Web-based Adaptive Learning Environments and Open Learner Model – Use in Didactics of Informatics

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Abstract. In the context of this dissertation, issues concerning adaptive Web-based learning environments, the Open Learner Model and its exploitation towards the enhancement of the teaching and learning process are studied. The thesis focuses on the research of Open Learner Models in adaptive Web-based learning environments, aiming to design develop and exploit the open learner model of the Web-based, learning environment SCALE (OLM_SCALE). In the frame of this thesis two empirical studies were conducted: The first one aims to investigate how the educational material in form of activities that exploit the learning design of SCALE, can support the learning process in the context of the undergraduate course "Introduction to Informatics and Telecommunication". The second one aims to investigate how the facilities offered by OLM_SCALE can be exploited towards the reengagement of disengaged students.

Keywords: Open Learner Model, Web-based Learning Environments, Introductory Computer Science Courses, Learning Activities, Tutoring Feedback Components.

1 Introduction

The contemporary tendencies for supporting and promoting students' learning process in undergraduate curricula suggest the use of learning environments [1], [2], [3], [4]. A negative aspect of this trend is that students might become disengaged when using tutoring software and try to *game* the system by moving rapidly through problems without really studying them and by seeking the final hint that might give the answer away [5]. Recognizing this fact many researchers have placed focus on developing pedagogical approaches for the detection and guidance of online students who become disengaged. The majority of those approaches are based on models that are trained through extensive analysis of the log files that represent students' interaction with the learning environment. Specifically Cocea and Weibelzahl in [6] propose the exploitation of several data mining techniques in order to find the best method and the indicators for disengagement prediction. The authors argue that motivational level could be predicted from very basic data commonly recorded in log files, such as events related to reading pages and taking tests. The students identified to be disengaged are engaged in a dialog in order to assess their self-efficacy, self-regulation and other related motivation concepts. Baker et. al. in [7] propose a machine-learned Latent Response Model that is highly successful at discerning which students frequently *game* the system in a way that is correlated with lo[1]w learning. Specifically the research team uses three data sources in order to train the model to

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predict how frequently a student gamed the system. The results of the empirical study shows that the model is successful at recognizing students who game the system and show poor learning. Johns and Woolf in [8] propose a dynamic mixture model based on Item Response Theory (DMM-IRT) to detect students' motivational level and estimate their proficiency. The results of the corresponding experiments suggest that the DMM_IRT model can better predict students responses compared to a model that does not account for motivation. In the work of [9], a detailed log file analysis is used as input for the actions performed by the animated agent named "Scooter the Tutor". Scooter interacts with the student (by expressing negative emotion to gaming students), aiming to reduce the incentive to game, and help students learn the material that they were avoiding by gaming, while affecting non-gaming students as minimally as possible. Whenever "Scooter" detects a *gaming* student, he provides him/her with supplementary exercises focused on exactly the material the student bypassed by gaming.

Although the aforementioned approaches manage to identify and guide the disengaged students, they require time consuming and skilfully log file analysis in order to retrieve data suitable for training the specific models. Since a web based learning environment can generate thousand lines of information per hour, specific applications designed to analyze and impact meaning to raw log file text are required.

Recently a new proposal for the detection and guidance of online students who become disengaged has been introduced. This proposal is based on the principles of the Open Learner Model [10], [11], [12], aiming to help students focus reflection on their learning and progress. Learner models are models of learners' knowledge, difficulties and misconceptions and are essential for an adaptive learning environment to behave different for different students. Learner models are usually accessible to the students they model. Open learner models are learner models that are accessible to the student being modelled and sometimes also to other users (e.g. peers, teachers, instructors, tutors). It has been argued that the act of viewing representations of students' understanding can raise their awareness of their developing knowledge and difficulties at the learning process [13].

Arroyo et al., in [5] argue that non-invasive interactions can change a student's engagement state. More specifically, they propose the use of an open learner model as a mean to guide students into reengagement. Through the open learner model, performance and progress charts accompanied by tips and encouragement are presented to students, aiming to reduce gaming, enhance learning, while at the same time generate a more positive perception to the system and of the learning experience.

