# Towards Open Learner Models Including the Flow State

Sergio Iván Ramírez Luelmo
CIREL (EA 4354),
Université de Lille,
Lille, France
sergio.ramirez-luelmo@univ-lille.fr

Nour El Mawas
CIREL (EA 4354),
Université de Lille,
Lille, France
nour.el-mawas@univ-lille.fr

Jean Heutte
CIREL (EA 4354),
Université de Lille,
Lille, France
jean.heutte@univ-lille.fr

## ABSTRACT

Lifelong Learning encompasses vast learning opportunities and MOOCs are a learning environment that can be up to the challenge if current modeling challenges are addressed. Studies have shown the importance of modeling the learner for a more personal and tailored learning experience in MOOC. Furthermore, Open Learner Models have proven their added value in facilitating learner's follow-up and course content personalization. However, while modeling the learner's knowledge is a common practice, modeling the learner's psychological state is a relegated concern within the community. This is despite the myriad of scientific evidence backing up the importance and repercussion of the learner's psychological state during and on the learning process.

Flow is a psychological state characterized by total immersion in a task and a state of optimal performance. Programmers often refer to it as "being in the zone". It reliably correlates favorable learning metrics, such as motivation and engagement, among others. The aim of this paper is to propose a functional and technical architecture (comprising a Domain Model, a Flow Model, and an Open Learner Model for MOOC in a Lifelong Learning context) accounting for the learner's Flow state. This work is dedicated to MOOC designers/providers, pedagogical engineers, psychology, and education researchers who meet difficulties to incorporate and account for the Flow psychological state in a MOOC.

## CCS CONCEPTS

• Applied computing~Education • Human-centered computing~User centered design • Computing methodologies~Modeling and simulation


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## KEYWORDS

MOOC, Domain Model, Learner Model, Lifelong Learning, Flow state, Autotelic experience

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## 1 Introduction

Lifelong Learning (LLL) refers to the systematic and purposeful learning happening throughout a person's life involving formal (schools) and informal (work, recreation, leisure, social relations, family life) domains [1]. Open Learner Models (OLM) aim, just like Learner Models (LM) since their original inception [2], to represent each of the learners' knowledge. More specifically, within the learning environment (usually a MOOC) they represent the system's beliefs about the learner's specific characteristics, relevant to the educational practice [3]. They also often model learning difficulties and misconceptions [23]. LM and OLM differ in that OLM allow communicating its contents to the learner (or to any other actors) through visualization and/or editing [4]–[7]. They employ a vast myriad of techniques, methods and thereof variations to achieve this (cf. [7]–[11]). However, most of them limit themselves to modelling Knowledge (a.k.a. 'Domain') while relegating many of the other very important student characteristics during the design phase [7]–[12]. This is, while characteristics such as 'learning environment', 'learning styles', 'learning preferences', etc. are an addressed concern within the modeling community, very few consider the learners' mood or their psychological state as a relevant, measurable and acting aspect to take into account while designing a LM. This represents a serious setback for the learner, as the learner's psychological state carries a preponderant weight in the learning process [8], [10], [13].

This motivates us to propose an OLM that accounts for one of the learner's psychological states: Flow. Flow is "a gratifying state of deep involvement and absorption that individuals report when facing a challenging activity and they perceive adequate abilities to cope with it" [14]. The reason behind choosing the

Flow state among all other psychological states (shame, reproach, distress, joy, pride, admiration, and for some authors, motivation and engagement as well [8]) is multifold: it has shown to reliably correlate learning-favorable metrics, such as motivation, self-efficacy [15], [16], self-regulation [17], [18] or goal attainment [19], [20], some of which are also central dimensions of any given LM [8]. Moreover, the EduFlow-2 tool [15], [21] as a research-tried, self-reporting measuring mechanism specifically designed for educational contexts, has proven to accurately determine this psychological state in MOOC contexts. The advantages presented by the choice of this instrument resolve the hurdles and challenges faced when modelling Flow: it differentiates the dimensions relevant to cognitive processes, it accounts for a decreased respondent burden, and it can be applied to different educational contexts, all without sacrificing accuracy nor resolution [21].

