

Proposal for a learner model adapted for personalized tutoring based on IMS-LIP and PAPI

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ABSTRACT

The effectiveness of online tutoring systems largely depends on their ability to adapt to the individual needs of learners, to personalize learning activities, and to provide immediate and effective assessment and remediation. This effectiveness can only be ensured if accurate information is available regarding learners' progress and learning profiles. In this article, we aim to propose a learner model tailored to the specificities of our academic support system, incorporating learning functions that enable personalized tutoring based on students' needs. For this purpose, this study began with a literature review of existing learner models. We focused on five representative samples of the most widely used learner models in current learning systems: instructional management system-learner information package (IMS-LIP), public and private information for learners (PAPI), CARCHIOLO, knowledge on demand (KOD), and learner model for personalized adaptation (LMPA). We examined their characteristics and then compared them based on the following criteria: adaptability, user preferences, personalized learning, pedagogical requirements, assessment, and remediation, to evaluate their potential for integration into our system. The study revealed that these models present several limitations, which led us to propose a new learner model based on the PAPI and IMS-LIP standards. This proposal incorporates a semantic ontological structure that categorizes learner characteristics into six domains: preferences, pedagogy, administration, identification, learning, and assessment. The proposed model represents a promising solution for adapting learning processes to individual learner profiles, thereby fostering more effective and engaging educational experiences.

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1. INTRODUCTION

In Morocco, students suffer from important difficulties in their academic career, particularly in some of the science subjects [1]. Based on the statistics released by the Ministry of National Education [2], [3], the rate of school dropout remains very considerable, with this mind, the Ministry of Education has made available to teachers, students and parents computer platforms (Massar) for communicating with students and monitoring their progress outside the classroom, while offering them all the services they need to simulate a virtual classroom from a distance [4]. In addition, several platforms have been created by private tutors

offering free tutoring sessions [5]. However, several research studies have raised concerns regarding these platforms [6]. Notably, the ergonomics and navigation of many such websites are only average, often limiting user engagement. Additionally, most of these websites are static, lacking the dynamic elements necessary for interactive learning experiences. Interactivity is almost nonexistent, which diminishes learner motivation and active participation. Some platforms include commercial advertising, which can distract from the educational content. Furthermore, the pedagogical strategies employed are generally underdeveloped; developers frequently transfer textbook content directly to the Internet without adapting it to the digital format. Assistance with learning methodology is entirely absent, despite its potential to help learners improve their study habits and work more effectively. Lastly, there is no systematic follow-up or feedback mechanism to identify and remediate learners' mistakes, which is crucial for effective personalized learning.

To overcome this problem, we need to adopt a strategy of adapting learning systems to learners' needs and tracking their progress on online tutoring platforms [7], by collecting data on these learners, the data identified as pertinent [8]. The ways in which they are obtained and exploited were the subject of many publications [9]. Various learner models have been proposed to monitor student learning online, such as instructional management system-learner information package (IMS-LIP), public and private information for learners (PAPI), CARCHIOLO, knowledge on demand (KOD), and learner model for personalized adaptation (LMPA) [10]. However, they have presented several limitations to meet the requirements of our tutoring system, which we designed in previous work, and whose objective is to personalize the monitoring and learning of students according to their real needs by assessing their acquired skills and presenting them with remedial activities ensuring the achievement of the learning objectives outlined in the official school curricula [11]. Consequently, in this article, we propose a learner model that meets the pedagogical requirements of our tutoring system.

This research aims to analyze five prominent learner models (IMS-LIP, PAPI, CARCHIOLO, KOD, and LMPA) to evaluate their strengths, weaknesses and overall effectiveness in addressing educational needs. The study seeks to answer the following questions:

- Which models are most effective in personalizing learning and remediation strategies? (RQ1)
- What are the limitations of each model in terms of evaluation and providing targeted remediation? (RQ2)
- How we can merge between all this model and create a new learner model? (RQ3)

In this research, we aim to investigate the hypothesis that designing a new learner model, built on the strengths and addressing the limitations of existing models, can lead to an effective solution that ensures the individualization of tutoring for learners. By refining and combining the best aspects of current models, this approach could enhance personalized learning experiences and better cater to individual needs. To answer these questions and validate this hypothesis, in the second section, we will provide a literature review on the existing learner models and their specifications. In the third section, we will introduce the methodology adopted in this paper to highlight the weaknesses of these models in relation to our system. In the fourth section, we will present an analysis of the results obtained, followed by a discussion. Then, in the fifth section, we will present a conceptual model of our proposed learner model, detailing the characteristics of each of its classes. Finally, we will conclude with a conclusion.

2. LEARNER MODEL APPROACHES

2.1. Learner model

Two terms are used to designate the information we have on the learner: “model” or “profile” of the learner, the term “profile” refers to information about a given individual in a given context, whereas the word “model” refers to the generic modeling of learners in a computer system [12]. Al Mamun *et al.* [13] defined the learner model as a framework of data (in the informatics sense) that describes the knowledge acquired by the individual learner, while Rizvi *et al.* [14] stated that a learner profile is a collection of interpreted data about a learner or a group of learners, collected or deduced at the end of one or more educational activities, whether computerized or otherwise. Some of the many benefits of modeling the learner, we cite helping a learner learn, adapting information, interface, and help to the user, facilitating information searches and offering to learner's feedback reflecting their learning path [15]. In this context, numerous research projects [16]–[18] have based their approaches on the IMS-LIP [19] and PAPI [20]. However, given the demanding nature of our tutoring platform [11], we need to create a new learner model that will help us offer students assessment activities for the competencies acquired at the final stage of one or more school units, as well as remedial activities in the event that students fail to validate the academic skills targeted by the assessment.