In the same line of non-invasive interactions based on the principles of the open learner model, we propose the use of the open learner model, as a mean for the detection and guidance of online students who become disengaged. More specifically we extend the work of Arroyo et al. in [5] by including in the open learner model not only performance and progress charts, but also a representation of students' working behaviour.

The open learner model described in this work (OLM_SCALE) was developed in the frame of a web-based, adaptive, activity-oriented learning environment referred to as SCALE (Supporting Collaboration and Adaptation in a Learning Environment) [14].

In order to investigate the impact of OLM_SCALE in guiding/stimulating disengaged students to work in a more effective and engaged way we conducted an empirical study. The main research questions of the empirical study were: (i) can OLM_SCALE stimulate students to work in an effective and engaged way? and (ii) what is students' opinion about the effectiveness of OLM_SCALE in supporting the learning process in the context of an introductory to Informatics and Telecommunications course?

2 Open learner Model maintained in SCALE (OLM_SCALE)

OLM_SCALE combines and expands ideas coming from the areas of computer based interaction and collaboration analysis [15], [16] and open learner modelling. In particular, we collect raw data from students' interaction with the system using a set of indicators and visualize this information alongside with comparative information coming from selected peers aiming to support the learning process at awareness and metacognitive level. At awareness level, the value of the indicator is presented to the student and at metacognitive level, the calibrated (through a predefined form) value of the indicator is presented to the student.

Specifically, we designed a set of indicators that focus on individual activities and reflect the structure of SCALE's educational material. The indicators aim to:

(i) *reflect student's knowledge by using skill meters (*metacognitive level): indicators for student's performance level at activity, sub-activity and question items level,

(ii) *offer comparison to peers views of the learner model data*: indicators for answers given by other peers (awareness level), the minimum, maximum and average performance level, calculated from all the students enrolled in the specific subject matter (metacognitive level), and

(iii) *present students' working behaviour* (awareness & metacognitive level): indicators for student's interactions with the system (received feedback components, activities/subactivities elaboration attempts, minimum, maximum and average knowledge level as well as average elaboration attempts).

OLM_SCALE follows the simple model representation, that uses skill meters, as the structure of SCALE's educational material is already hierarchical and more complex learner views would require the definition of additional relations between the various concepts. As stated in the work of [17] a simple representation of the open learner model data that uses skill meters can have positive effect on students' learning and metacognition. Moreover the simple skill meter representation of the open learner model data has found to be an adequate representation for sharing learner models with peers and instructors [18], [19].

3 Indicative screenshots of the OLM_SCALE

Figure 1 illustrates the main screen of OLM_SCALE for the concept of "Algorithms" in the context of the subject matter "Introduction to Informatics and Telecommunications". Four activities are included in the specific concept, i.e. *Definition of an Algorithm*, *Pseudocode*, *Sequential Search* and *Binary Search*. For each activity the following indicators are illustrated: (i) the current knowledge level (*metacognitive* - based on skill meters), (ii) the elaboration attempts (*awareness* - i.e. how many times the activity's questions have been submitted), (iii) the activity's status (i.e. how many subactivities have already been elaborated) (*awareness),* and (iv) the minimum, maximum and average knowledge level (*metacognitive*) and (v) average elaboration attempts (*awareness)*. Also, the learner model includes functionalities that allow students: (i) to choose whether the information held in the model will be visible from their co-students, and (ii) to select their preferred feedback types.

As can be seen in Figure 1, the specific student inspects his own model and compares his developing of understanding of the target concept to that of the two peers he has chosen to inspect their models. For each activity the following information is externalized: (i) the student's knowledge level, (ii) the minimum, average and maximum knowledge level, (iii) the activity's elaboration attempts (e.g. for the activity *Definition of an Algorithm* the specific student has attempted twice to elaborate the corresponding subactivities), (iv) the activity's status presented either by the fraction indicating elaborated subactivities / available subactivites (e.g. for the activity *Pseudocode* the specific student has elaborated correctly two out of the three available subactivities) or by a specific icon indicating that all the available subactivites have already been elaborated (e.g. for the activity *Definition of an Algorithm* the specific student has elaborated correctly all the available subactivities), (v) the activity's average elaboration attempts and (vi) the peers' knowledge level and the corresponding elaboration attempts and status. By pressing the *Open/Close* button, the student can choose either to open or to close the model to his/hers peers. Through the *Users* button the student can choose the peers whose models s/he likes to inspect.

