Towards a Conceptual Framework to Scaffold Self-regulation in a MOOC

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Abstract. MOOCs are part of the ecosystem of self-learning for which self-regulation is one of the pillars. Weakness of self-regulation skills is one of the key factors that contribute to dropout in a MOOC. We present a conceptual framework to promote self-regulated learning in a MOOC. This framework relies on the use of a virtual companion to provide metacognitive prompts and a visualization of indicators. The aim of this system will not only be to improve the quality of learning on the MOOC but also to help reducing attrition.

Keywords: MOOCs · Dropout · Self-learning · Meta-cognition
Self-regulation · Virtual companion

1 Introduction

Massive Open Online Courses (MOOCs) are a recent innovation in the field of e-learning that allows individuals to take a course for free. The term coined in 2008 refer to the course “Connectivism and Connective knowledge”- CCK08 given by Downes and Siemens and taken by 2500 learners online. CCK, like ITYPA[1], is a cMOOC based on the theory of connectivism where learners build and share knowledge and contents within a community of people.

MOOCs have really taken off with Thurn’s course on artificial intelligence from Stanford University in which 160,000 learners registered, with 15% of them successfully completing the course. This course, like “ABC de la gestion de projet” (GDP)[2], is a xMOOC based on a transmissive approach, which is a teacher-centered approach in which the teacher is the dispenser of knowledge and final evaluator even if some activities are peer-evaluated. xMOOCs usually comprise videos presenting the pedagogical content, quizzes and homework for self-evaluation and a forum to interact with the pedagogical team and other learners. Platforms like Coursera, Edx, Udacity and FUN in France offer courses

[1] ITYPA: “Internet Tout y est pour Apprendre” is the first French cMOOC.

[2] GDP (Introduction to Project Management) is the first French xMOOC and one of the most prominent French MOOC with over 130,000 persons registered in 8 sessions over 4 years.

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in a wide range of topics: Mathematics, Computer Science, Social Sciences and so on.

Despite their popularity, MOOCs are characterized by a high dropout rate (80–90% on average [9,13]). Several factors that contribute to attrition in MOOCs have been identified:

1. student's intent and engagement [6,11,15,16],
2. social factors like low participation to interactions or influence of peers dropping out thus reducing the social interactions within the MOOC [17,21],
3. weakness of metacognitive skills like self regulation skills and poor time management skills [10,12,14].

MOOCs, like all self-learning environments, require learners to be able to self-regulate their learning. Self-regulated Learning (SRL) is one of three pillars of self-learning and it is demonstrated that, when they master SRL skills, students become more engaged in their learning and achieve stronger gains in learning [19]. These skills should therefore be promoted and developed during learning [22].

In Computer-Based Learning Environments (CBLE) like Intelligent Tutoring Systems and Adaptative Hypermedia, many strategies have been used and have demonstrated they can have a positive impact on students' SRL skills. Among these, we can mention the visualization of indicators and the use of metacognitive prompts which can be supported by pedagogical agents to introduce more emotional and affective elements into learning. These tools have been evaluated on "closed context" CBLEs [1], but little has been done to scaffold these competences in an open system like a MOOC. "Closed context" refers to the use or the evaluation of a CBLE in a classroom context and a short learning session.

Based on prior research on scaffolding SRL skills on CBLE and the fact that weakness in these skills is a dropout factor in a MOOC, we propose a scaffolding framework based on a combination of techniques of visualization and prompts. This framework is developed to promote SRL skills and is generic enough to be used in a self-learning context like a MOOC.

The paper is organized as follows: the next section provides the background of our framework, SRL skills. Next, we present related work on strategies used to scaffold SRL skills in a learning environment, both in "closed context" and in MOOCs. Then we present the scaffolding framework and indicators before concluding by making suggestions for future research.

2 Self-regulation

SRL skills refers to students' skills to create specific goals for their work, to plan strategies for achieving these goals, and to monitor and adapt these strategies as they progress. For [19], "self regulated learning refers to the process by which learners personally activate and sustain cognitions, affects, and behaviors that are systematically oriented toward the attainment of learning goals".