2.2. PAPI standard

PAPI learner information (public and private information) learner [20] is an official standard, produced by learning technology standards committee (LTSC) of the Institute of Electronic and Electrical

Engineering (IEEE), which specifies both the semantics and the syntax of the learner data [21]. It enables various views of the learning model (student, professor, parent, and employee). The six categories of information are identified by the PAPI learner information standard [22], as shown in Figure 1. The first category, personal information, contains basic details such as the learner's name, address, and contact information. The second, relational information, describes the learner's connections with other participants in the learning environment, including peers and tutors. The third category, security information, covers elements such as access rights and passwords to ensure data protection. The fourth, performance information, records the learner's skills, prior experiences, current work in progress, and learning objectives. The fifth category, portfolio information, compiles samples of the learner's work that illustrate their achievements and competencies. Finally, the preference information category specifies the learner's individual preferences, which can be used to adapt educational systems to their personal needs and learning style.

2.3. IMS-LIP standard

IMS-LIP utilizes an XML-based format designed to facilitate the exchange of learner data across various educational systems, including learning management and educational administration platforms [23]. It serves as a comprehensive data model that builds upon the specifications of the PAPI standard by incorporating additional attributes and structures to enrich learner information representation [24]. As illustrated in Figure 2, this model enables detailed descriptions of learner characteristics essential for a variety of purposes, such as recording and managing a learner's educational history, actively engaging the learner within diverse learning environments, and identifying potential learning opportunities tailored to the individual [25]. Table 1 provides a detailed breakdown and description of each category defined within the IMS-LIP standard, highlighting its role in standardizing learner data exchange.

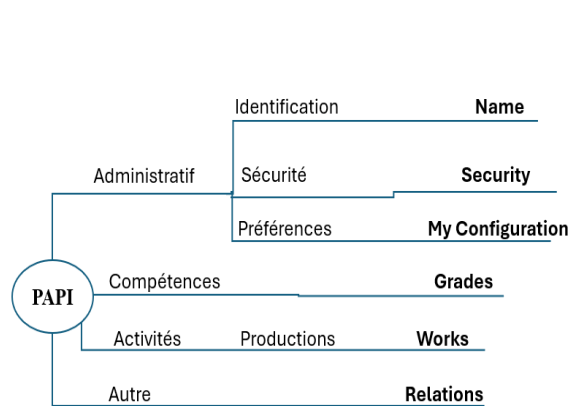


Figure 1. Thematic grouping of PAPI elements [20]

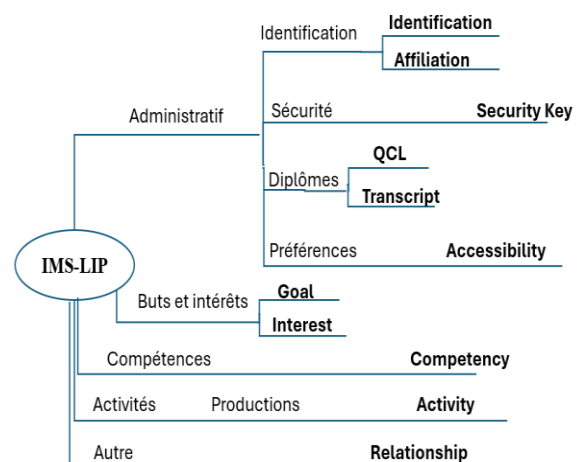


Figure 2. Thematic grouping of LIP elements [26]

Table1. Different categories of the IMS-LIP standard [27]

Category	Description
1. Identification	Elements to identify oneself such as the name, the address, the e-mail address.
2. Accessibility	Learner or tutor preferences, languages, and possible disabilities.
3. QCL	Qualifications, certifications, and diplomas awarded to a learner.
4. Activity	Activities related to the learner's work and training.
5. Goal	Information about the learner's goal.
6. Competency	The learner's skills and experiences.
7. Interest	A learner's hobby activities.
8. Transcript	Data on the learner's learning content.
9. Affiliation	Description of the organization associated with the learner.
10. Security key	An individual's security data, such as passwords and access rights.
11. Relationship	Description of the relationships between the data structures for storing learner data used in the model.

In this study, we conducted a detailed analysis of the PAPI learner and IMS-LIP learner models, focusing on mapping their structures to identify correspondences between their respective attributes. This attribute mapping process, illustrated in Figure 3, involves aligning the fields of both models to improve data consistency and promote interoperability. Establishing this alignment is essential for enhancing our

understanding of learner data and for enabling seamless integration between different systems. By carefully mapping these attributes, we aim to develop a learning model tailored to the specific needs and characteristics of our tutoring system. This foundational step facilitates the combination of diverse learner models and ultimately improves the system's overall functionality, supporting more personalized and effective learning experiences.