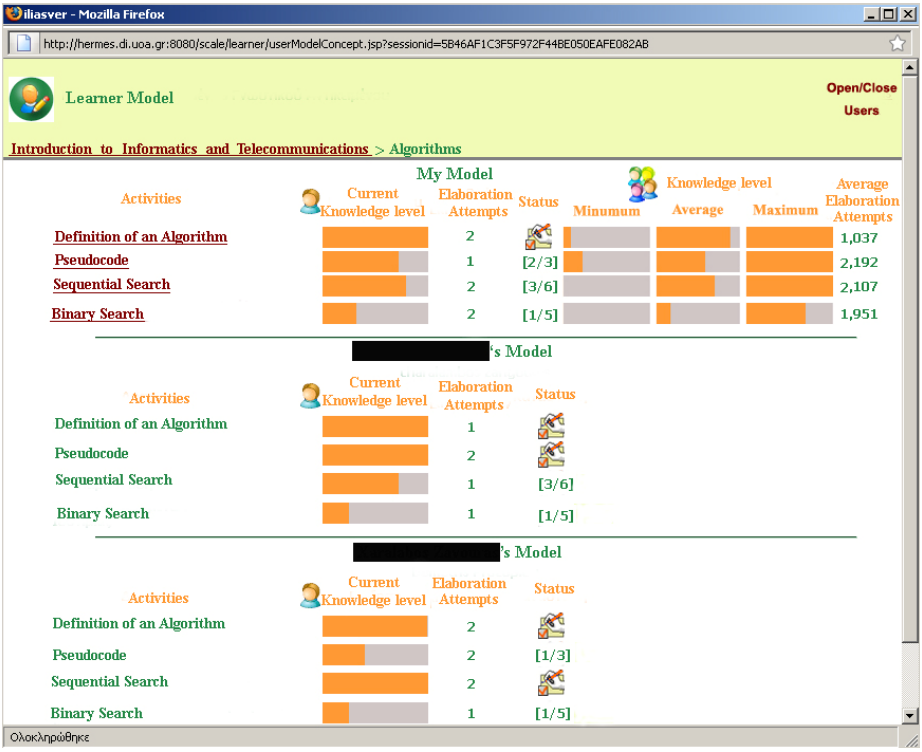

Figure 1: OLM_SCALE Screenshot of a specific learner-model's main screen of the concept "Algorithms" (translated in English)

4. The empirical study

During the academic year of 2007, SCALE and the corresponding educational material developed have been used for the first time aiming to improve the teaching and learning processes of the undergraduate course "Introduction to Informatics and Telecommunications" [20]. The course is compulsory and is taught 3 hours per week. The course objectives are as follows: (i) to give students a strong background in the following topics of computer science: Data Storage, Data Manipulation, Operating Systems, Networking and Internet, Algorithms and Programming Languages, (ii) to make students comfortable with computers and eliminate any fears about computers and (iii) to establish basic foundations of further study. The evaluation of SCALE's application during the academic year 2007 showed that although SCALE has been proved as a valuable tool in supporting and enhancing the teaching and learning processes, a considerable percentage of the participated students (27.8%) seemed rather disengaged while working in the environment. This fact encouraged us to develop an open learner model for SCALE and to conduct an empirical study in order to investigate the issue of guiding/tutoring the disengaged students to work in a more effective and engaged way. The empirical study was conducted during the winter semester of the academic year 2008-2009 in the context of the aforementioned course "Introduction to Informatics and Telecommunications" [21].

