Analyzing the Impact of Using Optional Activities in Self-Regulated Learning

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Abstract— Self-regulated learning (SRL) environments provide students with activities to improve their learning (e.g., by solving exercises), but they might also provide optional activities (e.g., changing an avatar image or setting goals) where students can decide whether they would like to use or do them and how. Few works have dealt with the use of optional activities in SRL environments. This paper thus analyzes the use of optional activities in two case studies with a SRL approach. We found that the level of use of optional activites was low with only 23.1% of students making use of some functionality, while the level of use of learning activities was higher. Optional activities which are not related to learning are used more. We also explored the behavior of students using some of the optional activities in the courses such as setting goals and voting comments, finding that students finished the goals they set in more than 50% of the time and that they voted their peers' comments in a positive way. We also found that gender and the type of course can influence which optional activities are used. Moreover, the relations of the use of optional activities with proficient exercises and learning gains is low when taking out third variables, but we believe that optional activities might motivate students and produce better learning in an indirect way.

Index Terms—Khan Academy, learning analytics, MOOCs, optional activities, self-regulated learning.

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1 INTRODUCTION

V IRTUAL Learning Environments (VLEs) provide their learners with informational assets such as video lectures or text documents as well as with interactive learning activities like answering questions and receiving feedback. While these learning activities are often mandatory, i.e., they need to be fulfilled to pass the course they belong to, VLEs also provide functionalities and tools that offer users the possibility to perform voluntary, optional activities, e.g., commenting on a video, setting a learning goal, or uploading an avatar photo. Within the scope of our research we thus define optional activities as those activities that are not mandatory in a course. As it is usually up to the teachers which activities are mandatory for a course and which are not, some activities might be assigned as optional in one case but not in another depending on the learning context. For example, a forum activity like answering questions can be optional in one course but mandatory in another. Optional activites can either be advertized to the students by teachers or the students can be left to explore their VLE and discover the functionalities of their VLE by themselves. On one hand, the use of

optional activities might engage and motivate students to use the platform. On the other hand, the use of optional activities might be a consequence of a greater engagement and motivation of students, and can be an indirect measurement of intrinsic motivation. Both facts are compatible at the same time. Teachers could also decide to only explain some of the optional activities to their students. Their choice depends on what they deem important to their course and what they think an interaction between the students and the environment should look like. The use of optional activities can play an important role in self-regulated learning (SRL) since this implies students taking control of their own behavior and making decisions.

Although there are often many types of optional activities in VLEs (e.g. updating an avatar, setting goals, wikis, supplementary materials, changing colors or voting activities), research studies usually focus on the analysis of learning activities and do not take the optional activities into consideration. The study reported by Dyckhoff et al. [1] shows a list of learning analytics indicators used in the literature and their categorization. Most of the indicators presented by Dyckhoff et al. are related to learning activities only, and ignore optional activities. In addition, the meta-study by Sitzman and Ely [2] clearly shows which SRL constructs and methods best support learning in work-related learning. While the use of SRL is well researched (e.g. in [3]), possible additional factors are yet to be considered. This article therefore presents a study that deals with the analysis of optional activities in VLEs using a SRL approach. In the case study presented in this article, the teachers did not inform the students about the optional activities, but the students discovered these functionalities on their own during their interactions with the

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system.

The presented study analyzes the use of optional activities in a SRL setup and is divided in two different experiments. The first one analyzes data within three different courses (physics, chemistry and mathematics) with a total of 291 unique students on the Khan Academy[1] platform whereas the second experiment analyzes data of 186 unique students from two other different courses (chemistry and physics) on the Khan Academy. The objectives of this analysis focus on:

1. Knowing the level of use of the different types of optional activities, giving the percentage distribution between them and with respect to the learning activities.

2. Knowing students' behavior patterns with optional activities, e.g., check if students finish the goals they set for themselves (e.g. finishing a specific video or exercise) or if they voted positively or negatively on their classmates' comments on videos (they can vote them down (-1), be indifferent (0) or vote them up (+1)).

3. Relating the use of optional activities with the learning outcomes, represented in this research as the amount of proficient exercises achieved by the student, taking out the effect of third variables, thereby gaining insights into how much optional activities might contribute to correctly carrying out learning activities.

4. Relating the use of optional activities with learning gains, taking out the effect of third variables, in order to gain insight about the relation between the use of optional activities and learning achievement. Although it is expected that some optional activities (e.g. setting an avatar) might not be related with learning outcomes and learning gains, there are others that are assumed to be related such as setting goals.

5. Relating the use of optional activities to other student behavior metrics and parameters such as hint abuse, hint avoidance, total time, progress in the platform, etc. to contribute to the identification of further influential factors for the use of optional activities.

6. Identifying categorical associations between the use of the different optional activities and further variables such as gender.

The remainder of the manuscript is organized as follows. Section 2 explores related work, first in the context of self-regulated learning and then presenting studies related to learning and optional activities. Section 3 describes the context and pedagogical setup, participants and design, calculation of optional activities and the architecture of the two experiments and case studies carried out in this work. Section 4 presents the results regarding the objectives of this analysis and a discussion about the findings. We finish with conclusions and future lines of work.

2   RELATED WORK

2.1. VLEs and self-regulated learning

Virtual Learning Environments and computer-assisted instruction have been described and developed in case studies since the 1990s when the developments in computer technology improved so significantly that the digital simulation of learning environments became possible [4]. Since then the use of VLEs has spread widely in the educational domain, covering a whole range of stakeholders and learning scenarios [5, 6, 7]. From early on VLEs were liked due to their allowing the learners to control the learning process and their making learning a personal experience. Often, VLEs are thus used in the pedagogical approach of self-regulated learning: VLEs allow students to access learning resources, possibly with additional features like personalized learning paths and adapted material as well as recommended additional learning resources. Furthermore, VLEs allow students to communicate and collaborate remotely on learning activities. Finally, many VLEs provide insights into the students' learning activities with dashboards, sometimes compared to the activities of co-students thereby stimulating reflection on the students' own learning activities. VLEs therewith provide a highly usable set of tools to enable self-regulated and self-reflective learning.