In the literature, it is recognized that SRL is an ongoing cyclic process that consists of three phases [23] (cf. Fig. 1):

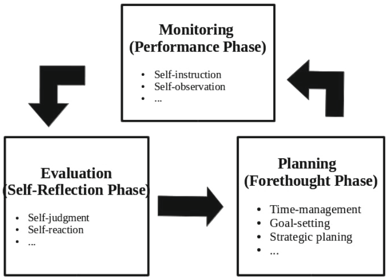

Fig. 1. The three phases of SRL [23]

1. planning (Forethought Phase): planning phase consists for students in setting achievable short and long term goals and to select strategies that best address a specific learning challenge.
2. monitoring (Performance Phase): during the monitoring phase, students implement the selected strategies and make ongoing adjustments to their plan as they monitor their progress.
3. evaluation (Self-Reflection Phase): the evaluation phase consists for students in estimating results and evaluating the effectiveness of each strategy. Feedback from the evaluation phase is then applied at the start of the next SRL cycle.

There are different processes subsumed by metacognitive skills such as (1) goal-settings and time-management, that refer to specifying intended action or outcomes and time estimation and allocation, (2) self-monitoring, that refers to observing and tracking performance and outcomes, (3) self-evaluation, that is a process comprising self-judgments of present performance and self-reactions to these judgments. These skills should be developed during learning, which is why many strategies are used to scaffold these competences [1,8].

3 Related Work

As mentioned earlier, in CBLE, many tools have been used to try to scaffold SRL like visualization of indicators, metacognitive prompts and so on:

Visualization of indicators grouped into a dashboard is used to inform learners regarding the state of their action and interaction. In the same register, **Open Learner Model (OLM)** makes all or part of the learner model available to them, and is not so much about state of action and interaction as it is about the state of the learner's knowledge. Learner model represents part or learner's knowledge/misconceptions inferred by the system based on the learner's performance. These tools are evaluated on many CBLE and provide feedback to learners, leading them to self-evaluate and to use SRL strategies [1,5].

Metacognitive Prompts are alerts or questions designed to scaffold metacognitive processes. They are designed to induce planning, monitoring or self-evaluation of one's learning processes. It is recognized that questions such as "What is our plan?" and "Have our goals changed?", and reflection prompts such as "To do a good job on this project, we need to..." can help guiding students self-monitoring. As we mentioned, prompts can be supported by **pedagogical agents** which are Human-Machine Interfaces simulating a human-like interface between the learner and the learning environment. They can also be combined with an OLM visualization [7]. Several research works mention that metacognitive prompts have a positive impact on SRL skills and that they help students to self-initiate SRL processes and then to improve learning in CBLE [1,3]. Supported by a pedagogical agents, their positive impact on SRL and on affect and emotion has been demonstrated [1,2,4].

Nevertheless, these strategies have been used and evaluated mostly in a "closed context" (4 h in [2], 2 h in [4]).

In the context of MOOCs, many strategies have been proposed to scaffold SRL like using a task-list or mind-maps, but not implemented yet [10,14,18]. [12] proposed and implemented a strategy to scaffold SRL that consisted in recommending SRL strategies at the beginning of a MOOC. First, based on a SRL framework, they coded SRL strategies used by highly successful learners during a previous session of that MOOC and synthesized them into recommendations. Then, in a experiment, they evaluated the effects of providing those recommendations to learners in the same course. Results suggest that merely prompting recommendations of SRL strategies at the beginning of the course was not enough to improve SRL process and that therefore it is a mandatory to embed "technological aids that adaptively support SRL throughout the course to better support learners in MOOCs".

4 Proposition

Our long term objective is to support the learner in a MOOC in metacognitive dimensions and also in affective and emotional dimensions with an expressive and adaptative virtual companion. According to the learners' goals and behavior obtained through previous direct interaction with them and by analyzing the traces of interaction with the MOOC platform, the virtual companion interacts with them in different phases of self-regulation through notifications and gives them access to indicators. This will allow learners to better organize their progress, improve their learning and thus may help in reducing attrition and increasing the performance of learners present throughout the MOOC.

From a technical point of view, we propose to develop a companion as a standalone widget, giving the possibility to integrate it into any MOOC platform such as Canvas, Open edX, Moodle... It will be based on a traces extraction engine, an indicators generation engine, an inference engine and a display engine (cf. Fig. 2).