The main research questions of the empirical study was: Can the open learner model embedded in the SCALE environment stimulate students to work in an effective and engaged way?

154 first year's students, that enrolled to the course "Introduction to Informatics and Telecommunications" at the Department of Informatics and Telecommunications of the National and Kapodistrian University of Athens, participated in the study. All participants aged between 18 and 23 yeas attended General Lyceum in Greece during their Secondary Education years.

In order to investigate the effectiveness of the open learner model in the context of the specific course, educational material in the form of individual activities was developed. This material exploits the learning design of the SCALE environment and can be used (i) by the teacher as laboratory based exercises or as homework, and (ii)

by the student as a mean to deepen his/hers knowledge in the underlying topics or prepare him/herself for the corresponding university courses [22], [23], [24].
During the first lecture of the course the two responsible teachers presented an outline of the covered topics. Following that, one of the teachers presented the SCALE environment, the developed educational material and the open learner model. Results (see section Results) were obtained from system logs and questionnaires.
The eight weeks empirical study consisted of the following phases:

(i) *Pre-test* (1st week) – lasted 1,5 hour: All students participating in the empirical study, took the pre-achievement test.
(ii) *Working out activities* – lasted 7 weeks (1st week – 7th week): The participating students worked out the activities embedded in the SCALE environment. It was suggested to (a) access the environment and work out the corresponding activities at a week's basis following the material of the lectures and (b) use the open learner model. The estimated weekly time that students had to work with SCALE was 2 hours. At the end of the 3rd week a log file analysis was performed, in order to reveal (a) the students that were engaged / disengaged in working out the activities and (b) the students that used/did not use the open learner model. The students who did not use the open learner model were prompted (via email) to do so. The same log file analysis was repeated at the end of the 7th week of the empirical study.
(iii) *Post-test* (8th week) – lasted 3 hours: All students took the post-achievement test (course's final exam).
(iv) *Filling the questionnaire* (8th week) – lasted 30 minutes: The participating students were asked to express their opinion concerning the open learner model.

All students attended the weekly lectures and studied the relevant educational material (course book and lecture notes), in order to prepare themselves for the final exams. The lecture notes and supplementary material (e.g. announcements concerning the course, answers to questions posted during the lecture) were delivered to students through the course management system (http://eclass.di.uoa.gr/).
Moreover, educational material in form of individual activities was developed and delivered through the SCALE environment, covering the following topics: (i) Data Storage, (ii) Data Manipulation, (iii) Operating Systems, (iv) Networking and Internet, and (v) Algorithms. Each activity consisted of one or more sub-activities; and each sub-activity of one or more question items. The activity/sub-activity addressed learning outcomes of the Comprehension and/or the Application level. The question items were (i) multiple choice questions with one correct answer, (ii) multiple choice questions with more than one correct answers, (iii) matching questions, (iv) two-tier questions, where the second tier explores students' reasons for the choice made in the first tier [25], [26], and (iv) open answer questions (assessed by the teacher). The activities under consideration cover all difficulty levels, provide multiple and different kind of feedback types and are automatically assessed by the system (except of the open answer questions).
During the first week of the course all students participated in the pre-test, in order to identify their prior knowledge (10 multiple choice and 5 open answer questions). Each question scored 10 points.
During the last week of the course, all students participated in the course final exam (post-test). The post-test aims to reveal the differences in students' conceptions with the pre-test, after their involvement with the weekly lectures, the course educational material and the SCALE environment. The students had to answer the same questions they worked out in the pre-test. The evaluation of both the pre-test and the post-test was performed by the two course teachers in a 10-point scale (1-10) for each question. The final score of each question was the mean of the two evaluators' scores.

5. Results

To determine whether the open learner model maintained in SCALE environment stimulate students to work in an effective and engaged way, we performed (during the 3rd week of the empirical) a log file analysis in order to reveal the disengaged students. This analysis was based on the actions that students mostly performed before reaching the correct answers of an activity, after initially submitting wrong answers.

In SCALE environment, whenever a student submits a wrong answer s/he has the possibility to identify and correct his/her errors (e.g. by receiving tutoring feedback components or by restudying the corresponding topic of the course book) and then resubmitting the answer.