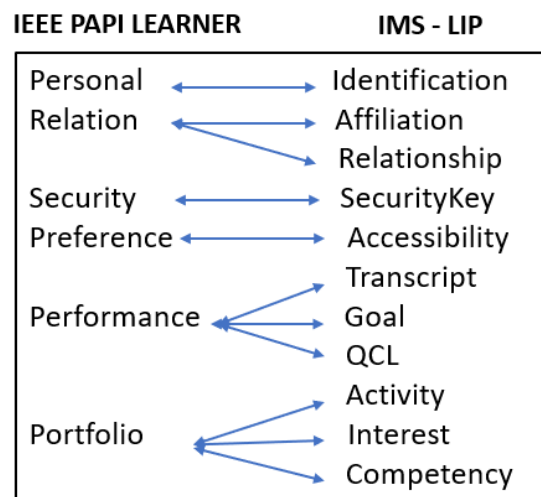


Figure 3. Mapping between the PAPI structure and IMS-LIP

2.4. Other learner profile models

2.4.1. The approach of CARCHIOLO

Research by Carchiolo *et al.* [28] suggested a flexible structure to support distance learning. Student profiles are mainly used to describe knowledge and personal preferences in order to generate personalized learning paths. To achieve this, they proposed a triplet $\text{StudentProfileST} = \{\text{GIST}, \text{CIST}, \text{SIST}\}$, where: GIST represents the learner's general information in the form of a 4-uplet $\{\text{SPDST}, \text{MSST}, \text{STKST}, \text{HST}\}$ in which SPDST represents personal data; MSST represents the appropriate media for learner ST; STKST describes learner ST's knowledge; HST stores the learner's history [29]. CIST represents course-specific information. Course i is presented by $\text{CIST}, i = \{\text{CidentST}, i, \text{PathTreeST}, i, \text{LastNodeST}, i, \text{INITST}, i, \text{GOALST}, i\}$. This is an ordered set representing the course identifier $\text{CidentST}, i$, the possible paths $\text{PathTreeST}, i$ leading to the objective of course i ; the last lesson of course i $\text{LastNodeST}, i$, initial knowledge INITST, i and attainable knowledge GOALST, i . SIST is an 8-tuplet representing session information, i.e. learner preferences (time available SATST, desired learning style DLLST, and difficult levels DLDST) [30].

2.4.2. The approach of KOD project

The research by Akhtar [31] focuses on the learner model of the KOD system, which is inspired by the IMS-LIP model [32]. The system provides an interface that allows learners to input personal information, preferences, goals, accessibility needs, and performance data. This information is then stored in a profile for each student, maintained in XML format. The KOD system uses this data to create personalized learning experiences, adapting content and support based on the individual needs and characteristics of each learner. This approach emphasizes the importance of tailoring educational experiences to enhance learning outcomes and engagement.

2.4.3. The approach of the LMPA modeling language

This language is a theoretical model describing four levels [33]. Profile modeling language (level 3) is at a high level of abstraction [34], guaranteeing genericity. It does not contain disciplinary information or information linked to a given school level, or even to the types of information that will be stored (knowledge, skills or meta-knowledge, for example). Profile models (level 2) is at a lower level of abstraction than the profile modeling language, enabling it to take into account the specificity of needs for a given context, while remaining independent of the data for a given learner. It is a general model of the learner profiles that will subsequently be established. A profile model is a description of the organization and structure of learner

profiles. So, to create a profile model from a profile description language, the designer uses different language building blocks, instantiating each one in its own context. A basic element can of course be used several times, and not all basic elements are necessarily used [35]. Learner profiles (level 1) is instantiated with learner data, constituting individual learner profiles. The learner profile defined by the teacher or by the computer system that performed the diagnosis, has the same structure as the profile model it instantiates. The learner profile has a lower level of abstraction: it is a model of the state of knowledge of a given learner in a given context at a given time. Learners in a learning situation (level 0) considers that the learners in learning situations are the only reality, and not a model of them [36].

3. METHOD

This literature review allowed us to explore several learner models developed in different projects [37]. We specifically focused on the most widely recognized models, critically evaluating their strengths and weaknesses in the context of the requirements for our tutoring platform. The analysis used in this research involves a comparative evaluation of a sample size of five prominent learner models, including IMS-LIP, PAPI, CARCHIOLO, KOD, and LMPA, based on several key criteria relevant to online tutoring systems. The approach is designed to assess how well each model can meet pedagogical needs, adapt to learner progress, and personalize learning experiences. The evaluation focuses on the following steps, as shown in Figure 4.