Self-regulated learning has been important in educational and psychological research for many years [8, 9, 10, 11, 12, 13, 14]. Over the years, the tenor has been to give the learner a greater responsibility and control over all aspects of technology-enhanced learning [15] which is beneficial for their actual learning outcomes [16]. Proposed models of self-regulated learning, e.g., the General Framework for Self-Regulated Learning [17, 18], deal with self-regulation as a process that involves goal setting and planning, monitoring and control processes, as well as reflection and evaluation processes [19, 20]. Finally, a study by Greene, Moos & Azevedo [21] outlines that students with significant skills in self-regulated learning benefit most from the use of VLEs in their education.

2.2. Relevance of learning and optional activities

Several recent studies deal with the question of what is most important for student learning. Some of these works are overviews and reviews, e.g., about factors of effective teaching for student learning outcomes [22] or factors of student persistence [23], others are collections of studies, e.g., about the use of wikis, blogs and webquests to increase student engagement [24], yet others offer a synthesis of meta-analyses, e.g., on visible learning and achievement [25], while others present individual experiments and analyze the relation of different behaviors on the students' learning gain and success in online learning platforms [26].

For example, Muñoz-Merino et al. [27] analyzed which tools and functionalities offered by Moodle[2] and .LRN[3] are of most importance to their students. The results indicate that among the most useful functionalities and tools

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[1] https://www.khanacademy.org/

[2] https://moodle.org/
[3] http://dotlrn.org/

are the submission management systems where the students submit and receive feedback from their teachers, the frequently asked questions about course contents, as well as the options to solve assessments, or to download files. All of them are learning activities. However, students also showed a great interest in optional activities such as search within the portal, the use of the forum or knowledge of their own learning evolution and status. All of this shows the relevance and importance of optional activities for students.

Koedinger et al. [28] compared the effect of passive forms of learning, e.g., watching a video lecture or reading a text, with more interactive forms of learning, e.g., answering questions or solving problems. They found that although only watching videos can be predictive of dropout in the analyzed psychology MOOC, and although students doing more interactive activities were more successful in the course than students watching more videos or reading more pages, the combination of interactive activities and watching a large number of videos led to the highest success rates. The study's authors attributed this to reflection about the declarative content of the videos about concepts or skills not required in the interactive activities.

Santos et al. [29] analyzed the activities conducted by learners in two language learning MOOCs. They found that students who did more activities had higher chances to pass the course in which all proposed course activities are equally important. In fact, if a student skipped around 10% of these course activities (independent of the type of activity), the likelihood of passing the course decreased by 25%. Furthermore, the activities in the forum – which can be regarded as optional activities – correlate with the students' success as well. This is in line with the findings of the study conducted by Cheng et al. [30] with over 2,000 students in two undergraduate introductory psychology courses that showed that students who voluntarily participate in forums tend to perform better in the course.

A few works have also incorporated new activities in the analysis, which can be considered as optional, in a SRL approach, e.g., that by Gašević et al. [31] regarding video annotation. They report on a study that explores the behavior of students using a video annotation tool in which two different instructional approaches are deployed, i.e. graded and non-graded self-reflection annotations. The study found that the students in the group with the graded self-reflections used more complex language which is an indicator of more complex cognitive processes and critical thinking.Coetzee et al. [32] created a reputation system for forum activities in an open edX MOOC. More precisely, users can vote for forum contributions and the contributions' authors receive a reputation score based primarily on how many upvotes their posts received. The study shows that in their learning setting, the use of the forum is correlated with higher grades and higher retention and that reputation systems produce faster response times and larger numbers of responses per post. However, a study by Davies and Graff [33] analyzing the online behavior of 122 first-year business students shows that the use of a forum alone, i.e., without further optional or learning activities, did not lead to higher grades for students in that context.

Muñoz-Organero et al. [34] conducted a study on the students' motivation in online learning with 160 participants in six different university courses. They divided the activities in three categories: studying the contents of the course, participating in e-learning activities (such as forums), and updating the student profile by uploading a photograph. It turned out that in all three categories the total number of activities is correlated with the motivation of the students. Additionally, the study shows that the students' motivation is directly related with the final grade.

A study in the field of computer-assisted language learning [35] shows that those students required to communicate were less effective in producing language output than those where the communication process task was optional. How this affected the students' overall success in the language learning course is not reported.

To conclude, online learning is composed of diverse activities (e.g., passive or interactive activities) that fulfill different functions (e.g., gaining basic knowledge as well as deepening or applying it) and can be supported by several methods (e.g., rewards or hints). Some activities are directly related to learning and are often mandatory to pass the course (e.g., video lectures or homework) while some activities are optional and might strengthen the learning success (e.g., forum activities, setting goals or setting an avatar). While the relation between the usually optional forum activities and the learning success has been analyzed in many studies, there is less or no knowledge about the effect of other optional activities that focus on individual goals (e.g., personalizing the profile or setting a learning goal) and/or comunication (e.g., voting in a forum or commenting on learning resources). Therefore, this paper analyzes the effect of optional activities in online learning using the example of several Khan Academy courses that aim to freshen the knowledge of students before their first year of university starts. More precisely, five optional activities are analyzed of which three are related to learning (giving feedback to video learning resources, voting, and setting goals) and two are related to the learners' profiles (uploading an avatar and personalizing a selection of badges to be displayed in their personal profile).

3 TESTBED DESCRIPTION AND SETUP

3.1. Context

Several of the so called 0-courses at Universidad Carlos III de Madrid have been chosen as testbeds. These courses are for those first-year students who are entering a science degree and would like to review the concepts required for physics, chemistry and maths during their first year at the university, i.e., the courses are not mandatory for students entering at university but they can subscribe to them to reinforce their knowledge. Most of the participants are freshmen around 18 years old.

