentation of learning content according to the VARK learning style or gamification. The last one targets the learner’s affective state, especially his/her engagement in the learning process. It is also shown in the development of exercises, personalized comments, and adaptive feedback through indices, attempts, and feedback messages. This proposal has been tested and has shown improvement in learner outcomes. The authors (Chang et al., 2022) developed an online learning management system compatible with the Moodle platform, including various management modules and customized services that include synchronized SIMS service, personalized learning map service, learner portfolio service, and learning feedback service. To compare the benefits of the platform, the authors experimented on a group of students in the "Programming" course at the Central Taiwan University of Technology. The experimental procedures consisted of five steps: Programming requirement learning, Mid-term assessment, and according to the results, the learners perform the next step Personalized Learning, then Final assessment, and finally, The learning feedback service used to understand the learning status and reflections.

3 Methodology

Based on the researchers’ concerns to personalize the learning process to reduce dropout rates. There has been a great interest in building an accurate and complete learner model. The methodology is based on the different studies realized and presented in the previous section. Our approach attempts to answer three questions: What are the learner’s information and characteristics that we desire to model? How do we model them? And how will the model be used?

We propose that our model incorporates the most appropriate learner information and characteristics using learner modeling approaches, fuzzy logic, and similarity techniques.

4 The architecture of the proposed system

Learner modeling is the most important step before the realization of personalized services. It permits not only representatives of the learner’s image but also allows the system to interact. According to (Millán et al., 2010; Nguyen & Do, 2009) to elaborate the model, it is necessary to identify the information that needs to be taken into consideration, the way in which it will be modeled, and the way in which it will be used to achieve a personalized learning experience adaptation. Therefore, the issue of developing a learner model is addressed in three questions: What are the
learner’s information and characteristics that we desire to model? How do we model them? And how will the model be used?

Compared to a real classroom, the first step for a learner in a learning environment is to identify him or herself. Therefore, the first question that needs to be asked is “What information needs to be considered before the learning process begins?”

The answer to this question aligns with the types of static information. According to (Jeremić et al., 2012), the information is defined before the beginning of the learning process by the learner, which remains unchanged throughout the process, or it can be modified by the learner himself if necessary. As well as, during the learning process, some information is the result of the learner’s interaction with the learning environment and is the one that the system updates relative to the collected data. This type of data is known as the dynamic type.

However, Brusilovsky (2001) affirms that data can also be classified into two groups, depending on the nature and form of the information collected: domain-specific information (DSI) and domain-independent information (DII). DSI contains the level of knowledge, level of skills, and records about learning evaluations and activities. DII is not related to the content delivered. It facilitates the process of personalization. It includes the learner’s learning goals, cognitive aptitudes, motivation, learning styles, background, and preferences.

### 4.1 Identification of the learner’s characteristics

#### 4.1.1 Learner profile and model

Before identifying the parameters considered in our model, it is interesting to present the difference between two terminologies that are often used in this context, we talk about the "Learner Profile" and "Learner Model" (Fig. 1). The learner profile contains the learner’s personal information without interpretation, such as name, email, and gender… However, the learner model expresses a description of what is considered important and relevant about the learner’s knowledge and/or behaviors in the educational context to adapt the system to each learner (De Koch, 2001). Therefore, the learner model shows an overview (Nguyen & Do, 2008) Able to infer more information about the learner. The learner in the real environment is perceived by the learning environment through the «human–machine interface " (Tadlaoui et al., 2016).

#### 4.1.2 Contents of a learner model

The extracted information is data stored in the learner’s model. It can be analyzed and regrouped to allow the system to serve itself. This learner model presents an important role and the first step in learning personalization. Figure 2 shows the components of our learner model.

For every learner, the model consists of:
Fig. 1 Learner’s Model in adaptation

Fig. 2 Components of the learner model
• **Personal data** presents a pre-identification of the learner, containing name, age, gender, email, and desired language. This learner-defined data is of less importance for the personalization of learning.

• **Learning Style Preference** is one of the most frequent topics in the educational psychology literature (Wininger et al., 2019). It indicates how a learner observes, interacts with, and replies to the learning content (Blakemore et al., 1984) in a personal way that allows him to have positive results and thus optimal learning (Klašnja-Miličević et al., 2011). Researchers have agreed that considering this characteristic, can lead to an increase in learning performance, motivation, and a reduction in learning time (Felder & Silverman, 1988).

It is necessary to integrate this parameter into our model in order to entrain what is more appropriate to maintain the learner in a state of concentration, processing, assimilation, and retention of knowledge in the long term.