Thus, in this paper we address the problem of including Flow state in the OLM. This situation usually arises for a MOOC (Massive Online Open Course) in an LLL context. We build up our proposal from the OLM literature review presented by [12], the Domain Model and Functional architecture in the works of [22], and the Generic Bayesian Student Model (GBSM) [23].

The paper is structured as follows: Section 2 tackles the theoretical background of this study. Section 3 details our proposed approach to the addressed problem by presenting the functional and technical solutions, including the Domain, Flow and Learner Models, and the chosen Flow instrument to model. Finally, Section 4 summarizes this paper and presents its future work perspectives.

## 2 Theoretical Background

To address the problem addressed in this paper we begin by briefly describing the role of MOOC in LLL, then we present OLM as a viable solution to modeling the learner in MOOC in an LLL context. We then proceed to broadly introduce the Flow state and its impact on the learning process.

As non-formal, informal or incidental learning represent the vast majority of adult learning [24], Access to and effective use of relevant information and continuously learning in MOOCs (among other things) is essential for LLL [22]. However, MOOC abandonment rate is very high [12], whereas engagement, intention and motivation [25]–[27] are among the top factors to affect performance in MOOCs. Research has shown that personalization can have a positive effect to decrease MOOC abandonment rate [28] at the same time that learner's personalization is one of the essential concepts in LLL [29].

### 2.1 Open Learner Models in LLL

OLM, just like LM, are to be dynamically updated, and they are usually enriched by data collection techniques [30], as students learn and build knowledge. They represent the latest understanding of the students [5] on a given subject. OLM are a type of LM, of whom they share common traits, such as their the importance [7], [31] of their added value to facilitate the learner's follow-up and course content personalization. According to [32], the use (and design) of predictive LM, allow us to have an insight into the nature of the dialogical interactions and learning, as each reasoning step can be traced, and the misconceptions can be detected. This is opposed to the view of a Closed Model, in which the student has no direct view of the Model's contents [6]. Moreover, OLM can be "negotiable" [7], [33], when a learner can "appeal" the system's decisions on his/her own LM, as long as satisfactory, valid evidence is provided. A negotiable OLM improves the accuracy of the LM and supports metacognitive processes of reflection [7]. In a MOOC platform, OLM accuracy improves the system representation of the learner to allow for a more personal learning experience. OLM provide thus the scaffold to represent a dynamic complex learner [4], [24].

### 2.2 The Flow State

The Flow State (a.k.a 'autotelic experience' or 'optimal experience') is a phenomenon that explains why people perform activities for the sake of the activity itself, without extrinsic rewards [34]. This Flow experience is triggered by a balance between a person's skills in an activity and the challenges afforded by the LLL environment. Flow state has been shown to promote learning and personal development because deep and total concentration experiences are intrinsically rewarding, and they motivate students to repeat any given activity at progressively higher challenging levels [35].

Recently, research on this psychological state has seen a considerable growth, potentially due to its positive consequences on well-being as well as learning. Studies [36], [37] show that it is crucial, if we are to provide customization in any e-learning system, to store not only the learner's characteristics (static and dynamic personal information, skills, knowledge, environment, goals, etc.) in the OLM, but also to consider, as faithfully as possible, the learner's psychological state, preferences and reasoning process to promote positive emotions [8], [11], [38], [39].

We deem important to consider the Flow state in OLM for MOOC in a LLL context because the study of Flow in education is often linked to indicators such as motivation, self-efficacy [15], [16], self-regulation [17], [18] or goal attainment [19], [20]. Given this link, some authors consider the Flow experience as a state of 'Optimal motivation' [40].

## 3 Proposed approach

This section presents an overview of our approach grounded on the Open Learner Model selection (based on the literature review of [12]), the Domain Model and the Functional architecture of the proposal (both from the works of [22]), as well as the core of our proposal; the Flow Model and its corresponding Learner Model (based on the work of [15], [23]). We end the section with a reviewed Technical architecture of our proposed changes.