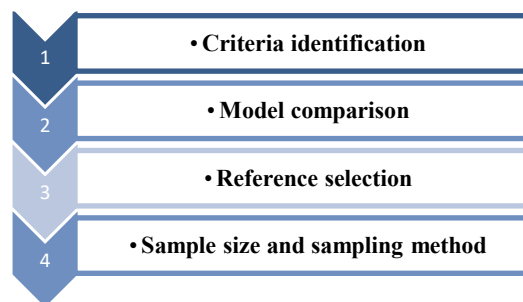


Figure 4. Method

3.1. Criteria identification

The researchers identified key factors, such as adaptability, user preferences, personalized learning, pedagogical requirements, evaluation, and remediation, as essential elements for an effective online tutoring system. These criteria were selected based on their importance in creating a dynamic, learner-centered environment. For adaptability, the models were assessed on their ability to adjust content and learning paths in response to learner progress and needs. User preferences were evaluated based on how well the models incorporate learner behavior and choices into the learning experience. The personalized learning capacity was analyzed by considering how each model tailors learning experiences to individual students. Pedagogical requirements were examined by evaluating how each model aligns with curriculum goals and learning outcomes. For evaluation, the models were assessed on their ability to provide real-time performance tracking, while remediation was evaluated based on how effectively each model provides targeted interventions to address learners' skill gaps.

3.2. Model comparison

Each model was analyzed against these criteria by reviewing literature and analyzing the functionalities described in existing publications. The comparison focuses on how each model handles real-time adaptability, integrates user data for personalization, and provides both evaluation and remediation strategies.

3.3. Reference selection

The references were selected based on their relevance to the learner models' capabilities and their contributions to the field of online learning systems. Published research articles, conference papers, and other credible sources detailing the models' development, strengths, and limitations were used. Sources with comprehensive analyses of learner models were prioritized, ensuring a thorough and up-to-date understanding of each model's functionality.

3.4. Sample size and sampling method

This research primarily reviews existing models and does not involve direct empirical sampling of learners, the “sample” in this context refers to the five models chosen for the comparative analysis. The selection of these models was based on their prominence in literature, as well as their application in various online learning systems. The comparative method is qualitative, providing insights into how each model addresses the criteria, rather than statistical sampling of learners or interventions. Building on these findings, we proposed a new learner model specifically tailored to meet the needs of our system. This new model integrates the best features of the reviewed models while addressing their shortcomings, ensuring a more effective learning experience.

4. RESULTS AND DISCUSSION

4.1. Results

The comparative analysis of learner models IMS-LIP [38], PAPI [39], CARCHIOLO [40], KOD [41], and LMPA [42], based on the criteria of adaptability, user preferences, personalized learning, pedagogical requirements, evaluation, and remediation, summarized in Table 2, reveals distinct strengths and limitations in addressing the needs of personalized tutoring systems. IMS-LIP [43] focuses mainly on storing learner metadata, offering a structured profile organization but lacking dynamic adaptation and personalized remediation capabilities. This static approach limits its effectiveness in modern personalized learning contexts. Similarly, PAPI [44] depends on predefined learner profiles, restricting flexibility and failing to accommodate diverse learner needs essential for personalized tutoring. CARCHIOLO [45] presents a more complex structure but suffers from inconsistent tracking and limited adaptability, hindering long-term learning support. KOD [46] emphasizes knowledge delivery through a rigid curriculum, which limits learner engagement and personalized skill development, making it unsuitable for adaptive learning environments requiring continuous feedback. In contrast, LMPA [47] incorporates adaptability and personalized learning paths with real-time data processing, making it more suitable for intelligent tutoring systems. However, its computational demands pose challenges for practical implementation, especially in resource-constrained settings.

This evaluation reveals that while foundational models such as IMS-LIP and PAPI are important for structuring learner information, they lack the responsiveness demanded by modern pedagogical frameworks. Models like LMPA reflect a shift toward adaptive and learner-centric approaches, even if they present scalability challenges. In fact, the findings reinforce the need for a new learner model that balance adaptability, personalization, and feasibility, in line with evolving pedagogical practices and the goals of intelligent tutoring systems.

Table 2. Comparison of IMS-LIP, PAPI, CARCHIOLO, KOD, and LMPA

Learner model	Adaptability	User preferences	Personalized learning	Pedagogical requirements	Evaluation	Remediation
IMS-LIP	Low: focuses on static learner info.	Limited: basic metadata.	Not suited for personalization.	Lacks flexibility for real-time learning needs.	Basic, no real-time assessment.	No targeted remediation.
PAPI	Moderate: adapts based on profiles.	Limited: cannot fully adjust to changing preferences.	Some personalization but lacks deep remediation.	Meets some needs but lacks real-time interventions.	Basic, lacks deep skill assessment.	Some remediation, but lacks depth.
CARCHIOLO	High: dynamic but complex.	Some flexibility, inconsistent.	Supports personalization, struggles with perfect skill remediation.	Aligns with pedagogical goals but inconsistent tracking.	Dynamic, but inconsistent long-term tracking.	Possible, but not always targeted.
KOD	Low to moderate: focus on knowledge goals.	Limited: predefined knowledge objectives.	Constrained by rigid curriculum.	Strong in curriculum alignment, weak in individualized paths.	Focusing on knowledge acquisition.	Limited to addressing knowledge gaps.
LMPA	High: adapts in real-time.	Actively integrates user data.	Strong personalization with targeted remediation.	Fully aligns with pedagogical goals.	Continuous, real-time assessment.	Real-time, targeted remediation based on performance.