• **Domain-related data** is an essential component to satisfy the learner’s needs. In this category, the learner defines the desired learning domain and the expected objectives. It also includes the level of knowledge mastery which can be used according to the instructor before the beginning of the learning process to check that the learner has all the necessary prerequisites, or during/at the end of the learning process to be sure of the assimilation of the knowledge by the learner and therefore the mitigation of the previously defined objectives.

• **Data related to assessments**: This category is a form of interaction of the learner with the system, not very similar to a real environment where the teacher observes and analyzes the learner’s behavior to constantly adjust the knowledge construction mechanism to suit the learner’s objectives and needs as much as possible. It includes implicit parameters, namely the number of tentative, errors and the duration of the learner’s learning, in which the system knows the state of the learner at an appropriate moment.

The choice of these parameters is not random. The number of tentative errors can be explained by the lack of understanding of the knowledge. For the third parameter, when the duration exploited by the learner is higher than the duration defined by the instructor, this can be explained by a difficulty in assimilating the knowledge. On the opposite, when the duration exploited is inferior to the duration defined, this can be explained by two forms either the level of the learner is advanced or the lack of commitment of the learner in the learning process. And to affirm this learner state, it is important to consider another element.

• **Affective Data**: Taking into consideration the emotional state of the learner is one of the most important elements for the personalization of learning. Emotions are identified as one of the key factors influencing the learning process (Lee & Choi, 2011). It has a significant effect on decision-making and knowledge acquisition (Willingham et al., 2015; Javanbakht et al., 2017). Recognizing the learner’s emotion in real-time at an appropriate moment allows not only for the
adjustment of the content and learning path but also for the readjustment of the learner’s emotional state, which facilitates the accomplishment of the goals.

- **Dashboard**: This element has two purposes. It helps the learner to visualize his progress in the courses to be aware of his learning status. Thus, it allows him to keep the courses he wants to learn in the future on the waiting list as soon as he finishes the current one.

The parameters of our model are collected in two classes as shown in Fig. 3: Static information and dynamic information. The first class is composed of two subclasses: Personal data, and Learning Style Preference. It’s considered to be the learner profile. However, the second class consists of three subclasses: Domain related data, Data related to assessments, Affective data, and Dashboard.

### 4.2 Modeling of learner characteristics

After identifying the different parameters of the learner’s model in the previous section. The next step is to determine how to collect and represent these parameters. Therefore, it is necessary to use different methods and techniques for modeling the learner that already exists in the literature, such as Overlay Model (Hammad et al., 2017; Reddy & Sasikumar, 2014; Sosnovsky & Brusilovsky, 2015; Suleman et al., 2014), Stereotype Model (Papanikolaou et al., 2003; Tsiriga & Virvou, 2002; Carmona et al., 2008; Popescu et al., 2009), Machine Learning (Grawemeyer et al., 2015; Hernández et al., 2017; Huang et al., 2017; Sawyer et al., 2017), Fuzzy logic Model (Sweta & Lalet, 2017; Peña-Ayala & Sossa, 2013), Perturbation Model (Tourtoglou & Virvou, 2008, 2012; Surjono & Maltby, 2003; Faraco et al., 2004), and Bayesian Methods (Schiaffino et al., 2008; Conati & MacLaren, 2009; Millán et al., 2010). These techniques describe how the model will be generated and maintained to increase learner retention, quality, and efficiency of learning.

In order to create an adaptive and intelligent model, we have chosen in our work to develop a learner model by combining the stereotype approach with machine
learning techniques. For each learner, the model is made up of the following characteristics:

- **Personal data**
  
The information will be collected through a form that will be given to the learner before starting a learning situation.

- **Learning Style Preference**

  Many models have been developed that attempt to represent the way learners treat information, namely the Learning Style Inventory model (LSI) (Kolb, 2014), Felder-Silverman model (Felder & Silverman, 1988), and VARK model (Fleming & Baume, 2006). In our work, we chose to use Felder Silverman’s model (FSLSM) because it responds to our needs, and it has been declared the most convenient model, covering as much as possible the behavioral aspects and the most practical to implement in e-learning environments (García et al., 2008; Carver et al., 1999; Fasihuddin et al., 2014). In addition, based on the chosen model, a popular questionnaire was developed by Felder and Soloman, called the Index of Learning Style (ILS) (Soloman & Felder, 1999). It is a data collection instrument, in the form of a questionnaire composed of 44 questions, that leads to a classification of four dimensions where each dimension groups two categories of learners (Table 1): active/reflective, sensory/intuitive, visual/verbal, and sequential/global.