The log file analysis revealed that some students had extremely low *resubmitting time* (i.e. the time elapsed between the initially wrong submission and the subsequent resubmission) and considerable high average rate of activities' elaboration attempts. Accordingly to the works of [6] and [27], we presume that these students were rather disengaged while working in the environment and were only trying to guess the correct answer, in contrast with the rest of the students, that before resubmitting the answer either restudied the question or consulted relevant educational material or received relevant tutoring feedback components.

In order to identify the presumed disengaged students, we calculated (i) the elapsed time between the initial submission of a wrong answer and the final correct submission the same question and (ii) the estimated time for random submission of answer to the specific question. For example, if the estimated time for random submission for a specific activity was 10 sec and a student resubmitted in less than 10 sec then this attempt to answer the question is considered a blind guess and the student rather disengaged when answering the specific question. The estimated time for random resubmission was calculated from the data derived by the two course teachers that deliberately tried to submit blind guesses to each activity's questions as quickly as possible until they reached the correct answer. Comparing these times (the actual resubmission time and the estimated time for random resubmission), we divided students in two subgroups:

- *Disengaged:* students that retry to answer the question very rapidly (less than the estimated time).
- *Engaged:* students that retry to answer the question after a considerable time interval (equal or more than the estimated time) or after receiving tutoring feedback components.

The next step was to classify each student according to their resubmitting time as *Engaged* or *Disengaged* by using Two-Step cluster analysis.

Moreover, we classified each student according to the extend s/he used the open learner model. More specifically, we calculated for each student the rate $Mu=T_M/T_T$ (*Model Usage*), where T_T represents the Total Time spent working in SCALE environment up to the end of the 3rd week of the empirical study and T_M represents the time spent using the open learner model during the same period. Out of all the occurred Mu vales, the value Mu_{30} was calculated, that corresponds to the specific Mu value of which 30% of the students have smaller Mu value. This way the students were divided in two subgroups:

- *Non Model Users* ***(NMU)****: students with* $Mu <= Mu_{30}$
- *Model Users* ***(MU)****: students with* $Mu > Mu_{30}$

The results of the students' classification according to their way of working (engaged – disengaged) and according to the extent they used the open learner model are presented in Table 1. As can be seen in Table 1 a great percentage of the **disengaged** students were Non Model users (80.8%) and a great percentage of the **engaged** students were Model Users (81.5%). This fact was an indication that the exploitation of the facilities offered by the open learner model can stimulate students to work in an engaged way. In order to verify this assumption, we encouraged the students who did not use the open learner model to do so, by informing them (via email) that using the open learner model might enhance and support their learning. More specifically, these students were encouraged to access the learner model, to make the information held in it available to their peers (i.e. *open* their model) and to choose their peers whose models they would like to inspect.

Table 1: Classification of students according to their way of working (Engaged – Disengaged) and to the extent they used the open learner model (Non Model Users – Model Users) at the end of the 3rd week of the empirical study

Model Usage / Way of working	**M**odel **U**sers	**Non M**odel **U**sers
Disengaged	14 (19.2%) Type *D_MU*	59 (80.8%) Type *D_NMU*
Engaged	66 (81.5%) Type *E_MU*	15 (18.5%) Type *E_NMU*

At the end of the 7th week of the empirical study we repeated the aforementioned log file analysis in order to investigate whether the 3rd week's email intervention would result on the students' more engaged way of working. The analysis revealed that several changes of students' types had occurred. More specifically we registered the students' change of types. The results are shown in Table 2:

Table 2: Registered changes of students' types (3rd vs. 7th week of the empirical study) – ranked according to occurrences