4.2. Discussion

The analysis of the five learner models IMS-LIP [38], PAPI [39], CARCHIOLO [40], KOD [41], and LMPA [42] demonstrates persistent limitations in their capacity to meet the evolving demands of

personalized tutoring and school-based support systems. While these models offer structured methods for managing learner information, they often neglect key aspects necessary for effective individualization and responsiveness. As previous studies have shown, adaptive educational systems must integrate learner profiles with dynamic feedback mechanisms to support continuous learning [42].

A key limitation of these models is their inadequate consideration of learners' individual preferences, cognitive styles, and changing contexts. For example, IMS-LIP [43] and PAPI [44] primarily store static metadata and lack real-time adaptation mechanisms. Research shows that effective personalization must include not only knowledge but also motivation, emotion, and preferred learning modalities [44]. Many models also fall short in accurately tracking skill acquisition and mastery. CARCHIOLO [45] and KOD [46] provide structured learning paths but lack detailed skill monitoring [46]. Another critical gap is the absence of real-time error detection and analysis of learning gaps, essential for timely remediation and customized learning paths. Although LMPA [47] offers better personalization, it faces scalability challenges. Additionally, these models often lack formative assessment and actionable feedback, which are vital for learner motivation and engagement. Timely, specific feedback significantly improves learning outcomes and supports sustained progress [48], [49].

Finally, despite their structured design, these models often fail to link assessment data with pedagogical adaptation, which is necessary for continuous improvement. As noted in Zangerle and Bauer [50], a disconnect between skill assessment and instructional adaptation leads to inefficient teaching and unmet learner needs. The absence of automated cycles of data collection, analysis, and instructional refinement makes it difficult to scale these models in real-world educational contexts. Considering these gaps, it is evident that existing learner models require substantial enhancements to align with the real-time demands of personalized school support systems [51]. The model proposed in this study addresses these shortcomings by integrating multidimensional learner data, real-time feedback mechanisms, and personalized remediation pathways tailored to individual learner profiles. This design supports both diagnostic assessment and adaptive intervention, creating a more responsive, equitable, and effective learning environment [52].

5. PROPOSAL FOR A NEW LEARNER MODEL

Building upon the established IEEE PAPI and IMS-LIP standards, we propose a comprehensive learner profile description model that offers a holistic perspective by integrating pedagogical, personal, administrative, and preferential aspects of the learner. This model is carefully tailored to address the specific functional and pedagogical needs of our tutoring system. It facilitates an accurate and detailed representation of the learner's progress, with a particular focus on assessment outcomes and remediation efforts. By doing so, it supports personalized, adaptive, and continuous learning pathways, ultimately improving both the effectiveness and the relevance of the educational experience for each learner.

5.1. Learner model ontology

In our approach, we modeled the characteristics of the learner by organizing them into well-defined and structured facets to ensure clarity, consistency, and coherence. The core element of this model is the learner class, which comprehensively encapsulates all essential and specific information related to individual learners. This central class is closely interconnected with several specialized subclasses, including administrative, identification, preference, pedagogy, assessment, and remediation, with each subclass representing a unique and important dimension of the learner's profile. Together, these components create a detailed, flexible, and holistic representation of the learner's identity, preferences, educational progress, and support needs. The overall architecture of this proposed learner model is illustrated in Figure 5.

5.2. Administrative class

The administrative class is designed to capture comprehensive information about the learner's academic background and educational journey. As shown in Figure 6, it includes 18 attributes organized into two primary categories: affiliation and qualification, certification, and license (QCL). The affiliation category gathers detailed data regarding the learner's schooling environment, such as the name of their home institution, its geographic region and city, the associated university, the type of institution (whether public or private), the study cycle (primary, secondary, or higher education), and the learner's current educational level. The QCL category focuses on the learner's formal qualifications, documenting details such as diploma names, dates of issuance, and the institutions that awarded these credentials. This detailed classification supports a thorough understanding of the learner's administrative and academic context.