An "inverted classroom" methodology [36] is being

used for those courses, that is, students first learn and review concepts at home by using an online platform during the month of August, and next take the face to face lessons in the university during the month of September.

The learning resources and activities that are prepared by teachers for the online phase are composed of sets of videos and exercises, which have been designed by the instructors. Although it is not mandatory for the students to access these online courses, it is strongly recommended; this is an important fact when measuring the use of the platform. It is also noteworthy that students are not informed of the optional activities available but about the learning activities, i.e., videos and exercises.

3.2. Pedagogical setup: A SRL framework

For the online phase, a platform was needed that supported the uploading and playing of videos and exercises in an effective way. In addition, the platform had to be able to support a rich SRL approach. This SRL approach should allow students to be aware of and control their own learning as well as to make their own decisions in the learning environment. Following the SRL approach, videos and exercises should be available so that students can access them in any order they want to. Exercises should have a good level of interactivity and students should be able to decide when they need help, e.g., requesting a hint. A useful gamification environment should also be available to allow students to earn points and badges. In addition, different optional activities related to SRL should be available, e.g., for setting goals, writing feedback for videos, setting the avatar or rating messages.

Based on all of these requirements and the SRL approach, the Khan Academy platform was selected to be used in our testbeds as it allows a rich use of videos and exercises, gamification functionality, learning analytics features or optional activities. However, the Khan Academy version that we used did not include neither a forum nor a clear structure of the contents, which is why in addition a Moodle platform was used to provide a clear structure with links to the different Khan Academy learning materials and also to enable forum discussions among students. All the considered optional activities of this research, however, took place in the Khan Academy platform.

3.3. Participants and design of the experiments

We conducted two experiments: one in the academic year 2013/14, and one in the academic year 2014/15. For the first experiment, we used the data generated in three courses (physics, chemistry and mathematics) that took place in August 2013. The number of students was different for each course, and some students took more than one course (depending on the science degree they were entering). There were 167 students in the physics course, 73 in chemistry and 243 in mathematics; this is a total number of 483 data cases. However, the total number of unique students was 291, as some students were enrolled in more than one course.

For the second experiment, we used data from two courses (physics and chemistry) that took place in August 2014. Although the mathematics course also took place, it was not possible to perform a pre- and post-test in that course and its data was thus not part of the study. The total amount of students who logged into the Khan Academy platform for the two courses was 156 students for physics and 69 for chemistry (186 different students as some of them took both courses), which is a very similar number to the first experiment.

It is important to note that when reporting descriptive statistics and overall use of optional activities in the courses, we use the total number of students in the courses, i.e., students can be counted more than once, as each student might have behaved differently in each course and that is also valuable. However, when we perform inferential statistics such as correlation, we use the number of unique students, i.e., every student is only counted once, in order to maintain the assumption of independence between cases for such statistical techniques.

With the purpose of being able to measure the learning achievement of students while interacting with the Khan Academy platform and to relate it with different indicators, we implemented a pre-test and a post-test design for the second experiment, which is shown in Figure 1. The rest of the experimental setup was the same as in the first experiment. The pre-test and post-test were offered in the Moodle Learning Management System. The pre-test aimed at measuring the students' prior knowledge in each one of the courses and was made available at the beginning of August. Students had to complete it in order to be granted access to Khan Academy contents. At the end of August, the post-test was enabled, so that the students' knowledge after interacting with the Khan Academy platform could be measured. The pre-test and post-test were a set of questions designed to have a similar level of difficulty. We inferred the normalized learning gains using the following formula where the max_{score} in the test can be 100:

$$LG = \begin{cases} \dfrac{post_{test} - pre_{test}}{max_{score} - pre_{test}}, & pre_{test} \leq post_{test} \\ \dfrac{post_{test} - pre_{test}}{pre_{test}}, & pre_{test} > post_{test} \end{cases}$$

In addition, the indicators related to optional activities were obtained from ALAS-KA (Add-on of the Learning Analytics Support of the Khan Academy), as well as the rest of the indicators. ALAS-KA only took into account the data after making the pre-test and before doing the post-test, so the exact times when students answered the post-test and pre-test are taken into account. Moreover, the calculation of learning gains was also incorporated in ALAS-KA. With all that information we were ready to perform the post-hoc analysis, i.e., to see if there exist any relations between the use of optional activities and learning gains.
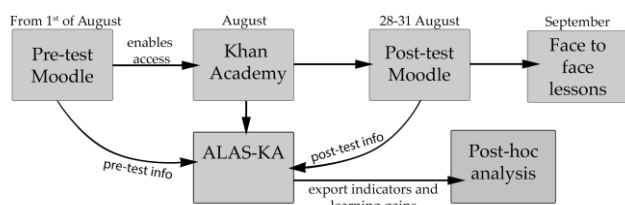
Fig. 1. Methodology flow of the second experiment with pre- and post-test.

The pre-test and post-test in physics had 10 questions each whilst the ones of chemistry had 21 as the contents which needed to be reviewed were broader. In order to guarantee that the difficulty of the pre- and post-test was similar, the questions were pulled from a pool of similar difficulty. A total of 163 students in physics and 77 in chemistry attempted the pre-test, but just 48 students in physics and 30 in chemistry then also did the post-test. This was due to the fact that students had to do the pre-test in order to be able to access the Khan Academy contents, while the post-test was a voluntary activity (although emails were sent in order to encourage students to do both tests). In addition, not all the students who did both tests were included into the analysis. We added a condition that students needed to spend at least 30 seconds multiplied by the number of questions of the test in each test as this is the minimum estimated time for a student to read a question and answer it. We set this condition in order to remove those students from the analysis that answered the test just randomly, as e.g. some students took only one minute or less to answer the complete test. With these restrictions, the total number of students that were considered for the analysis is 25 for chemistry and 44 for physics, which makes a total amount of 69 students.