  Despite the efficiency of the ILS questionnaire, the authors have presented some difficulties that learners find when answering the questionnaire. They have indicated that answers to certain questions should not be dichotomous, and the desire to have intermediate answers (Cataldi et al., 2006). For this, we propose to use the fuzzy logic proposed by Lotfi Zadeh to help the learner to express his degree of membership to each answer, as opposed to the classical approach that requires the learner to choose if he belongs or not to an answer item. We propose

| Preferred learning style | Dimension |
|--------------------------|-----------|
| Active/Reflective dimension | Processing |
| Active- prefers to work in a group and enjoys learning by sharing | |
| Reflective- learn on their own, but prefer to think and concentrate first | |
| Sensing/Intuitive dimension | Perception |
| Sensing- prefers the concrete, examples, and facts related to the real world | |
| Intuitive- prefer to innovate and discover different possibilities | |
| Visual/Verbal dimension | Input |
| Visual- has a visual memory i.e. remembers images, demonstrations, films, diagrams, etc | |
| Verbal- prefers written and oral explanations | |
| Sequential/Global dimension | Understanding |
| Sequential- prefers linear learning, following logical and well-defined steps | |
| Global- prefers to have an overview of the information before getting into the details | |
that the questionnaire be identical to ILS except that each question contains six possible answers instead of being dichotomous. Rule 1 corresponds to the first answer item extremity of the classical ILS questionnaire, and rule 5 corresponds to the second answer item extremity of the classical ILS questionnaire. In the following, we present the rules chosen as answer items for our questionnaire:

- Rule 1: Extremity A
- Rule 2: Mainly extremity A and some extremity B
- Rule 3: Mainly extremity B and little extremity A
- Rule 4: Sometimes extremity A and sometimes extremity B
- Rule 5: Extremity B
- Rule 6: No answer

When the learner chooses rule 6 as the answer to a given question, that question will not be calculated.

- Domain related data

As mentioned in the previous section, this parameter includes three components: Learning area (category), Learning objectives, and Level of mastery of knowledge.

The first component of this parameter is the desired learning domain. The identification of this component is made by the learner himself. The learner selects the domain he wants from the domains presented in the learning environment, and then he also determines the objectives that are appropriate for him.

To recommend resources that respond to the needs of the learner, a certain similarity or compatibility must exist between the goals expected by the learner and the goals identified by the instructor in the description of each resource.

For this purpose, we start by identifying the importance of the terms in the description of the objectives. To calculate this importance, we use the TF-IDF (Term Frequency Inverse Document Frequency) measure. Then, a cosine measure is used to compute the similarity between the vector of expected and determined goals. The goals with the highest cosine similarity value are the most similar to the goals expected by the learner.

We consider (TDOS) as the set of terms used in the description of the learner’s expected objectives (1) and then TF-IDF to identify the importance of the terms used.

\[
TDOS = \{T_{is}, \ldots , T_{ns}\}
\]  

Next, we consider (TDOR) as the set of terms used in the description of the objectives determined by the instructor and supposed to be acquired by the learner (2).

\[
TDOR = \{T_{i}, \ldots , T_{n}\}
\]

Each resource R is represented by a vector VR(3)
\[ VR = (VRT_1, \ldots, VRT_n) \] (3)

where \( VRT_i \) represents the TF-IDF value of the term \( T_i \) in the resource description \( R \).

The set (TDOR) is also represented by a vector \( V_{TDOR} \).

\[ V_{TDOR} = \{V_{TDOR_1}, \ldots, V_{TDOR_n}\} \] (4)

where \( V_{TDOR_i} \) represents the TF-IDF values of the term \( T_i \) in all objective descriptions of all the generated resources after the selection of the domain.

After that, we calculate the similarity through cosine similarity (5) between the TDOS vector representing the objectives described by the learner, and the TDOR vector representing the objectives determined by the instructor.

\[ CosSim(O) = \frac{V_{TDOS}.V_{TDOR}}{\|V_{TDOS}\| \cdot \|V_{TDOR}\|} \] (5)

The objectives with the highest \( CosSim(O) \) value are the most similar to the objectives described by the learner.

The level of mastery of knowledge classifies the learner into one of three groups corresponding to three stereotypes (Beginner, Intermediate, and Advanced) according to the results of the tests determined by the instructor \{\( R \}\), delivered either at the beginning or at the end of the course (Fig. 4). Each stereotype is more difficult than the previous one. The beginner stereotype corresponds to the test score \( \{R\} < 45\% \) of questions correct, the intermediate level corresponds to \( 45\% \leq \{R\} < 55\% \) of questions correct, and the more advanced level corresponds to \( 55\% \leq \{R\} < 100\% \) of questions correct.