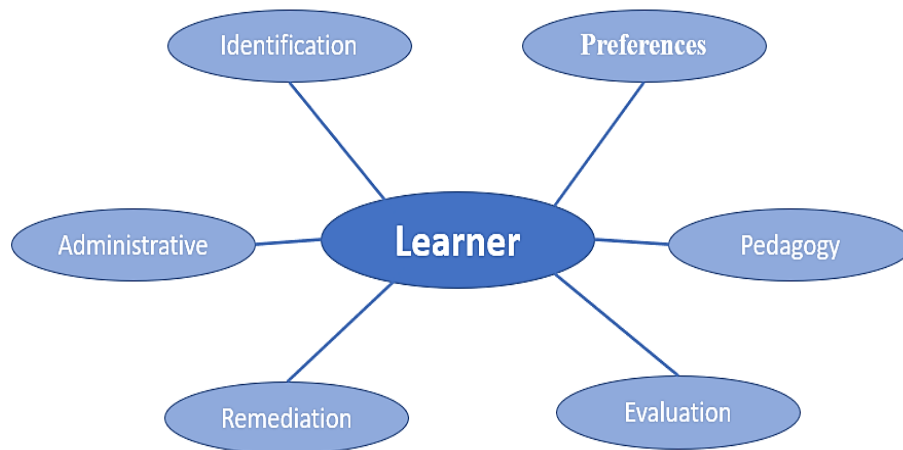


Figure 5. Learner model ontology

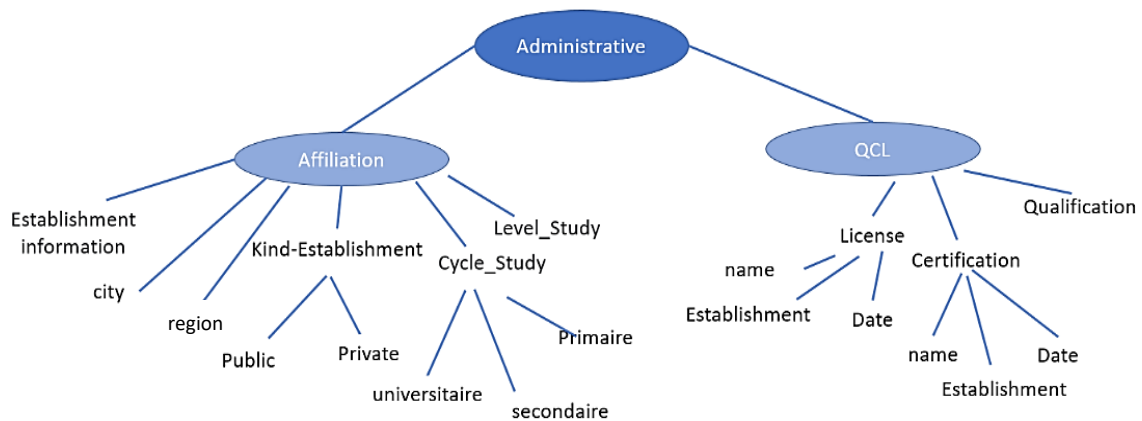


Figure 6. Administrative class

5.3. Identification class

This class contains all the essential information necessary for learner identification and consists of a total 15 attributes, which are organized into four distinct categories, as shown in Figure 7. The first category includes personal data such as surname, first name, Massar number, student number, national ID number, gender, date of birth, and place of birth. The second category covers learner's address details, including street, region, and city. The third category captures contact information, such as email address, phone number, and mobile number. Lastly, account identification data comprise the learner's login credentials and password, ensuring secure access to the platform.

5.4. Preferences class

This class represents each student's preferences regarding how they access and engage with the platform. It includes specifications such as language choice, areas of interest, hobbies, personal goals, current projects, and the preferred mode of reward whether through participation in a competition, a voyage of discovery, or free access to a training course. As illustrated in Figure 8, the class is composed of several key attributes. The reward_mode attribute describes the learner's preferred type of reward, including its name and category. The Hobbies attribute lists the learner's hobbies and personal interests. The current_project attribute outlines the learner's ongoing projects, specifying objectives, estimated completion time, and descriptive details. Lastly, the accessibility attribute identifies the language selected by the learner (English or French) and specifies any disabilities whether mental, physical, or related to learning that may influence platform accessibility and interaction.