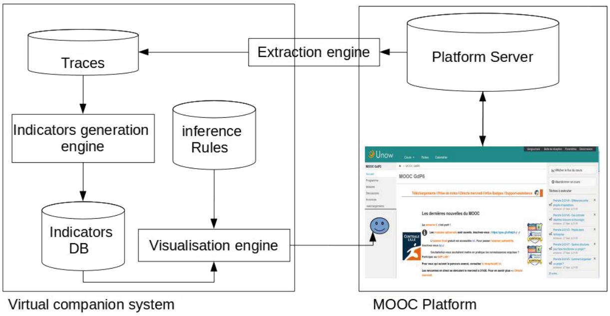

Fig. 2. Overall architecture of the companion

4.1 Scaffolding Planning of Learning

Throughout an analysis of several theories of SRL, [20] reports that *goal setting* is the strategy that is common to most and that it also becomes a central, foundational and critical strategy to be used when developing self-regulated learning. He also reports that effective *management of time* has been linked to student achievement in different studies and that it can be viewed as an anticipatory strategy that can prompt students to use other SRL processes. Therefore we choose to base our framework on these two strategies. Goal setting and time management are planning strategies, which consist for learners in listing their tasks and the expected results, and to estimate and allocate their time.

A MOOC learning scenario can be described as a succession of steps often scheduled for a week. Each step made up of mandatory or optional atomic activities. We consider that activities of the learning scenario can be classified into learning activities, assessment and access to information. To scaffold SRL processes, we propose to give learners the possibility to set their goals with the companion and to manage their time. First, we propose to offer the learner opportunity to set a global goal in the MOOC and a specific goal on each step and activity, and then to manage their time by setting deadlines for each training sequence of the MOOC and/or for activities that compose it. We therefore consider the following for each activity/sequence of each learner:

- learner's goal: we associate to each activity/sequence a goal indicator which takes a binary value indicating whether or not the learner has chosen to perform that activity. To reduce learner's interactions with the companion, it is deduced from the learner's overall objective that is requested as a choice within a limited list of options at the beginning of the MOOC.
- validation of activity/sequence: we associate to each activity a validation threshold as a binary value. For multiple choice questions, it is equal to the completion of the questionnaire. For the realization of a learning activity or an access to information resource, it will be deduced from the MOOC traces through the click of a validation button, or the approximate time of activity of the learner on the web page.

– deadline for completion: for each activity/sequence of the learning scenario, we define a deadline date to be chosen by learners. They can chose it for all activities of the current week and unrealized activities from previous weeks, the first time they connect each week. If the student does not define it, it can be inferred by the system based on its objectives.

Learners' goals will thus be requested during their first connection to the MOOC through notifications and their planning can be set, if they want, by choosing a delay associated to each sequence. So, at the date d, for each learner l using the companion, we have a planned scenario $plan_d(l)$ such as:

$$plan_d(l) = \{(A, Goal(A), CT(A))\}$$

Where A is an activity or a step, $Goal(A)$ is the goal of the student for this activity and $CT(A)$ the completion time chosen by the learner or inferred by the system.

This will educate learners in the use of SRL skills and provide us with a planned scenario from which indicators on metacognitive skills can be deduced. Social interactions are not considered in the planned scenario.

4.2 Scaffolding Monitoring and Evaluation

Even if both these strategies (time management, goal-setting) are the basis of our framework, we have to help students on the monitoring process and the evaluation process. Research supports the hypothesis that effective self-regulated learning depends on correct evaluations of one's capabilities and progress in learning and that self-observation is necessary. So, we propose to support learners on self-observation and in evaluation process on self-judgment strategy.

To scaffold self-observation, we rely on a permanent display of indicators on the metacognitive virtual companion. Displayed indicators are relative to the profile of the learner inferred by the system based on traces. We present some indicators that can be deduced from this framework in the following section, independently of the visualization eventually chosen to display them.

To scaffold self-judgment, we offer the learner the opportunity to issue a personal judgment on each of the sequences/activities through the virtual companion. We associate to each completed activity a value of judgment on a Likert scale for each of the following dimensions corresponding to an evaluation strategy: judgments of learning, content evaluations, feelings of knowing, ease-of-learning. So, we associate to each learner a set of judgments for each step/activity of the effective learning scenario. Practically, at the date d, for each learner l, we have an effective scenario $sc_d(l)$ such as:

$$sc_d(l) = \{(A, VT(A), \vartheta(A))\}$$

Where A is an activity or a step, $VT(A)$ is the validation time for this activity and $\vartheta(A)$ the set of judgments of activity A done by the learner l.

This will raise awareness about self-reflection on the evaluation process but will also allow to build indicators related to metacognitive skills.