As soon as the learner joins the system, he is automatically assigned to the initial stereotype (Beginner) to solve the model initialization problem (Tsiriga & Virvou, 2002). After collecting the data from the test result, the system will assign the learner to a convenient stereotype that is more adapted to his/her performance.

To perform the most appropriate stereotype prediction for a learner, the fuzzy logic technique is used according to the intervals shown in (6).

![Fig. 4 The knowledge level selection process](image-url)
\[
U(R) = \begin{cases} 
0, & R < 45 \\
0.1 \times (R - 45), & 45 \leq R \leq \frac{1}{0.1} + 45 \ (6) \\
1, & R \geq 55 
\end{cases}
\]

• **Data related to assessments**

During the assessment, the instructor identifies the number of errors, tentatives, and the duration of the learner’s response to a question. To be sure that the learner will be assigned to the most appropriate stereotype, the data extracted from this component has implicit parameters, that not only help the system to recognize the learner’s condition but also help the learner to evaluate him/herself. For example, the learner may answer the test incorrectly not only because of non-assimilation of knowledge, but perhaps due to other factors such as lack of understanding of the question asked or hesitation due to lack of self-confidence.

The number of errors and tentative is limited to a certain number. In addition, the duration can be identified from the comparison of the duration set by the instructor, and the duration exploited by the learner.

• **Affective Data**

The modeling of the learner’s state is constituted of two sub-elements: the recognition of the facial expression that consists of the detection of the emotion, and the module of the exploitation of these data to maintain the learner in a state that allows him to achieve his learning process.

### 4.3 Use of the learner model parameter

Figure 5 below provides an overview of the use of the parameters in our model.

The following steps present the prototype use of our model:

1- The initialization process of the model represents the first step to gathering information about the learner in an adaptive system. In our work, as soon as the learner joins the system and before starting a learning situation, he fills in a form containing his personal information.

2- To respond to the need to learn knowledge in a specific domain, the system allows the learner to choose the domain and to describe the objectives he/she wants to achieve.

The description of the objectives helps the learner to express himself and gives him the opportunity to describe what he wants. Sometimes the learner doesn’t have enough knowledge and skills to know the learning process that he needs to follow to achieve his objectives, so when he describes his ideas, the system calculates the importance of the terms used through the TF-IDF measure and then uses cosine similarity between the expected objectives and the objectives determined by
the instructor. Learners who have identified the same domain and objectives will be clustered into stereotypes.

Each stereotype groups learners and each learner has his/her way of assimilation of information and content. To respond to the specificities of each learner, the FSLSM questionnaire will be issued to group learners with identical learning styles into well-defined categories representing the dimensions of the FSLSM.

3- Then, the system generates resources that correspond to the learner’s objectives and learning style, deduced from the FSLSM questionnaire. Once the learner registers for a resource and decides to take it, he/she will be assigned by default to the Beginner stereotype that determines his/her level of knowledge mastery. Each resource has its standards, some instructors do not require any prerequisites, while others require prerequisites to construct new knowledge and thus maintain the continuity of the learning process.

If the selected resource needs a prerequisite, the learner will necessarily pass a test that will be determined by the instructor at the beginning of the learning. Based on the results obtained, the system will change the beginner stereotype to a more adapted one. If not, the learner will directly start the learning process.

4- In addition, the system also proposes to the learner to answer the test at the end of the learning section to evaluate his knowledge against the knowledge supposed to be acquired. His model is updated with an appropriate stereotype. Then, a recommendation process will be triggered to generate adapted resources for him.
It is preferred that the assessment test will be also presented during the learning process to examine the degree of knowledge assimilation before the end of the learning section.

5- During the learning process, the learner might be in a state of misunderstanding, which probably results in a lack of concentration and motivation, which can lead to the learner’s over-learning. To solve this problem, we have integrated the learner’s affective state into our model, which will allow us to detect and adjust the learning process. When a state of misunderstanding is detected, the system will be able to generate resources that will allow the problem to be solved, so the learner will be able to continue learning.

Assessment of knowledge both during and at the end of the learning process helps the learner to supervise, think, adjust the learning process, and also promote critical thinking.