3.4. Description and calculation of optional activities

The optional activities that we offer in the testbeds are divided into two groups: those that are related to learning and those that are not. First, the activities related to learning are:

1. *Feedback*: Comments that students post to videos of the course are considered as feedback (Figure 2).
2. *Votes*: Students can vote down (-1), be indifferent to (0) or vote up (+1) the feedback that other students have posted to videos. Figure 2 shows an example of a comment that has some votes. The name and message of the author have been blurred to preserve anonymity.
3. *Goal*: Students can set goals, i.e., they choose a selection of videos or exercises that must be completed by them. When they finish the goal, they obtain an additional amount of points. Figure 3 shows an example about how to set a custom goal.

On the other hand, we have taken into account other optional activities that are not related to learning. These activities come from social networks and games environ-

ments:

4. *Profile avatar*: Students can change the default avatar of their profile. They have access to a selection of six different avatar images at the beginning of using the platform and can earn access to more images by acquiring points in their interaction with the platform functionalities.
5. *Badge display*: Students can personalize a selection of badges to be displayed on their personal profile. The badges that can be displayed are the ones that each student has earned previously. Figure 4 shows a portion of the personal profile where the profile avatar and the badge display can be observed.
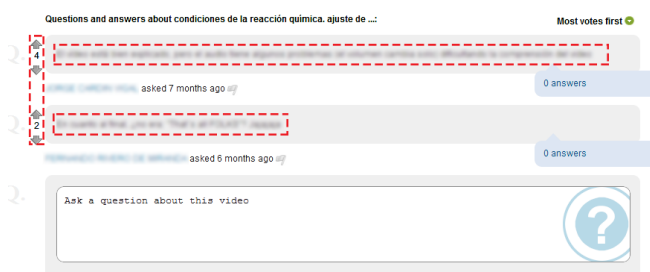

Fig. 2. Students' feedback and votes to a video can be observed inside the red dotted line. The authors and comments have been blurred to preserve anonymity.

Fig. 3. Custom goal setting example.

Fig. 4. Personal profile of a student in the Khan Academy instance. The default avatar image and badge display are pointed out by the red dotted line.

For a global indicator of optional activities, all activities are weighted equally, i.e., students can gain one point per activity (with the exception of setting goals as explained below) as we did not wish to give more importance to any of the optional activities but just wanted to check the number of times the activities have been used. A global indicator gives insight as to which number of different optional activities were used, regardless of whether they were used a lot or not individually. More specifically, the scoring method is designed as follows: A user gets one point whenever he selects an avatar image, selects at least one badge to be displayed, writes a feedback about a video, votes for any of the comments of other students or

starts at least one goal. An additional point is given when the user finishes at least one started goal.

Consequently, there are five different optional activities, and students can earn a maximum quantity of six points if they do them all and finish one goal. Therefore, the global use of optional activities is calculated as a summative number of points earned in each optional activitiy i, and then expressed as percentage, as we can see in the next formula:

$$optional\ activities\ = \frac{100}{6} \sum_{i=1}^{5} points_i$$

3.5. Technical architecture for the detection of optional activities

Figure 5 shows a summary of the complete architecture and the different elements involved in the case study. The VLE that is used is Khan Academy, which natively runs on the Google App Engine system and the source code is mainly written in Python. Khan Academy stores the regular learning activities such as videos and exercises, but also provides the optional activities described above. When students interact with these activities, they generate raw data about these interactions which are stored in the App Engine Datastore.

Another important element of this case study is ALAS-

KA (Add-on of the Learning Analytics Support of the Khan Academy) that has been presented in previous work [37]. It is used to obtain the indicators related to optional activities as well as those learning activities used in the case study. ALAS-KA has been designed as a Khan Academy plug-in and uses very similar technologies as it runs in the Google App Engine and is written in Python. ALAS-KA uses the Khan Academy's raw log data and transforms it to get useful higher-level indicators [38]. ALAS-KA has several scheduled jobs that invoke the functions which process all the indicators used in this case study in regular time intervals, i.e., functions are called and indicators are processed two times a day. These functions will access the raw data generated by students when interacting with Khan Academy, process the indicators, and then store the results in ALAS-KA App Engine Datastore, which is a schemaless NoSQL datastore. Instructors can access ALAS-KA ad-hoc visualizations while the course is running; for these visualizations Google Charts API is used. Finally, once the course is finished, all the optional activity indicators and the rest of them are extracted from ALAS-KA, in order to locally perform a post-hoc analysis and learn more about these Khan Academy experiences.
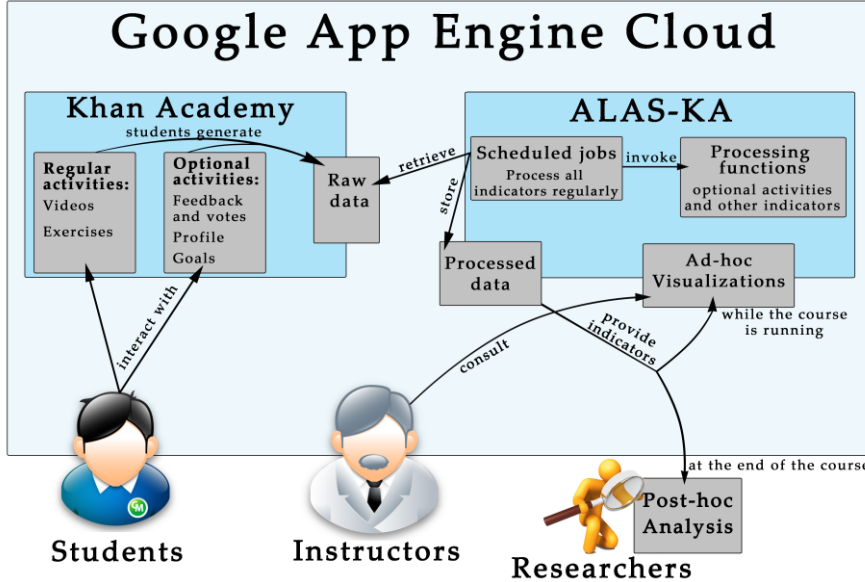

Fig. 5. Technological overview and architecture for the detection and visualization in ALAS-KA.