4.3 Indicators

This framework allows us to use metacognitive prompts and to deduce indicators for self-observation. Some conventional indicators on learner's activity and interaction and on cognitive processes and social dynamic are presented in Table 1

Table 1. Cognitive and social indicators

Indicators	Nature of indicator
Duration of Activity on the MOOC	Activity
Number of actions in the MOOC	
Number of connections	
Score on sequence/activities validated for each type (learning/evaluation)	Cognitive
Average marks in assessments	
Timeline of sequence/activities done	
Duration of activity on the forum	Social
Number of post on the forum	
Graphic of relations on the forum	

Despite the poverty of MOOCs' traces compared to what can be available in some CBLE in closed context, we checked availability of traces allowing to calculate indicators mentioned on Table 1. A first analysis of traces coming from a MOOC which is hosted in a customized Canvas platform provided by French company Unow and traces of a standard Moodle platform allowed us to confirm the availability of data on both platforms. This data will be retrieved from the database used by the platform and log files.

It should be noted that although the data are available, their format can be very heterogeneous between different platforms. To give the possibility to embed the virtual companion into any MOOC platform, we designed the extraction layer with a connector and a data transformation module which are specifics to each of them.

The advantage of this framework is to make available indicators relative to SRL skills that can be used by educators. They can also be accessible to the learner to promote SRL skills. We give in Table 2 some indicators related to this dimension. Traces for calculating metacognitive indicators are obtained through interactions between the learner and the companion. If learners are not using the companion, we would display their cognitive, social and activity indicators.

4.4 Example of Application

In order to illustrate the way our framework will be used, we consider here an example of a concrete application on the GDP MOOC, which is one of our envisioned testbed. GDP is the first French xMOOC and is taught by R. Bachelet

Table 2. Metacognitive indicators

Indicators	Nature of indicator
Score on sequence/activities validated on time for each type (learning/evaluation)	Planning process
Timeline of sequence/activities done on time)	
Score of judgment of the learning on activities/sequences	Evaluation process

from "Centrale Lille". In the latest session (the eighth), three certificates corresponding to different workloads were offered. In our work, we are interested in the basic one and the advanced one. The course lasted seven weeks, provided quizzes, weekly assignments and a final examination. The course has a core composed of four modules and two specialization modules had to be chosen from a list of 13 available modules.

To obtain the basic certificate, it was required to complete the quizzes and the exam with a minimum of 2800 points out of 4000 and to validate at least two specializations modules. Modules were opened each Monday and the deadline for quizzes was set to the last day of the course. In order to obtain the advanced certificate, participants were required to submit three assignments out of four, to participate to peer-evaluation and auto-evaluation of assignments, and to pass the basic one. They also had to reach a minimal score of 4900 points out of 7000. Assignments were based on a case study and assessed through peer evaluation. Learners could lose or gain some points according to the quality of their peer-evaluation. In interactions, some new discussion threads were initiated every week and were accessible during the course. Threads were opened and moderated by the MOOC staff.

In this context, we envision the following scenario. At the first connection of learners in the MOOC, we offer them the option to use the companion and to choose their goals (Fig. 3). We describe the weekly process followed by the companion in Fig. 4. Depending on learner's goals, the companion has a specific behavior. Let us take as an example the first week of GDP. The basic certificate track for the first week S1 is composed of 18 activities: 2 informational resources to read S1I1 and S1I2, 8 learning activities in video format $[S1V1, S1V8]$, 7 MCQ $[QS1V2, QS1V8]$ and 1 assignment QS1. We present in Table 3 the activity of a learner who wants to validate the basic certificate and plans to do learning activities and MCQ of this first week on day 4, and the assignment on day 5. But that learner validates only one part of their planned scenario on day 4 and validates the other part on day 7.

We show in Table 4 methods initiated by the companion (column 2), scores on learning activities, MCQ and assignments validated and scores on those validated on time or delayed (column 3) and the effective scenario of the learner (column 4). So his planned scenario is set by the companion to

$$plan_{j1}(l) = \{(A, 1, j4)\} \bigcup \{(QS1, 1, j5)\}$$

where A represents all activities of week 1 without QS1.

