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Learner model: A Learning Analytics Tool for Amazigh Mooc

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Abstract: *In Computing Environment for Human Learning (CEHL), it is more difficult for a tutor to know which learners are participating and which need help. Learners may not participate for many reasons. Sometimes a learner may need encouragement; he may encounter technical or other difficulty. When analysis can help, it also allows for timely action to remedy blocking situations. In this article, we propose a learner modeling approach. This modeling process gathers a set of treatments allowing elaborating and updating relevant information about the learner (personal data, learner's characteristics, learning state, interactions between the environment and the learner, and the learner's knowledge, etc.) from the data collected in the course. This information is based on the analysis of the learner's behavior.*

Key Word: *Computing Environment for Human Learning; Learning Analytics; Learner model; Mooc Amazigh.*

I. INTRODUCTION

Faced with the computer and interactive educational resources, the learner is both a winner and a loser in terms of his or her learning context. On the one hand, the user of educational software has a great deal of flexibility in the activity that he/she implements, he/she controls the software through the proposed interface, and manages his/her time and rhythm. On the other hand, the isolated or remote learner is much more helpless than in a classroom situation: the sociological isolation of the learner; the loss of motivation; the autonomation of the learner; the lack of continuous presence of the teacher, the absence of immediate advice and the lack of orientation in the training course create a set of difficulties that make the learning situation less comfortable. Indeed, even before the existence of computerized training devices, one of the major problems of distance learning (DL) was the high dropout rate. The tutor has to explain why a learner fails to complete the learning task correctly and to intervene during the problem-solving process.

In addition, a Distance Learning Systems (DLS) are supposed to display a pedagogical behavior specific to face-to-face teaching. Among other things, it must be able to adapt learning to the learner who uses it. As learners have diverse and varied attitudes that need to be modeled in order to adapt distance learning systems and platforms to their needs, learner modeling aims at creating a cognitive (learner profile) and affective model for the observation of the learner's behavior at the interface of a learning environment. This model should represent the learner's profile, goals, plans, actions, beliefs and knowledge, and lead to a better individualization of learning by taking into account the knowledge specific to each individual.

The problem related to learner modeling is relatively a complex task, which can be broken down into three complementary parts:

- Determine what learner information is useful to model,
- Choose a formalism to represent this information,
- Develop a process that builds the Learner Model (LM).

This paper is organized as follows: in section 2, a state of the art of learner modeling is presented. Section 3 describes the different types of indicators to model the learner. In section 4, we present a visualization system and an experiment we conducted, before concluding.

II.LEARNER MODELING

Moocs can be seen as a means to help teachers increase the quality of their teaching. They can also help learners to learn more effectively and achieve a better result. A Mooc consists of four main parts: Learner Model (LM), Tutor Model (TM) (also called Expert Model in some systems), Domain Knowledge and Communication Model (DKCM). An LM is one of the major components of a MOOC. It allows to keep information about the learner, e.g., his level of knowledge, his frequent errors/understandings, his psychological characteristics, etc. An LM can be defined as a structured set of information about the learning process, and this structure contains values about the learner's characteristics (Lee, 2022). It provides necessary data for other modules to realize the adaptation of teaching to the learner (Urdaneta-Ponte, 2021). Yaunfanzhang classified the proposed LMs in the literature into several categories (Yuan fan zhang, 2010) (See figure 1).

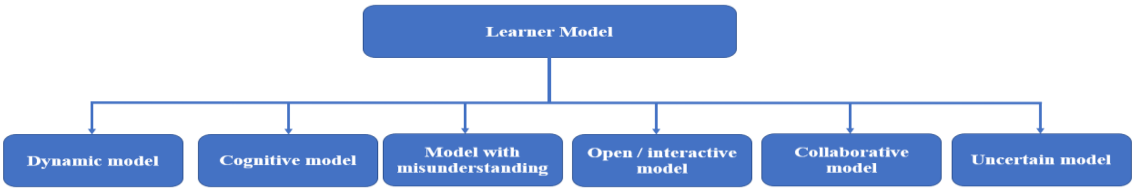

Figure No. 1: LM Categories

- **Dynamic model:** This category of LM accumulates and records information about the learner in real time. This information could be dynamically changed or updated according to the interaction between the learner and the system, e.g., visits to the system, answers to questions, etc. (Saba, 1994; Carmona & Conejo, 2004).