4   RESULTS AND DISCUSSION

This section presents the two experiments of our case study: the first one is based on 2013/2014 courses and the second one is based on 2014/2015 courses. The second experiment included a pre-test and post-test, which makes possible to measure learning gains.

4.1. First experiment 2013/2014

4.1.1. Analysis of the use of optional activities

This section describes the quantitative analysis of the optional activities' usage that is then also compared to the participation ratios with the regular items (such as exercises and videos) of the courses. We provide data from each of the courses separately as well as for the overall results of all courses. Figure 6 shows results of the op-

tional activities usage per activity and course and as a whole. Each bar represents the percentage of students in the class who have used the activity on the left axis. In addition, the last metric provides the percentage of users who have used at least one of the activities. Each one of the courses is represented by a different color where blue stands for chemistry, dark grey for physics, green for mathematics and red for the students in all classes.

The results shown in Figure 6 take into account all the students who logged in at least once to the Khan Academy platform. Consequently, some of these students did not interact much with the system, neither with optional activities nor with learning activities. From Figure 6 we can extract the following main conclusions: The optional activities used the most are the configuration of a profile avatar and the badge display. Although the exact percentage numbers differ from one course to another, on average this results in 10.8% (avatar) and 12% (badges) respectively for all courses, i.e., they are by far the most used optional activities in all courses. A possible reason for this could be that these students, who are aged around 17–19 years, are comfortable using activities originating from a social network or gaming context.

On the other hand, optional activities that are related to learning (feedback, vote and goal) have been used much less (4.1%, 6.6% and 6.2%, respectively) in all courses. The activity which has been used the least is feedback. A reasonable argument is that writing a feedback answer about a video generally requires a greater effort than just simply changing an avatar, for example. Furthermore, Moodle forums were also enabled for students during these courses, and most of the social interaction was conducted there.

Finally, 23.2% of the students of all courses who logged in at least once on the platform used at least one of the five optional activities considered in this study. In addition, results show a difference in the use of optional activities between the three courses. The chemistry course has the highest ratio of students who used at least one optional activity (30.1%), whereas physics has the lowest ratio (18%). Further research would be needed to establish possible reasons for these differences.

It is important to remember that students did not have knowledge of the optional activities available; they were only informed of the courseware. This can be one of the main reasons for the low use ratios for these optional activities in general. But even taking into account that these online courses were not mandatory, and that these activities were not announced, the usage ratios of optional activities are still low.
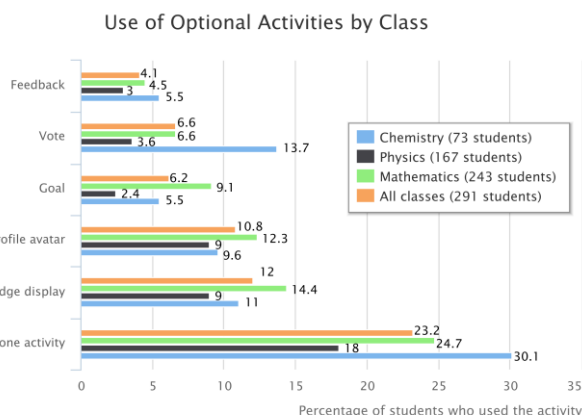

Fig. 6. Percentage of users who have used the different optional activities divided by courses.

4.1.2. Analysis of user behaviors with optional activities

It is also interesting to look at more specific details about students' behavior in some optional activites. For example, we can focus on the ratio of finished goals and the types of votes.

The number of students who set goals was 30, setting up a total number of 55 goals when taking into consideration all courses. The minimum number of goals set by a student was 1 while the maximum was 3. Taking into account all goals, 28 of them (50.9%) were reached. This finishing ratio seems to be rather high. However, the goal setting is optional but the selected goal, e.g. finishing an exercise, might be crucial for understanding the topics the course is covering.Furthermore, we assume students that use the optional functionality of setting goals to be highly self-motivated and confident about reaching a goal when selecting it which might bias the finishing ratio.Moreover, the number of students who voted was 32 and a total of 40 votes in all courses: 26 of them were positive (65%), 13 of them were indifferent (32.5%) and only one of them was negative (2.5%). These results indicate that most of the users vote for positive reasons given these conditions and it is very unlikely that they vote negatively on other students.

4.1.3. Comparison between the use of optional activities and regular activities

We can establish a comparison between the access to the regular learning activities such as exercises and videos and that to optional activities. This comparison can be seen in Table 1. It allows us to get a sense of how much students have used the regular activities in comparison to optional activities. We have divided the use of regular and optional activities in five intervals and we show the percentage of students from all courses in each interval. It is noteworthy that we have a total number of 483 student cases because some of the students participated in several courses and these statistics take into account all the cases. The first thing to notice is that only 12 students (2.48%) who logged in on the platform did not use any of the regular learning activities whereas 371 of the students (76.81%) did not use any of the optional activities. This is

a huge difference that already gives insight about the low use of optional activities compared to the use of regular learning activities. On the other end, we can notice that 19 students (3.93%) used all the regular learning activities while only one of the students (0.21%) used all the optional activities. We should also keep in mind that the amount of learning activities is above 40 in all courses whereas the number of optional activities taken into account in the study is only five. Finally, we can see that the use of activities in the 1-99% interval declines gradually and is always superior for the regular activities.

TABLE 1
COMPARISON BETWEEN THE USE OF REGULAR LEARNING ACTIVITIES VERSUS THE USE OF OPTIONAL ACTIVITIES

Type of activity	Percentage of activities accessed				
	0%	1-33 %	34-66%	67-99%	100%
Regular learning activities	2.48%	51.55%	23.19%	18.84%	3.93%
Optional activities	76.81%	18.43%	4.14%	0.41%	0.21%

Each cell represents the percentage of students for each interval.