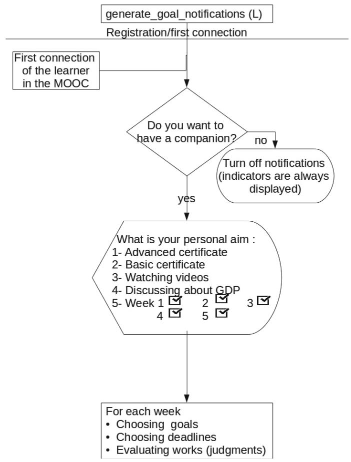

Fig. 3. First connection of the learner

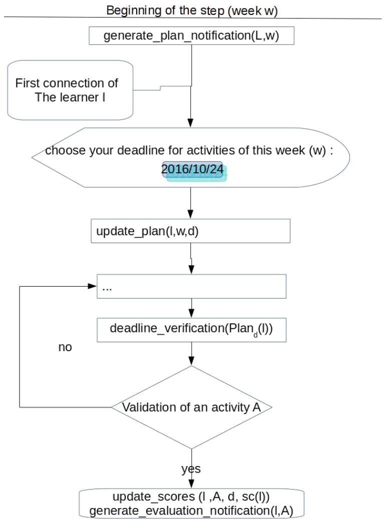

Fig. 4. Process of the companion in the week

Table 3. Example of learner activity

Day	Time spent on activities (mn)	Activities validated by the learner
1	S1I1:2, S1V1:8 ...	
2		
3		
4	S1V4:17, S1AI1:10 S1V5:22 QS1V5:7	SI1, $[S1V1, S1V4]$, $[QS1V2, QS1V4]$
5	S1V6:12 S1A-QS:12 S1V5:17 QS1V5:9	
6	S1V5:13	
7	S1V7:12 S1AI1:6	S1I2, $[S1V5, S1V8]$, $[QS1V5, QS1V8]$, QS1
8	...	

Even if we include only indicators generated in the case of delay, it is clear that all interactions with the companion and all actions in the platform generate traces which can be used for generating indicators. We can notice that the generation of indicators and inference rules is based on trace analysis and educational data mining techniques. According to the learner's behavior deduced from indicators such as the scores calculated in the previous example and the inference system, the companion should show relevant notifications and indicators. In this example, we can imagine two possible interventions from the companion:

– in days 4 and 5, the learner spent a lot of time between the learning activity 5, S1V5 and the MCQ related to this video, QS1V5. The companion should be able to detect this and propose them to go to the forum to interact with other learners.

Table 4. Example of companion activity

Day	Activity of the companion	Scores	Activities of effective scenario
1	generate_plan_notif, update_plan	LA = 8, MCQ = 7, QS = 1	∅
2			
3			
4	update_scores, generate_evaluation_notif	LAV = 4/8, MCQV = 3/7 LAVT = 4, MCQVT = 3	
5		LAD = 4/8 MCQD = 4/7	S1I1, $[S1V1, S1V4]$, $[QS1V2, QS1V4]$
6		Same as 5 + QSD = 1/1	
7	update_scores, generate_evaluation_notif	LAV = 8/8, MCQV = 7/7 QSVD = 1/7, LAVD = 4/8 MCQVD = 4/7, QSVD = 4/7	
8	generate_plan_notif		S1I1, S1I2 $[S1V1, S1V8]$, $[QS1V2, QS1V8]$, QS1

LA: Total of learning activities online, **MCQ:** total of MCQ online, **QS:** total of assignments online, **LAV:** LA validated, **MCQV:** MCQ validated, **QSV:** QS validated on time, **LAVT:** LAV on time, **MCQVT:** MCQV on time, **QSVT:** QSV on time, **LAD:** LA delayed, **MCQD:** MCQ delayed, **LAVD:** LA validated but delayed, **MCQVD:** MCQ validated but delayed, **QSVT:** QSV validated but delayed

– between days 4 and 7, the learner visited several times the informational resource about advanced certificate (S1AI1) and spent significant amount of time on that resource as well as on the advanced assignment (S1A-QS). In the beginning of week 2, the companion could therefore consider suggesting the learner to change their goals and to maybe try validating the advanced certificate.

5 Conclusion and Perspective

In this article, we introduced a conceptual framework generic enough to be seen as a tool for promoting SRL in a self-learning context, but particularly in a MOOC. Based on literature on SRL, we introduced this framework to underpin an adaptative virtual companion. This companion will interact with learners through prompts in the different steps of SRL processes and give them a feedback through some cognitive and social indicators to scaffold SRL process. The framework allows the availability of metacognitive indicators for educators but also for learners. However, we must consider the case where the learner does not use the tool and we do not have indicators in the metacognitive dimension.

This work is a first step for the implementation of a virtual companion on a MOOC, based on literature in SRL and on scaffolding of SRL on CBLE. Our aim in the future is to implement and evaluate the impact of the companion on SRL skills, learning process and persistence on a MOOC. We plan an initial experiment with a limited number of learners using a Moodle platform. Then we will make an experiment in a real context using Canvas platform. We plan to collect data and traces and use them to validate our strategy through an analysis based on educational data mining methods.

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