6- Also, Data related to assessments permits the system to collect data that will be complementary to the affective Data parameter. These data will present sources of recognition of the state of the learner and the level of mastery of the knowledge supposed to be acquired, allowing the system to generate a more adapted learning path.

7- All the data collected on the learner will be recorded in the Dashboard. It gives an overview of the resources already taken and those that the learner wants to learn after completing the present resource. The Dashboard not only allows the instructor to control learning but also allows the learner to monitor his/her learning process by examining his/her progress, which leads to an increase in self-understanding that will allow him/her to make decisions that are more adapted to his/her objectives and requirements.

5 Discussion

At the beginning of our work, we presented the characteristics of the learner identified, the techniques, and the types of modeling used to create the learner model. The characteristics most identified in the literature are knowledge; cognitive factors such as memory, attention, and perception; affective aspects such as emotion; personality; and motivation. This is in agreement with the study by Raj and Renumol (2021) in which they mentioned that learning style, learner preferences, knowledge level, learning paths and patterns, learner skills, predefined tags, context present the most used learner modeling attributes between 2015 and 2020 in adaptive content recommender systems.

Two major problems of adaptability in a learning environment, namely disorientation and cognitive overload (Zhong et al., 2019). In this context, several researchers have emphasized the importance of the affective aspect (Shephard, 2008; Tsai et al., 2017; Tseng et al., 2008; Snow & Farr, 2021). The latter
indicated for the theory to be good, comprehensive, and little practical, it must contain holistic perspectives.

Based on the literature, most works include the level of knowledge mastery in the learner model (Abyaa et al., 2019) as it represents the main objective of all learning. This is consistent with the results obtained by (Hwang et al., 2020) that the most cognitively and affectively successful learners were able to complete learning tasks and have better results. However, the most commonly used technique to represent the learner’s knowledge level is the overlay model (Chrysafiadi & Virvou, 2013). However, we have chosen to represent this parameter using fuzzy logic with stereotypes because knowledge is not a certainty. It requires a certain degree of membership. It is possible that the learner knows absolutely nothing about the domain, or he knows some information, or he also perfectly knows it. The integration of the learner into the appropriate stereotype allows the system to situate the learner, and to offer him/her a more personalized learning process adapted to his/her learning situation.

Learning style has been considered by a considerable number of research studies. It is elementary to attain the personalization of learning (Shemshack et al., 2021). The two major learning style models most commonly used are FSLSM and VARK. The stereotype model seems most applicable to modeling learning styles and preferences (Chrysafiadi & Virvou, 2013). The modeling of the learning style, in our work, is done by using the FSLSM questionnaire because it meets our needs and it includes as much as possible the behavioral aspects of the learner. However, we have integrated the fuzzy logic technique at the element of the answer. Contrary to the classical approach, which requires the learner to choose if he belongs or not to an element of the answer. We have identified six rules as elements of the answer. Other important characteristics have been also integrated into our model, namely:

- Domain-related data determines the anticipated needs of the learner, such as the learner’s desired domain, learning objectives, and level of knowledge mastery.
- Data related to assessments also informs the system about the learner’s knowledge and status. They must be considered to give an accurate level of knowledge mastery. The model proposed by (Swartout et al., 2016) predicts the current and long-term level of knowledge mastery. (Clemente et al., 2014) have modeled the learner’s level of knowledge through the identification of inconsistency in the learner’s responses, and the identification of errors and misunderstandings. In a different work (Hernández et al., 2017), the authors modeled the learner’s level of knowledge according to the degree of error committed. In our work, we are based on three sub-parameters namely the Number of tentative; Number of errors, and Duration.
- Affective data influence the learner’s learning process. In general, the recognition of the learner’s emotion can be done by different methods such as facial recognition, voice recognition, gesture recognition, implicit parameters, learner request, vital signals, and hybrid methods (Imani & Montazer, 2019).
6 Conclusion

Learner modeling represents a core of personalization in the field of adaptive learning applications in which the characteristics, interests, and needs of each learner have been studied. It corresponds to a process of data collection and representation that is useful for the system.

In this context, our target in this paper was to present our architecture of the learner model, which includes a large number of parameters representing the characteristics of the learner. It is highly recommended to take into account relevant information for higher personalization and efficiency throughout the learning process.

Our approach suggests that the combination of the stereotype method, fuzzy logic, and techniques of similarity is an appropriate approach for the initialization and update of the learner model in the adaptative environment.

In the future, we will work on the recognition of the learner’s emotion and how to integrate this approach into the personalization recommendation system of learning.

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Data availability My manuscript has no associated data.

Declarations

Conflict of interest statement 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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