TYPE 3rd week →7th week	**DESCRIPTION** This category includes students that at the end of the… 3rd week of the empirical study were characterized as:	7th week of the empirical study were characterized as:	**STUDENTS**	**GROUP**
E_MU → *E_MU*	model users and worked in an engaged way	model users and worked in an engaged way	64	Group 1
D_NMU → *E_MU*	non_model users and worked in a disengaged way	model users and worked in an engaged way	37	Group 2
D_NMU → *D_MU*	non_model users and worked in a disengaged way	model users and worked in a disengaged way	13	Group 3
D_MU → *D_MU*	model users and worked in a disengaged way	model users and worked in a disengaged way	12	Group 4
E_NMU → *E_MU*	non_model users and worked in an engaged way	model users and worked in an engaged way	8	Group 5
D_NMU → *D_NMU*	non_model users and worked in a disengaged way	non_model users and worked in a disengaged way	7	Group 6
E_NMU → *E_NMU*	non_model users and worked in an engaged way	non_model users and worked in an engaged way	5	Group 7
E_MU → *D_MU*	model users and worked in an engaged way	model users and worked in a disengaged way	2	Group 8
E_NMU → *D_MU*	non_model users and worked in an engaged way	model users and worked in a disengaged way	2	Group 9
D_MU → *D_NMU*	model users and worked in a disengaged way	non_model users and worked in a disengaged way	2	Group 10
D_NMU → *E_NMU*	non_model users and worked in a disengaged way	non_model users and worked in an engaged way	2	Group 11

As can be seen in Table 2, 60 out of 74 students (81%) of the initially non model users (74 students – see Table 2) responded positively to our suggestion to use the open learner model (60 students – see Table 2 Groups 2, 3, 5, 9). More specifically,

37 out of 59 initially disengaged - non model users not only became Model users, but also managed to improve their way of working towards a more engaged way (Table 2 - Group 2). 13 out of 59 initially disengaged - non model users (22%) although responded positively to our suggestion to use the open learner model continued to work in an disengaged way (Table 2 – Group 3). 7 out of 59 initially disengaged - non model users (11.8%) avoided to use the open learner model continued working in a disengaged way (Table 2 – Group 6). Finally, 2 out of 59 initially disengaged - non model users (3.3%) avoided to use the open learner model but managed to improve their way of working towards a more engaged way (Table 2 – Group 11).
The majority (97.5%) of the initially model users (80 students – see Table 1) continued to use the open learner model till the end of the experimental study (78 students – see Table 2 Groups 1, 4, 8). The reader may notice that almost all initially type E_MU students (Engaged - Model users) remained in the same category throughout the duration of the empirical study.

Moreover, we examined the performance differences (pre-test vs. post-test), regarding the groups that contained more than 10 students (i.e. four groups: Group 1 (64 students), Group 2 (37 students), Group 3 (12 students), Group 4 (13 students)). No significant difference was found in the One-Way ANOVA between the four groups on the pre-test performance. (see Table 3 – pre-test column). As can be seen in Table 3 the four groups where initially equivalent in their pre-test performance ($p>0.05$).

Table 3: Evaluation of the pre-test and post-test – Between groups (Group 1, Group 2, Group 3, Group 4) One-Way ANOVA

pre-test		post-test	
F(3)	*p*	F(3)	*p*
0.647	0.899 (ns)	18.324	<0.01

As can be seen in Table 3 (post-test column), the results of the One-Way ANOVA revealed that the mean post-test performances are not equal across the groups and that at least one of the group means is significantly different from at least one other group mean ($p<0.05$). In other words the fact that the significance value of the F test is less than 0.05 suggests that the mean post-test performances of the four groups differ in some way. In order to obtain which groups are different and which are not, we performed LSD Multiple Comparison tests based on the four groups (see Table 4)

Table 4: One-Way ANOVA Multiple Comparison between groups (Group 1, Group 2, Group 3, Group 4)

(I) Type	(J) Type	Mean Difference (I-J)	sig
Group 1 (64 students)	*Group 2*	0.39	0.07 (ns)
	Group 3	2.02	<0.01
	Group 4	1.65	<0.01
Group 2 (37 students)	*Group 1*	-0.39	0.07 (ns)
	Group 3	1.62	<0.01
	Group 4	1.26	<0.01
Group 3 (13 students)	*Group 1*	-2.02	<0.01
	Group 2	-1.62	<0.01
	Group 4	-0.36	0.39 (ns)
Group 4 (12 students)	*Group 1*	-1.65	<0.01
	Group 2	-1.26	<0.01
	Group 3	0.36	0.39(ns)