4.1.4. Relation between optional activities and proficient exercises

In order to measure the learning outcomes, we use the percentage of proficient exercises by a student, which are the exercises that students have mastered at the maximum level in Khan Academy, i.e., repeating similar types of exercises and solving them correctly.

Table 2 first shows the Pearson correlation between the percentage of proficient exercises with the global measure of optional activities and each optional activity separately. The results show that the use of optional activities is significantly correlated with the percentage of proficient exercises. The most significant correlation (0.553) is with the global measure of optional activities; this strong relation points out that the use of optional activities might be used as an indicator to know how well students have mastered the exercises. Avatar and display badge (0.415 and 0.418) are the optional activities that have been most highly correlated with the percentage of proficient exercises, whereas feedback and vote (0.205 and 0.243) have been the least. This might be surprising at first sight because feedback and vote are supposed to be related to the learning process and one might thus think that they should have a higher correlation with solving exercises correctly than avatar and display badges which are not related to the learning process. However, the use of the avatar and display badge are moderated related to the total time spent on the platform (correlations of 0.28 and 0.24 respectively) and people that spent time on the platform is related to perform better (correlation of 0.70) when solving exercises, so the cause of an improvement in proficient exercises might not be the use of optional activities by itself.

In order to gain more insight about the results, Table 2

also shows the partial correlation between the same indicators taking out the effect of the rest of the variables considered in the study (i.e., the ones listed in Table 3). After controlling the effect of the rest of the variables, the significant correlation disappears in the case of proficient exercises with feedback and votes, and decreases in the case of proficient exercises with optional activities (0.282), goals (0.250), avatar (0.235) and display badges (0.229). Indeed, these are low levels of relations. Therefore, when removing the effect of other variables, the relation between proficient exercises and optional activities is not so strong. However, there is some relation between optional activities and the amount of proficient exercises, taking out third variables like the effect of total time spent.

According to these results, our hypothesis (which we would like to prove or disprove in further experiments) is that the use of any of the analyzed optional activities by themselves (taking out other important third variables) does not produce any learning gain with proficient exercises (or the effect is low according to the levels of relation) as the percentage of proficient exercises are related to third variables such as the amount of platform usage and time. Therefore, when we take out the effect of these third variables, the relation is weakened a lot. But the use of optional activities might engage students in such a way that they use the platform more and as a consequence might learn more. The optional activities that might engage students more according to these results are avatar, display badges and setting goals. The fact of setting an avatar or display badges might motivate students to do more activities and thus to learn more. In addition, setting goals might engage students to finish them and thus to master the exercises and increase their learning during the interaction with the platform. In addition, it is also possible that the use optional activities might be an indicator of students' engagement and motivation. For example, students who are more motivated and engaged might make use of more optional activities. Indeed, both hypotheses are compatible, i.e., more motivated students might use more optional activities and the use of optional activities might motivate and engage students more.

4.1.5. Relation between optional activities and other indicators

Different relations between the usage of the optional activities and other indicators have been calculated previously [38]. Several of the indicators related to hints have been adapted from [39]. The indicators are the following: exercise and video access, exercise and video abandonment, total time spent in exercises and videos, following of recommendations (the platform recommends an exercise to continue students' training), hint avoidance (not solving an exercise correctly but not asking for hints), hint abuse (asking for too many hints without reflecting on previous ones), video avoidance (not solving an exercise correctly but not watching a related video) and unreflective user (those who submit answers too fast without reflecting on their previous answers).

Table 3 shows the Pearson correlation (N = 291, two-tailed significance) of the optional activities measured

with each of the aforementioned indicators. The correlations that are significant at the 99% level are marked with an asterisk. The data shows that the most significant correlations are with the total time (0.491), and also with the percentage of accessed exercises and videos (0.429 and 0.419). These results make sense as usually the more time a student spends on the platform, the more videos, exercises and optional activities can be done.

In addition, another significant but negative and low correlation exists for exercise and video abandonment (-0.259 and -0.155). This negative correlation means that users who abandon exercises and videos use a bit less optional activities than others.

Finally, the results indicate that other behavioral indicators (following recommendations, video and hint avoidance, hint abuse and unreflective user) are not significantly correlated to the use of optional activities. We found that there is no relation between the follow recommendations profile and using the optional activities, although we initially thought that there could exist a relation due to the fact that the use of optional items can be regarded as an exploring behavior.

TABLE 2
CORRELATION AND PARTIAL CORRELANTION OF THE PERCENTAGE OF PROFICIENT EXERCISES WITH OPTIONAL ACTIVITIES

Pearson Correlation. Proficient exercises sig. (2-tailed) N = 291	**Optional activities:** 0.553* (p=0.000)	**Goal:** 0.384* (p=0.000)	**Feedback:** 0.205* (p=0.000)
	Vote: 0.243* (p=0.000)	**Avatar:** 0.415* (p=0.000)	**Display badges:** 0.418* (p=0.000)
Partial Correlation. Proficient exercises sig. (2-tailed) N = 291	**Optional activities:** 0.282 (p=0.000)	**Goal:** 0.250 (p=0.000)	**Feedback:** - 0.040 (p=0.498)
	Vote: - 0.031 (p=0.605)	**Avatar:** 0.235 (p=0.000)	**Display badges:** 0.229 (p=0.000)

(*): Correlation is significant at the 0.01 level (2-tailed)