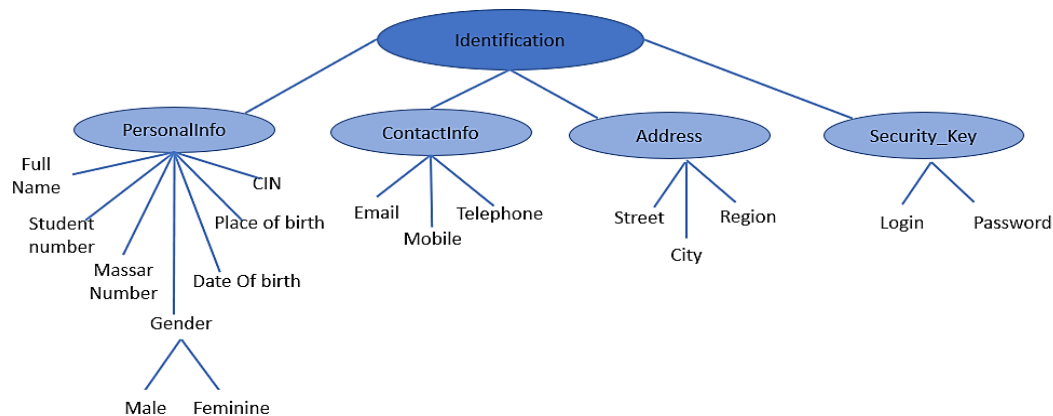


Figure 7. Identification class

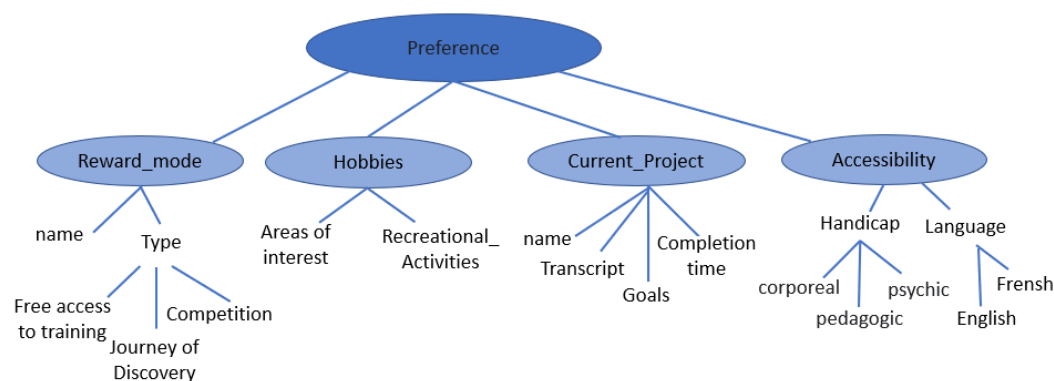


Figure 8. Preferences class

5.5. Pedagogy class

This class has two subclasses: pedagogical preferences and acquired skills as indicated in Figure 9. Pedagogical preferences represent the didactic and pedagogical means that facilitate the learner's learning. These means can be the pedagogical techniques and methods adopted, the teaching materials used, the learning style, and the format of the learning content. Acquired skills describe all the knowledge, skills, and attitudes acquired by the learner. It comprises the following two sub-classes: academic skills and transversal extracurricular skills. Academic skills are those related to the official curricula of the subjects taught. However, cross-curricular or transdisciplinary skills are defined by the set of skills required to acquire specific knowledge or acquired in the course of acquiring such knowledge. These skills are not specific to a particular field or area. They can be, for example, communication skills, social skills, comprehension skills, and analytical skills.

5.6. Evaluation class

The evaluation class contains detailed information about the evaluation sessions completed by the learner. As illustrated in Figure 10, this class is composed of several sub-classes named *session_evaluation*, each representing a distinct assessment instance. Each session includes a *session_evaluation* reference, which serves as a unique identifier for the evaluation session. It also includes the title of the unit being assessed, providing context for the evaluation. The targeted competencies represent the specific skills addressed in the learning unit, while the educational objectives define the broader goals derived from these competencies. Additionally, each session contains one or more activities described by the *activity_evaluation* subclass, which includes specific properties related to each learning activity assessed within the session.

The *activity_evaluation* subclass provides a detailed description of each individual evaluation activity within a session. It begins with an *activity_evaluation* reference, which records a unique identifier for the specific activity. The specific objectives define the educational goals being assessed, while the targeted cognitive levels specify the intellectual demands the activity is designed to address. The pedagogical methods adopted describe the instructional approaches used during the activity, and the didactic materials identify the

tools and resources required to complete the task. The content field outlines the actual tasks and instructions given to the learner. The production component captures the student's submitted work and includes the file path to their responses. The errors property documents any mistakes made during the activity, providing valuable diagnostic insight. The score field contains the learner's grade or the number of correct responses. Finally, the level of skill acquisition is determined based on the student's errors and score, allowing educators or the system to assess whether the learner has achieved the expected competence or requires further remediation.