### 3.1 Modelling technique for knowledge representation

According to [12], there are nine relevant features an OLM within a MOOC learning environment in an LLL context. Such features are condensed by the authors into four dimensions, which are the basis for their discerning OLM study. Now, for our OLM proposal, we chose one of the final four publications candidates of this study[1] featuring Bayesian representations (over Conceptual Graphs). In their current modelled state (described in their respective papers), Bayesian representations comprise most of the characteristics of Conceptual Graphs (relationships and concept hierarchization), plus a knowledge representation based on weights which allows for uncertainty representation [41], but more importantly, a robust updating method. Furthermore, we posit that, a Bayesian representation would allow for an effective Flow state representation, which is the core of this paper.

### 3.2 Functional architecture

We partake the proposal of [22], compliant with different MOOC platform architectures, and accommodate the Flow state representation therein. Therefore, we envision four main roles instead of three: the pedagogical engineer, the teacher, the learner, and the psychological researcher. This is shown in Figure 1. The Learning Map (LMAP) editor is a replacement for a typical linear course description where content is static. It is used by the pedagogical engineer to upload the course content and structure as one entity, as the course structure is part of the Domain Model (DM). It is also used jointly by the psychological researcher and the teacher to define the Flow Model (FM), pertaining the Flow instrument and the jointly agreed situations in the course structure where to apply it. Thus, the learner gets personalized content through a Course navigation plug-in (according to the learner's own OLM, the DM and the newly implemented FM). Both teacher and learner have access to the OLM through the OLM dashboard where they can visualize the learner's progress and negotiate a modification, if needed.

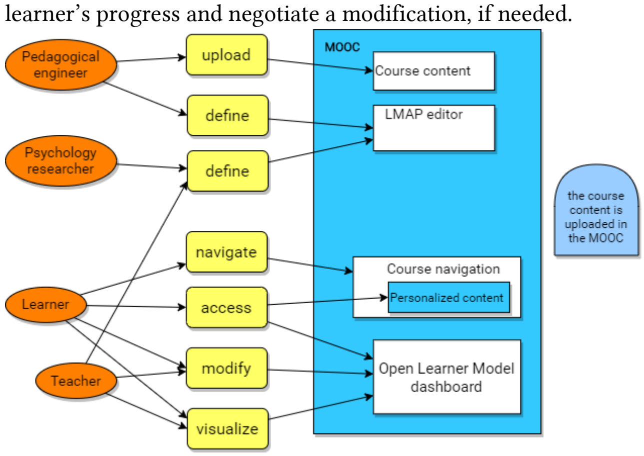



**Figure 1: Functional architecture**

Next, we proceed to briefly review the Domain Model proposed by [22], which we use as a basis for the core elements of our proposal; the Flow and Learner Models and its corresponding Technical architecture.

### 3.3 Domain Model & Flow Model

The existing Domain Model of [22] comprises three main layers on which sets of interconnected and related nodes, representing hierarchically subjects ($S_n$), topics ($T_n$) and concepts ($C_n$) instantiate any given Knowledge. We reprise it without changes.

Our Flow Model proposal relies on the EduFlow-2 psychometric instrument developed by [15]. It is a twelve-item scale[2] purposefully designed with educational scenarios in mind. It differentiates four Flow dimensions (FlowD1 – FlowD4), with three items per dimension (e.g. $FD1_a$, $FD1_b$ and $FD1_c$ for FlowD1): (1) FlowD1 – Cognitive Control: a strong feeling of control, specifically over one's actions, characterized by a feeling of ability to deal with the situation and a feeling that the student knows how to deal with whatever comes next ("I feel completely in control of my actions"), (2) FlowD2 – Immersion and Time Transformation: alteration in the perception of time, sometimes leading to a lengthened duration of immersion in the task ("I am wholly absorbed in what I am doing"), (3) FlowD3 – Loss of Self-Consciousness: lack of self-concern related to an increase in importance of the psycho-social dimension of learning ("I don't care about what others may think of me"), and (4) FlowD4 – Autotelic Experience: well-being provided by the activity itself enhances persistence and the desire to engage in the activity again ("This activity brings me a sense of well-being").