As can be seen in Table 4, the mean of Group 1 is 0.39 points higher than the mean of Group 2. Since the significance level is larger (i.e. 0.07) than the required 0.05 alpha level, we conclude that the differences in post-test performance for Group 1 and the Group 2 are not significant. This fact suggest that the students of Group 2 although initially disengaged and non model users, (i) managed to improve their way of

working towards a more engaged way, (ii) became model users and (iii) improved their post-test performance at the same rate as the students that throughout the run of the empirical study were model users and worked in an engaged way (i.e. students of Group 1).
On the other hand the means of Group 3 and Group 4 are significantly lower from the means of the other groups. Specifically the students of Group 3 scored 2.02 & 1.62 points lower than the students of Group 1 and Group 2 respectively. The students of Group 4 scored 1.65 & 1.26 points lower than the students of Group 1 and Group 2 respectively. This fact suggests that the students of Group 3 and Group 4 remained disengaged while working in the environment and although they used the open learner model could not improve their post-test performance at the same rate as the students of Group 1 and Group 2. This could be explained due to the fact that these students tried to elaborate the requested activities either by trying to blind guess the correct answers or by trying to guess the correct answers through the open learner model.

The empirical study, that was conducted, showed that the exploitation of OLM_SCALE can guide the online students who become disengaged towards reengagement. More specifically although 38% of the participated students initially did not use OLM_SCALE and worked in a rather disengaged way, 63% out of these students not only managed to improve their way of working towards a more engaged way after they were prompted to use OLM_SCALE but also improved their post-test performance at the same rate as the students that throughout the run of the empirical study were model users and worked in an engaged way. This fact suggests that non invasive interactions based on the principles of the open learner model can help students focus reflection on their learning process and coax them to reengagement. It seems that including in the open learner model performance and progress charts, and a reflection of the students' working behaviour can effectively lead disengaged students to work in an engaged way. In the frame of this empirical study no further tips or encouragement were given to the participating students. Our results are in line with the results of [5] in terms that disengaged students became engaged by accessing the open learner model. But, our works goes one step further showing that additional tips (that may require skilfully log file analysis) and encouragement are not necessary (as reported in the work of [5]); students may think of their interaction and reflect both on their own working behaviour as well as on their co-students' and friends' working behaviour. The log file analysis performed in the frame of the empirical study presented in section 4 has been conducted in order to investigate whether OLM_SCALE can stimulate students to work in an effective and engaged way. Our results show that simply through the exploitation of the facilities offered by OLM_SCALE and without performing any log file analysis, disengaged students can be guided into reengagement. 22% out of the students that initially did not use OLM_SCALE and worked in a rather disengaged way, although responded positively to our suggestion and used OLM_SCALE continued to work in a rather disengaged way. These students improved their post-test performance at a significantly lower rate as the students that either throughout the run of the empirical study were model users or became model users after our suggestion. Moreover, 12% out of the students that initially did not use OLM_SCALE and worked in a rather disengaged way chose not to use OLM_SCALE even after our suggestion, and continued working rather disengaged till the end of the empirical study. Finally 3% out of the students that initially did not use OLM_SCALE and worked in a rather disengaged way although did not respond positively to our suggestion and chose not to use OLM_SCALE, manage to work in an engaged way at the end of the empirical study.
A considerable percentage of the students (43%) chose by themselves to use OLM_SCALE from the beginning of the study and were found to work in a rather engaged way. 97% out of these students continued to use OLM_SCALE and to work in a rather engaged way till the end of the empirical study. The rest 3% out of these students although continued to use OLM_SCALE were found to work rather disengaged at the end of the empirical study.
The participated students expressed their satisfaction regarding SCALE environment and in particularly they characterised the open learner model maintained in SCALE as a valuable and supportive mean in learning.

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