- **Cognitive model**: The cognitive model means that the cognitive aspects of the learner are considered in the modeling. For example, the principles of cognitive psychology are adapted and incorporated into the modeling, to track the state of the learner's memory, the attitude of learning, the time, a fact remains in the memory, the capacity of the memory, are frequently included in this category of LM (Chen, 2002; Carmona and Conejo, 2004).

- **Model with misunderstanding:** In this category, the LM mainly keeps track of learners' frequent errors or misunderstandings and also the causes or explanations of these errors. This type of model is often used to simulate a learner's problem-solving process in order to diagnose possible errors (Lokare, 2021).

- **Open / interactive model:** This model is built jointly by the system and the learner. The system accumulates its own views on the learner's knowledge. The model is used to encourage learners to reflect on their learning, as well as for tutors to adapt instruction to the individual or group (Zapata-Rivera, 2021). The openness of the model may also make it easier for learners to compare their own progress over time or their own progress with that of peers in the same or other groups (2000 Denoël, 2022).

- **Collaborative model:** This model is used in the context of collaborative learning. The success of one learner could help the success of other learners in the group (Silva, 2022). The learner could also search for a peer online, with the system matching students on relevant attributes, to solve a problem cooperatively.

- **Uncertain model:** this category of LM focuses on dealing with uncertainty in the learner's knowledge. Knowledge modeling is used to represent, train, and update this uncertain knowledge (Kavčič, 2004). Uncertainty processing could also help to reach certain conclusions about the learner's knowledge or instructional strategies from the incomplete information (Abyaa, 2019).

Table No .1: Composition of LM

		Composition
1	**Personal data**	Containsgeneralinformationaboutthelearnersuchas**name**,**age**,**experiences**,**education**,etc.
2	**Learner Characteristics**	Includes general or psychological characteristics of the learner, e.g. ,**learning goal**, **learning type**, **learning style preferences**, **computer experiences**, **concentration level**, **availability**, etc. From this information, we can specify the learner's anticipated needs.
3	**Learning state**	This category contains information about **the learning plan, the program followed, the learning history**, etc. This information is used to analyze and maintain the learner's situation
4	**Interactions between the system and the learner**	This is one of the essential categories of learner information. The interactions between the system and the learner are recorded and updated. The information recorded is the **visits to the system**(e.g., number of visits, duration of visits, type of content, etc.) and the **answers to questions**(number of errors, frequency of an error, the most frequent errors, number of tries, etc.), correct answers, etc.
5	**Learner knowledge**	This is another important category. In this category, there may be the learner's **level of knowledge**, **exam** or **test scores**, **failure patterns**, learner's **beliefs** and their **degrees of correction**, **explanations of errors/misunderstandings**, **knowledge of prerequisite concepts**, **knowledge to be validated**, **knowledge acquired**, etc.

Most proposed LMs contain only parts of these five categories, especially the two last ones. Although, researchers place less emphasis on the learning state, it is useful for personalizing learning by considering the learner's learning path and progress (Chaabi, 2021, Ndiyae, 2019, Chaabi, 2020).

After analyzing the fundamental components of LM, another question follows: how to model the learner's knowledge. From this study, we realized that modeling is not a simple process. It involves several aspects of AM and contains many sub-questions and sub-processes. Building an AM requires the identification and calculation of a set of indicators.

In the following section, we will describe the indicators in the CEHL most frequently cited in the literature.

III.INDICATORS IN CEHL

According to (Batchakui, 2021) an indicator is a variable in the mathematical sense to which a series of characteristics is attributed**.** It is a **variable** that takes on numerical, alphanumerical or even graphic values. The value has a **status**: it can be raw(without a defined unit), calibrated or interpreted. The status identifies a specific characteristic: the **type of assistance** offered to users. Each indicator can depend on other variables such as time, or even on other indicators. An indicator is characterized by three properties: (i) its **Nature**, (ii) its **Status**, (iii) and its **Visualization mode**.

(i) The **nature of** an indicator corresponds to the aspects of the inter action that it tends to bring out. It is related to one or more of the following dimensions: (a) cognitive,(b)social or(c)affective.
(a) Cognitive dimension: These cognitive indicators concern the participants interactions related to the task and the content of the activity;
(b) Social dimension: These indicators concern activities that take place in a social technological environment, and refer to the modes or quality of communication, or even collaboration of a small group or community;
(c) Affective dimension: Indicators of an affective nature seek to characterize the more or less personal way of interacting (empathy, emotions, motivations, relationship management). The qualities and skills of an affective nature play a significant role in the construction of relationships in a group.