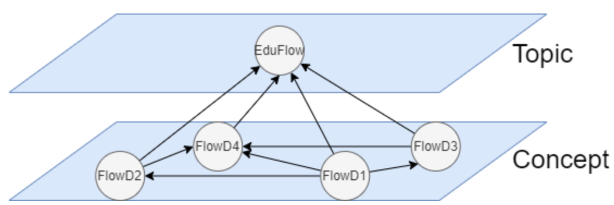



**Figure 2: Layered Structure of our Flow Model proposal with the EduFlow-2 instrument**

Our FM proposal relies on the DM (as per [22]) and on the current state of the LM: there is one FM for each subject $S_r$ in the LM. As such, the FM has no node on the Subject layer. The EduFlow-2 instrument sits on the Topic layer, with its four composing dimensions (FlowD1, FlowD2, FlowD3 & FlowD4) and thereof relationships [21] on the Concept layer. Therefore, our FM proposal is represented in Figure 2.

Now, the choice and use of this instrument carry three main advantages (1) It suits Flow measurement in various educational

[1] We note here that the student's Psychological state is also a feature considered by a few of the other 17 LM proposals in the study.

[2] http://refa.univ-lille.fr/news/eduflow2-heutte-fenouillet-martin-krumm-boniwell-csikszentmihalyi-2016

contexts, (2) It is a short instrument (reducing respondent cognitive burden) and (3) It highlights the difference between the four dimensions of Flow that are related to a cognitive process. Additionally, [15] confirmed that the EduFlow-2 tool showed significant improvement in all fit indices.

In the following section we view how the existing DM and the newly presented here FM instantiate in our proposed OLM.