(***): Controlling for the all the variables considered in the study

TABLE 3
BIVARIATE PEARSON CORRELATION OF OPTIONAL ACTIVITIES WITH OTHER INDICATORS

	Exercises accessed:	Videos accessed:	Exercise abandonment:	Video abandonment:	Total time:
Optional activities sig. (2-tailed) N = 291	0.429* (p=0.000)	0.419* (p=0.000)	-0.259* (p=0.000)	-0.155* (p=0.008)	0.491* (p=0.000)
	Hint abuse:	**Hint avoider:**	**Follow recommendations:**	**Unreflective user:**	**Video avoider:**
	0.089 (p=0.131)	0.053 (p=0.370)	-0.002 (p=0.972)	0.039 (p=0.507)	-0.051 (p=0.384)

(*): Correlation is significant at the 0.01 level (2-tailed)

TABLE 4
LOG LINEAR ANALYSIS

Used goal?	Used feedback?	Used vote?	Used avatar?	Used display badges?	Observed Count	%
No	No	No	No	No	371	76.8%
No	No	No	No	Yes	20	4.1%
No	No	No	Yes	No	14	2.9%
No	No	No	Yes	Yes	14	2.9%
No	No	Yes	No	No	15	3.1%
No	Yes	No	No	No	8	1.7%
Yes	No	No	No	No	5	1.0%
Yes	No	No	Yes	Yes	7	1.4%

4.1.6. Comparison of optional activities with other categorical variables

We compared the use of optional activities with other categorical variables by cross-tabulating the different results, i.e., by using contingency tables. The categorical variables we have used in this analysis are gender, the course and the separate use of each optional activity defined as 'yes' or 'no' per each student. Whether the established relation is really significant can be calculated by applying the Pearson Chi-Square Test for categorical data. If the expected count assumptions (the expected count of each cell must be above five) of the Pearson Chi-Square are not met, we can apply the Fisher's Exact Test.

The first cross tabulation is established between gender and the use of the different optional activities. Results reveal that women more often used goals, avatar and badge display whereas men used feedback and vote activities more often. However, the Pearson Chi-Square Test shows that the only significant relation is the one with feedback use. The test indicates (with a value of 2.80, $p = 0.048$) that it is statistically significant that men use the feedback activity more than women; the minimum expected count in each cell is higher than five, so the Pearson Chi-Square Test assumption is fulfilled for this case. The participation and other differences in web-based learning environments by gender have also been addressed in other works (e.g. [40], [41]).

The second analysis takes the course and the use of the different optional activities into account. The results reveal that chemistry is the course where feedback and votes were used the most whereas mathematics is the course in which goals, avatar and badge display were used the most. Furthermore, physics is the course that made the least use of optional activities. In order to know which of the results are significant, we applied the Fisher's Exact Test whose assumptions are met (as the Pearson Chi-Square Test assumption of a minimum count of five is not given). The test shows (6.58, $p = 0.034$) that the relation between course and goal is significant, so it is statistically significant that mathematics is the course where goal-activity is used most. In addition, the relation between the use of votes and the course is also significant (7.74, $p = 0.019$), where chemistry is the course that used votes the most. Therefore, the type of course can imply a different use of optional activities.

The last analysis carried out is that between all the categorical variables that represent the use of each optional activity. To this end we chose a log linear analysis which allows the comparison of three or more categorical variables in order to determine if there is an association between two or more of them. The factors of the test are the use of each optional activity separately (yes or no) for each student. Table 4 shows the cell count of a log linear analysis of only those associations where the observed count is above or equal to 1% of the cases.

Table 4 allows us to see which ones are the most typical associations in percentage. The higher counts are the use of display badge (4.1%), the use of avatar (2.9%), the use of both display badge and avatar (2.9%) and the use

of votes (3.1%). The data indicate that there are probably underlying associations between the use of these activities, consequently we check other tests to see if it is really significant. The z-score values show that the most significant relations are between the use of avatar and display badges ($z = 2.68$, $p = 0.007$), between the use of feedback and votes ($z = 2.26$, $p = 0.008$) and also between the use of goal and avatar ($z = 2.1$, $p = 0.036$). These results make sense because an association between the use of avatar and display badge is related to activities that come from customizing your personal profile, and the association between the use of feedback and votes are activities related to participation in a forum. In addition, there is a three-way significant relation between the use of goals, avatar and display badge ($z = 1.96$, $p = 0.05$), which is also interesting because these three activities are related to gaming or social networks environments.

4.2. Second experiment 2014/2015

The second experiment aimed at exploring the relation between learning achievement (with learning gains) and the use of optional activities. As our prior research revealed that there are some variables that might have a relation with optional activities such as resources accessed, total time, or proficient exercises we calculated here partial correlations controlling the rest of variables that were explored in the first study. Additionally, we provide the Pearson correlation without taking out the reset of variables so that a comparison can be established. Table 5 illustrates both correlations. The Pearson correlation shows that there are significant relations at 99% between learning gains and use of vote (0.333, p=0.005) but not with others. However, the level of relation might be due to third variables, such as for example the total time spent or proficient exercises that had a moderate/high correlation with optional activities in the first experiment. For example, the more time a student spent on the platform, the more probable it is that he/she votes or changes the badges, does more activities of all the types and thus learns more. Table 5 also presents the partial correlation of learning gains and optional activities taking out the variables considered in the previous experiment. The objective is to remove the possible influence of the other variables to better understand the relation of learning gains and optional activities. When removing the effect of the other variables in the partial correlation, there are no significant relations between optional activities and learning gains at 99%. In fact, only taking out the total time variable for the partial correlations is already sufficient to make the relation not significant. In addition, the total time spent in the platform and learning gains are significantly correlated (0.391, p=0.001).

A possible explanation for these results is that doing optional activities by themselves does not lead to learning gains. In addition, a possible explanation is that doing optional activities does not really lead to achieving proficiency in exercises (apart from some small correlations according to the results from the previous experiment). However, the use of optional activities might bring motivation for students, e.g., setting up badges or displaying

an avatar might make students feel better, setting goals might motivate students to finish them, or making votes and giving feedback might make students feel as a part of the community. Therefore, although these optional activities might not have a direct effect on proficiency on exercises and learning gains, the fact of making these activities might have the potential to motivate more students to devote more time on the platform and to learn more. These new hypotheses resulting from the conclusion will need to be clarified in further experiments.