(ii) **Status** Interaction analysis tools provide assistance to tutors by providing them with interaction indicators. The type of this assistance is directly related to the "status" of the indicator values. We can distinguish three cases: (a) Raw values, (b) Scaled values and (c) Judged or evaluated values.
(a) Raw values, numeric or (alpha)numeric, textual or diagrammatic (patterns, structures);
(b) Scaled values via a calibration mechanism, according to a predefined standard and adapted to a given context of the interaction;
(c) Judged or evaluated values: calibrated values are interpreted by the system itself by comparing them to the corresponding values of indicators in a reference model.

(iii) Concerning the **visualization mode,** three cases can be distinguished, depending on the number of indicators involved:
(a) **Variation of an indicator as a function of time**: There are graphs showing the variation of indicators as a function of time, especially for indicators that are highly dependent on the time variable (e.g., the participation rate, the level of interaction, the degree of activity of the actors, the popularity of a discussion topic, etc.).
(b) **Co variation of two indicators**: Other representations show the co variation of two variables at a given time or in a period.
(c) **Simultaneous visualization of certain indicators**: This type of graph offers a simultaneous visualization of a certain number of variables. These are complementary indicators, visualized in the same representation, corresponding to the analysis of the interactions of a learner or a group.

- **Type of indicators**

In the EIAH framework, the automatic exploitation of interaction traces during a learning activity does not directly inform on the emotional state, the feelings, the effects of the learners. The objective is to allow the tutor to have a perception of the whole learning activity in order to play all his roles.

The typology of (Fessakis, 2008) distinguishes three types of indicators: **Cognitive**, **Social** and **Affective** or **Technical**. Following this typology, we will present in the following paragraph a state of the art on the indicators reported in the literature (see Table 2).

Table No. 2: Summary of existing interaction analysis indicators (Oumaira, 2011)

ATI system	The users	The indicators	Nature	Point of view	Visualization Mode
Analysis of the activity triplet Attendance Availability and Involvement (JAILLET 2005).	Tutor	Attendance	Cognitive (Activity process)	Individual	Variation with time
		Availability	Cognitive (Activity process)	Individual	
		Involvement	Cognitive (Content of the activity)	Individual	
Typology of learner profiles (Santos et al.2003).	Tutor	Level of involvement	Cognitive (Activity process)	Individual	Textual
Semantics of the learner's journey (BOUSBIA & LABAT 2007)	Tutor	Time spent on a page of content	Cognitive (Content of the activity)	Individual	Digital
		Rate of open hyperlinks in the page	Cognitive(Content of the activity)	Individual	Digital
		Interest of the page	Cognitive(Content of the activity)	Group	Digital
		Percentage of activities completed	Cognitive (Content of the activity)	Individual	Digital
		Consultation timeline	Cognitive(Content of the activity)	Individual	Digital
Visualization of structured discussions (GEROSA & al.2005)	Tutor	Depth of discussion	Cognitive(Activity process)	Group	Tree graph
		Number of characters per message category	Cognitive (Activity process)	Individual	Graph (bar)
MOODOG (ZHANG & al.2007)	Tutor	Most popular course	Cognitive (Content of the activity)	Individual	Textual
		Number of times each learner accessed a course	Cognitive (Content of the activity)	Individual	Digital
		Time a learner has	Cognitive (Activity	Individual	Digital

		spent on a CMS	process)		
		Number of resources not accessed by a learner	Cognitive(Content of the activity)	Individual	Digital
		Number of discussions a learner has initiated	Cognitive(Activity process)	Individual	Digital
Visualization of e-mail communication graphs (REFFAY& CHANIER 2003).	Tutor	Group cohesion	Social	Group	Graph
		Centrality of the individual	Social	Individual	Graph
SPLACH (GEORGE 2003)	Tutor	Learner Behavior Profile	Social	Individual	Graph (Variation versus time)
CAF (FESAKIS& al. 2004)	Tutor	Level of collaboration	Social	Individual	Graph (Variation versus time)
Visualization system of a virtual classroom (FRANCE & al.2007).	Tutor	Status of learners	Cognitive(Content of the activity)	Individual	Interactive visualization
		Courses taken	Cognitive(Activity process)	Individual	Interactive visualization
		Activities completed or in progress	Cognitive (Activity process)	Individual	Interactive visualization
TrAVis(May & al.2008)	Tutor, Learner	Reading a message	Social	Individual	Interactive visualization
		User profile	Social	Individual	Interactive visualization
DIAS (BRATITSIS & DIMITRACOPOULOU 2005)	Tutor, moderator, researchers , learner	Indicator of contribution in a group	Social	Individual	polar graph
		Indicator of relative group activity	Social	Group	bar chart
		Contribution of the Members in Tree Structure	Cognitive (Activity process)	Individual	Tree graph

Let us recall that the objective of our research work is to develop a system for analyzing the traces of learners' interactions based on an LM that gathers the indicators reported in the literature, which will allow the teacher to play his cognitive and social role, within an adaptable generic system that we can graft to MOOC platforms. We have chosen Open edx as the platform for online training open to all.