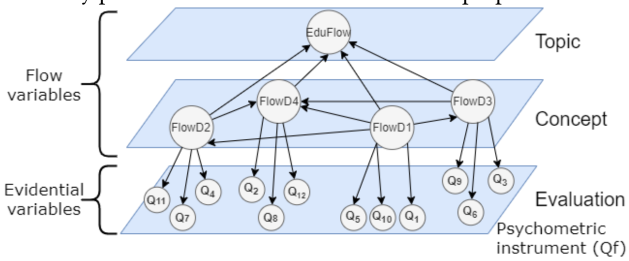


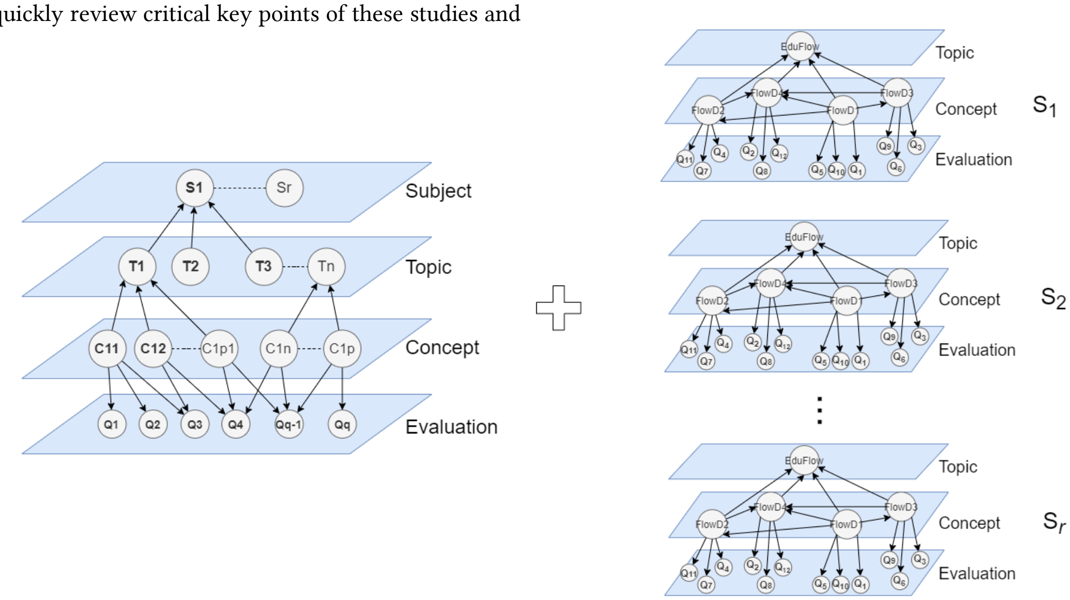

**Figure 3: Instantiated Layered Structure of the Flow Model proposal**

## 3.4 Open Learner Model

Our proposal is based on the works of [22], [23], [42]. In this section we quickly review critical key points of these studies and intercalate them with the changes proper to the development of our proposal.

The OLM, based on the Generic Bayesian Student Model (GBSM) [23], [42], is composed of knowledge and evidential - type variables nodes, in a four-layered structure. In one hand, knowledge variables nodes ($K_n$) represent the students' knowledge (in any form or type), with their values not being directly observable. Knowledge variables correspond to nodes sitting on any of the three layers of the DM.

In the other hand, evidential variables ($Q_n$), representing students' actions, are directly observable and they correspond to, for example, the results of a questionnaire. The evidential variables values will be used to calculate the values of the hidden knowledge variables [22]. In the GBSM, knowledge and evidential variables are binary, with possible values of 0 (unknown / incorrect) or 1 (known / correct). Evidential nodes sit on the Evaluation layer and are linked through relationships. Aggregation relationships occur between knowledge nodes (concepts (C), topics (T) and subjects (S)). Causal relationships link knowledge (K) and evidential nodes (Q), that is, they link concepts and evaluations.




(a) (b)

**Figure 4: Layered Structure of the Learner Model proposal**

Now, in our proposal we posit to treat the learner's Flow state as a set of knowledge variable nodes, distributed on the Topic and Concept layers ('Flow variables'). The results to the psychometric tools designed to detect the Flow state ($Q_n$) are on the Evaluation layer ('Evidential variables') and are causally linked to the Flow variables nodes (FD*n* in the Concept layer). The evidential variables correspond to the learner's results to the 12-item scale in the EduFlow-2 instrument presented in section 3.3. This is represented in Figure 3, showcasing the FM as an instance of the EduFlow-2 instrument results.

Now, in Figure 4, the OLM is represented containing subjects $S_1$ up to $S_r$. along with its *n* topics nodes, *p* concepts nodes and *q* evaluations nodes (a). As the Flow state depends on the subject $S_r$ and on the OLM state, there are as many FM as there are subjects ($S_1$ - $S_r$) in the OLM (b). This is to say that for every subject $S_r$, there will be one FM (b). As the OLM is automatically updated to reflect learner's knowledge (a), its corresponding FM must be updated as well (b). However, this FM update is not done in real-time as it requires human intervention (learner answering the EduFlow-2 instrument) at pre-set course moments (previously determined by the teacher and the psychology researcher).

This dynamic nature of the OLM implies that there will also be as many instances of the FM as there are predetermined moments to apply the EduFlow-2 instrument in the course, for all and every subjects $S_r$. This is, for any instantiation $S_r$ of the OLM, one corresponding instantiation of the FM also exist, at a specific moment in time.