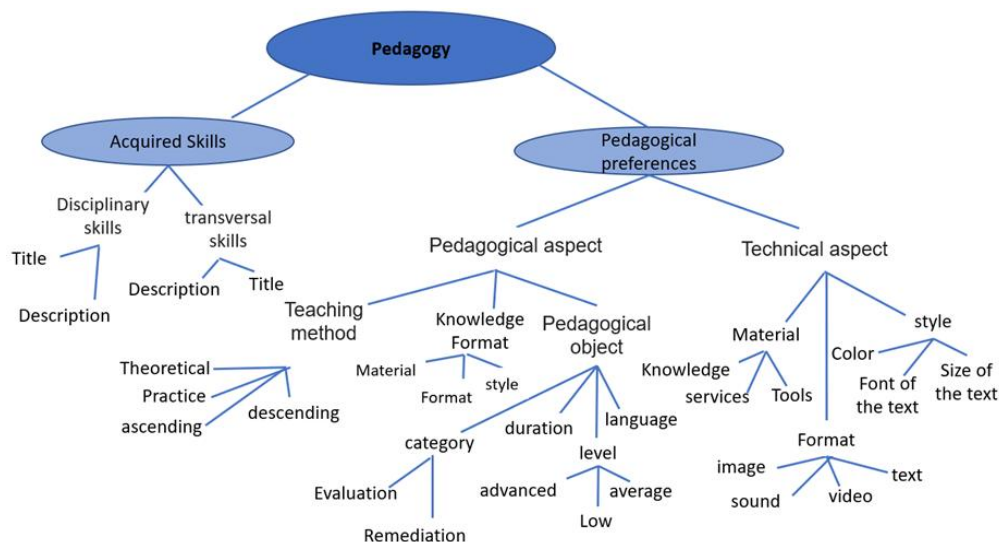


Figure 9. Pedagogy class

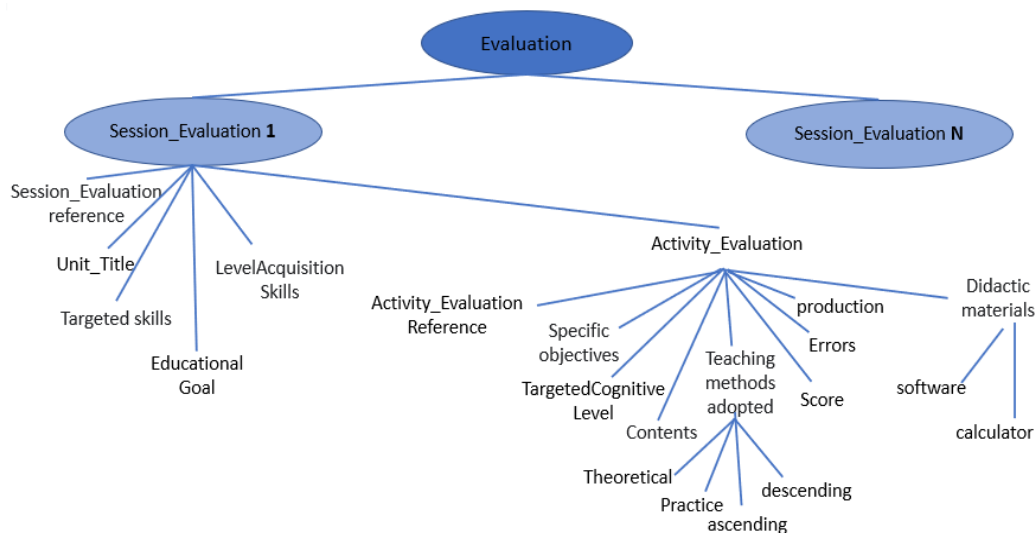


Figure 10. Evaluation class

5.7. Remediation class

The remediation class encompasses all remediation sessions undertaken by the learner. These sessions are organized under the subclass session_remediation, as illustrated in Figure 11. Each instance of this subclass includes several key elements. The session_evaluation reference links the remediation session to the corresponding evaluation session, thereby establishing a pedagogical record of the knowledge and skills that require reinforcement. The session_remediation reference serves as a unique identifier for each remediation session. Additionally, the activity_remediation component comprises the set of learning

activities assigned to the learner following difficulties encountered during the evaluation. These activities are designed to target the learner's specific weaknesses and support skill acquisition. They are further detailed by a set of descriptive properties, which ensure that each remediation task is purposefully aligned with the learner's needs and the learning objectives that were not achieved in the original assessment.

The `activity_remediation` property includes learning tasks assigned to students following unsuccessful assessment attempts. Each activity is identified by `activity_remediation` reference and is aligned with specific objectives to address targeted learning gaps. The prerequisites indicate the necessary prior knowledge, while the targeted cognitive levels define the skills to be developed. Pedagogical methods and instructional materials support the delivery of the activity. The content outlines the task, and the production captures the learner's work, including its file path. Finally, feedback provides performance evaluations, either given by the teacher or generated automatically.

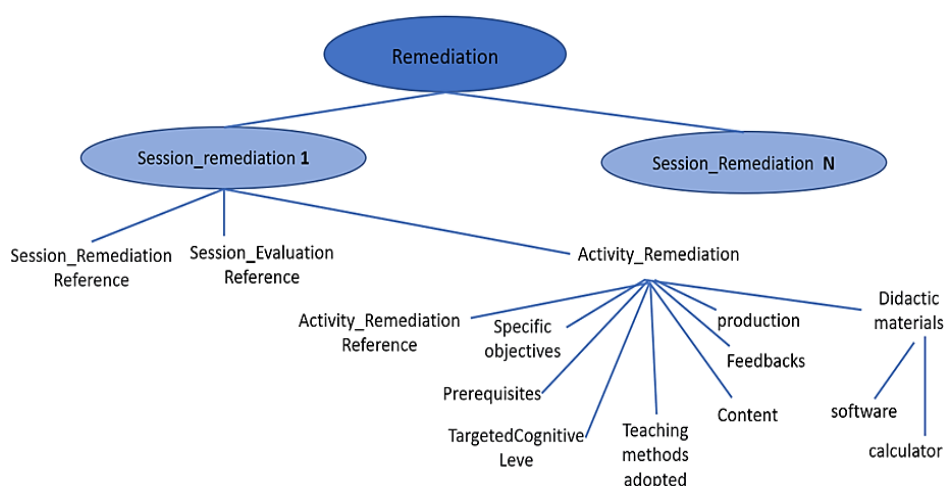


Figure 11. Remediation class

6. CONCLUSION

In this work, we proposed a learner model adapted to a school support system that we introduced in a previous study. The model aims to help students acquire academic skills and benefit from targeted remediation when necessary. By analyzing existing learner modeling approaches and examining the PAPI and IMS-LIP standards, we developed a model that integrates the strengths of both standards. This model organizes learner characteristics into categories such as preferences, pedagogical strategies, and performance, allowing the system to adapt to the needs of each learner, thereby improving learning progression and reducing dropout rates.

Future work could focus on integrating advanced analytics and artificial intelligence to predict student performance and provide proactive interventions based on past student outcomes. Another area for development would be the design of an intelligent system to assess the acquisition of learners' pedagogical skills. Additionally, incorporating additional international standards beyond PAPI and IMS-LIP could improve the scalability of our model and its application across various educational contexts. Expanding our model to support active and collaborative learning methods, while monitoring group interactions alongside individual progress, could offer a more comprehensive approach. Finally, longitudinal studies are needed to evaluate the long-term impact of the learner model on retention and academic success. These directions will ensure that the model remains adaptable, effective, and responsive to the diverse needs of learners.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data was created.

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