IV. PROPOSED SYSTEM

The system we have proposed is based on the LM which contains 4 categories mentioned in subsection 2.1 (Personal data, learning state, Interactions between the system and the learner, Learner's knowledge) includes the indicators of the cognitive dimension mentioned in subsection 3.1. The system will take care of the calculation of a number of indicators, the results of which will condition the system's action with learners and/or tutors.

The main idea of our work is to bring together interaction and content analysis indicators that have been developed in different environments and at the same time to build an architecture that can support the integration of new indicators.

- **System architecture**

The proposed system receives as input trace files in order to produce indicators. This process takes place in two main phases: transformation and analysis of the traces.

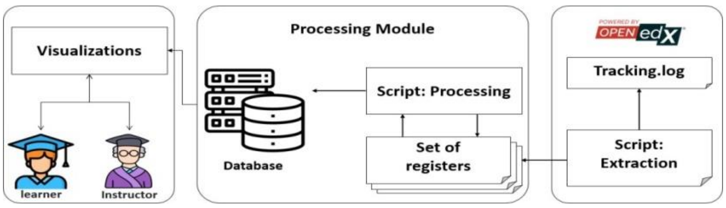

Figure No. 2: General architecture of the proposed system

The log file “Tracking.log” is a file generated by Open edx, it is a file recovered by our collection system. The first step is to extract the information stored in the log file in the suggested trace format. The system proceeds to two steps of (a) cleaning and (b) transformation of the data that will be recorded in its own database. The first step Cleaning consists in eliminating the noise: pages not found; intermediate pages of the platform, such as the processing pages of the connection form. In this last step “Transformation”, if the input log file does not correspond to the proposed trace model, it is transformed.

Once the collected traces have been formatted in the format of our model, they are fed into other processing and analysis modules in order to calculate a set of indicators, and then compared with the references recorded in the knowledge base. Based on the results of this comparison, the system undertakes actions with the learners and/or tutors.

- **Experiments**

To implement and evaluate our approach and the proposed indicators, it was necessary to carry out experiments. For this, we have realized a prototype to analyze the trace files of an experimentation we have conducted.

Setting up and analyzing this experiment was not a simple task. Indeed, applying statistical and data mining methods requires very large corpora to assert the hypotheses, which is difficult in the field of CEHL. Moreover, although this experimentation allowed us to improve and validate the calculation methods of the proposed indicators.

In this experiment, we contribute by presenting indicators with their associated visualizations in Opened X. The visualization of the interactions through graphs allowed teachers to have a global view on the behavior of learners and groups. These different visualizations evolve dynamically over time, depending on the traces left by the learner during the session.
The "number of sessions" indicator is an indicator that returns the number of sessions opened by each learner (see Figure 3).

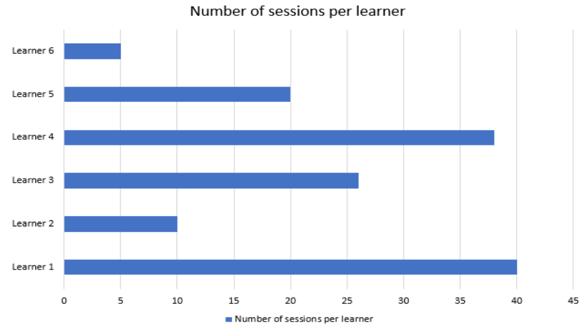

Figure No. 3: Number of sessions per learner.

The "learner attendance time" indicator is an indicator that returns the time spent by a learner on the platform during each login (see Figure 4).

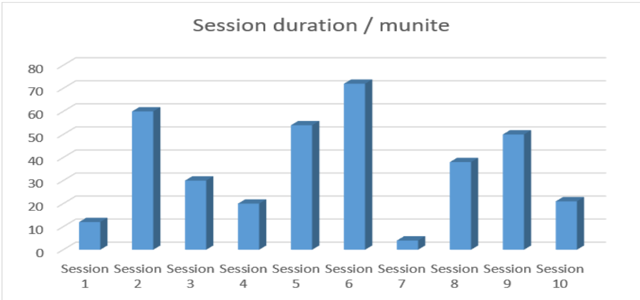

Figure No. 4: Duration of learner attendance.