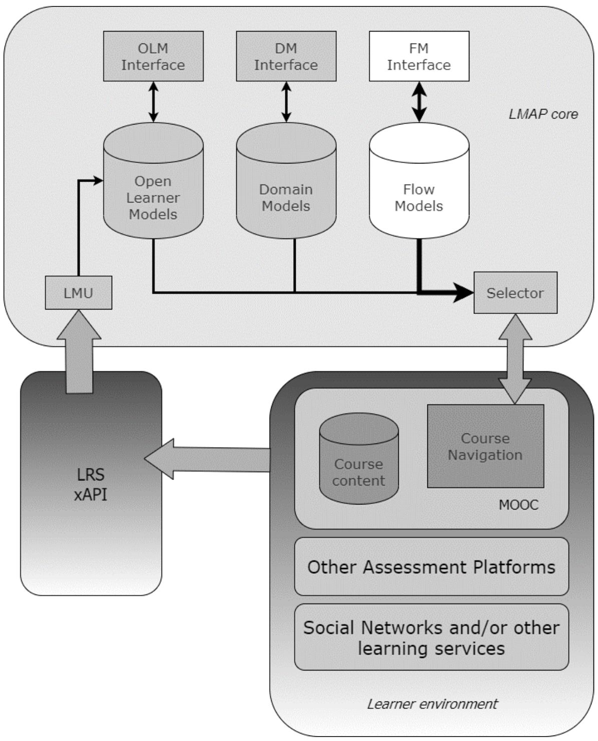



**Figure 5: Proposed Technical Architecture; Flow Models and Interface white-highlighted**

This closes our presentation of our OLM proposal. In the following section we introduce the changes carried out in the Technical architecture of the original proposal.

## 3.5 Technical architecture

The proposal of [22] relies on three main components, the MOOC environment, the Learning Record Store (LRS), and the LMAP core. Now, to accommodate the Learner's Flow state in the OLM we propose to extend the LMAP core with a Flow Models (FM) Database, bidirectionally linked to a FM Interface and unidirectionally feeding the existing Selector. Data is collected from the different learning services and platforms via xAPI [3] (Experience Application Performing Interface) and transferred to the LMAP core via the LRS. It is the LMAP core's task to store and update the DM, FM, and OLM. Inside the LMAP core, the Learner Model Updater (LMU) updates the OLM based on data collected by the LRS. The Selector chooses personalized content from the DM and the newly added Flow Model, according to the current OLM, communicating to the Course Navigation module data accounting for the learner's Flow state and thus, providing the Learner with a personalized, Flow state accounted access to content.

Access to the Models is provided separately by the DM Interface, the OLM Interface, and the newly added FM Interface. Akin to the original proposal, the OLM interface enables achievement updates, and access. The interactions with the learner and the teacher are done through the OLM Dashboard within the MOOC. The DM Interface enables Domain Models creation, modification, and deletion. The FM Interface enables Flow Models creation, modification, and deletion as well. Both FM and DM Interfaces are defined for the DM editor within the MOOC. This is represented in Figure 5 (additions from the original paper highlighted in white).

The use of the proven DM and OLM for our proposal allow accounting for the Learner's Flow state and thus, provides the Learner with a personalized, psychologically state-accounted access to content. Flow being a psychological state positively correlated to engagement, motivation, self-efficacy, goal attainment, self-regulation, and immersion in the task at hand, in educational contexts.

## 4 Conclusion and perspectives

This study approaches the issue of including the Flow state in OLM for MOOC in an LLL context. It addresses how to model the Flow state, what instrument to use to represent it in the OLM and what mechanisms to consider in order to access, update, store, visualize and edit the Flow Model to be used for learners' content personalization. It does so by extending and proposing a functional and technical architecture that accounts for the Flow psychological state to improve content personalization for learners in a MOOC in an LLL context.

Future work will aim to evaluate the accuracy of our proposal first on an ad-hoc created MOOC hosted by the University of Lille about Basic Python Programming[4] and second, on a French-spoken, international MOOC [5] about Project Management. Further research is planned to include additional instruments [43] to model the Flow state to improve the accuracy of the Model as well as envisioning to incorporate digital student traces (system logs) as Evidential variables to set course to an automatic, trace-based Flow modeling.

## ACKNOWLEDGMENTS

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[3] https://xapi.com/overview/

[4] https://moodle.univ-lille.fr/course/view.php?id=13223

[5] https://moocgdp.gestiondeprojet.pm/

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