The "time spent on each course" indicator is an indicator that returns the time spent in each course by the learner (see Figure 5).

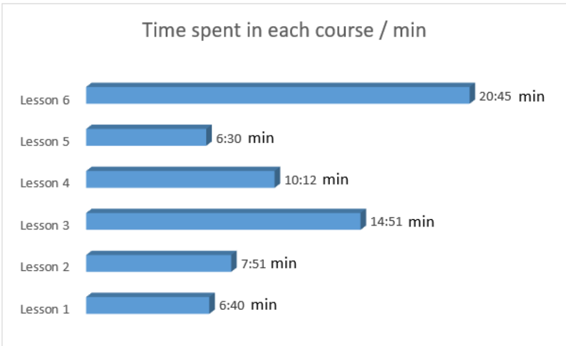

Figure No. 5: Time spent on each course and section.

The "degree of success" indicator is an indicator that returns the success rates of the quizzes (see Figure 6).

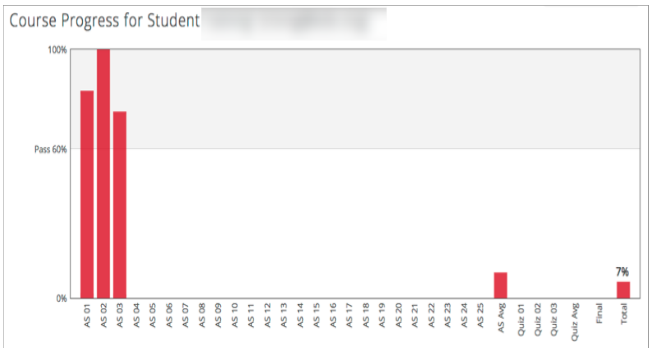

Figure No. 6: Degree of success.

The indicator "Problem time distribution": This visualization shows the amount of time spent by a learner in each of the problems in the course. Learners and tutors can select the problems they want to graph for comparison purposes (see Figure

7).

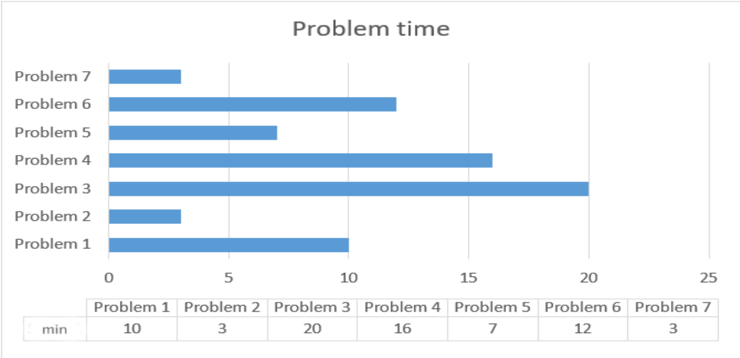

Figure No. 7: Problem time distribution for learner X

The video interactions indicator: presenting a general overview of the total number of video interactions of a selected MOOC (see Figure 8).

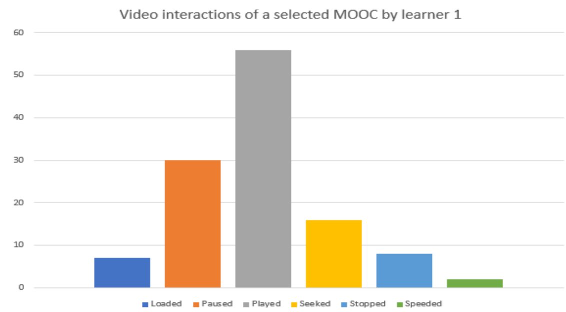

Figure No. 8: total number of video interactions of a selected MOOC by learner

V. CONCLUSION AND PERSPECTIVES

Our work contributes to the modeling of learners in an MOOC. This modeling is essential to design a new generation of CEHL that can evolve by placing the learner at the heart of the pedagogical situation according to his behavior, knowledge, skills, etc. Based on this observation, we proposed to develop a system that can be grafted to Mooc platforms to analyze interaction data in order to assist learners and tutors engaged in an online learning activity. The system allows to retrieve interaction data from the platforms, analyzes them by calculating a number of indicators and finally takes actions based on the reference model. This preliminary work is currently under development. Its confrontation with real and repeated situations will be very valuable to demonstrate the validity of the proposals and approaches we have adopted and to measure precisely the services that our system can provide.

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