TABLE 5
BIVARIATE PEARSON CORRELATION AND PARTIAL CORRELATION OF LEARNING GAINS WITH OPTIONAL ACTIVITIES

Pearson Correlation. Learning gain sig. (2-tailed) N = 69	Optional activities: 0.293** (p=0.015)	Goal: 0.102 (p=0.406)	Feedback: 0.219 (p=0.071)
	Vote: 0.333* (p=0.005)	Avatar: 0.221 (p=0.068)	Display badges: 0.296** (p=0.013)
***Partial Correlation. Learning gain sig. (2-tailed) N = 69	Optional activities: 0.142 (p=0.260)	Goal: - 0.070 (p=0.581)	Feedback: 0.124 (p=0.323)
	Vote: 0.214 (p=0.087)	Avatar: 0.170 (p=0.176)	Display badges: 0.261 (p=0.036)

(*): Correlation is significant at the 0.01 level (2-tailed)
(**): Correlation is significant at the 0.05 level (2-tailed)
(***): Controlling for the all the variables considered in the study

5 CONCLUSIONS

In this work, we analyzed the use of optional activities in a SRL environment using real data from experiments in the Khan Academy platform from several different courses. Results indicate that the use of the optional activities under the conditions of the experiment (the use of the platform was not mandatory and instructors did not inform their students about the optional activities) has been very low, so they are underused. This is also evident looking at the high difference of use between regular learning activities and the optional ones. Therefore, we would recommend telling the students about the availability of optional activities or tools for future experiments or other actions in order to promote the use of these optional activities.

Additionally, results show that the optional activities that were used the most are not related to learning (avatar and display badges). This might be due to them requiring less effort, and we would thus recommend instructors to specially encourage students to use optional activities related to learning such as feedback, votes, or goals.

Other interesting findings are that more than half of the goals that were set by students were finished and that most of the students' votes to their peers were positive. This indicates that students tend not to give up on their own goals once they set them up. Moreover, positive votes are nice since they can reinforce other peers. There might be cases, however, where a fair judgement by fellow students is needed and neutral or negative voting should be encouraged to support the learning process.

The relation mining analysis revealed that there are no significant relations between behavioral indicators and optional activities. This might be surprising, e.g., in the case of the recommender/explorer profile since students that do not follow the recommendation of exercises in the platform might have used the optional activities more, but this was not the case.

In addition, the relation mining analysis showed a significant correlation of optional activities with proficient exercises (i.e., proficiency in exercises), as well as of optional activities with learning gains using a pre-/post-test design. However, this analysis also indicates that the use of optional activities is significantly related to the total time spent in the platform and the progress in exercises and videos. The learning gains or high percentages of proficient exercises might not be caused by the use of the optional activites but might be due to other variables such as the time spent on the platform. If partial correlations are used to take out the effect of third variables such as the time spent in the platform, then the relation of optional activities with proficient exercises or with learning gains is not statistically significant or is low. This implies that doing optional activities does not seem to produce learning by itself. However, we hypothesize that the use of optional activities is an indicator of engagement and motivation and it can also engage and motivate students and makes students spend more time on the platform, doing more activities, etc., so that students then master more exercises and increase learning gains and proficient exercises. Therefore, the use of optional activities might not have a direct effect on learning but an indirect effect, generating motivation and motivation implying better learning as supported in previous works. The hypothesis needs to be clarified in future work.

It is also interesting to note how the level of relation of optional activities is higher with proficiency in exercises

rather than with learning gains. This can be explained because by it being easier to get the proficiency in some exercises rather than increasing the learning gain by solving several questions correctly in the post-test.

Finally, the categorical variable analysis revealed that there are several statistically significant co-occurrence associations; for example between the use of both display badge and avatar which come from the games context, and also the use of both feedback and votes which are related to forum activities. This could be used to cluster students or divide them in groups with similar preferences. Moreover, results showed that women more often use goals, avatar and badge display whereas men use feedback and vote activities more often. In addition, the type of course has also an influence in the type of optional activities that are used, as can be derived from the differences among mathematics, physics and chemistry in this course. The number of votes in the chemistry course is considerable greater than in the other courses, but the difference in the number of messages where voting is possible is not so high among courses as indicated by the feedback parameter. An hypothesis is that this might indicate that students need more help on videos in the chemistry course and students valued more these comments on videos in that course because the comments were helpful. In addition, goal activity was more used in the mathematics course. The interpretation of this result is not straightforward but we might hypothesize that students might set more goals when the topics are more theoretical (such as in mathematics) than practical.

However, despite several significant results and conclusions, some of the results are the discovery of hypotheses and more work is required to confirm the hypotheses discovered in this research. Furthermore, as already pointed out when discussing the results, some correlations presented in this paper might be spurious correlations, i.e. they might be caused by one (or more) additional factors. Finally, the studies were observational, thus, we cannot conclude on any causal relationships. Therefore, controlled experiments (e.g., randomly dividing students into two groups with one using optional activities and another without using them) should be designed in order to analyse the effect of optional activities on the students' motivation as well as on their learning gains and proficient exercises. In addition, another interesting line of future work might be to review the optional activities available in other VLEs and formulate a common framework.

We encourage other researchers to replicate this experiment with a similar set up. The general idea is to have a learning experience where on the one hand, students clearly know which are the mandatory learning activities, and where on the other hand, some optional activities are enabled. Students can be informed about these optional activities or not. Examples of optional activities that can be used are the ones utilized in this research, but also others such as wikis, glossaries, optional exercises or forum activity. Instructors and researchers can afterwards compare the use of mandataroy learning activities with optional activities, and also explore the relationship of optional activities with indicators related to the learning process.

REFERENCES

[1] A. L. Dyckhoff, V. Lukarov, A. Muslim, M. A. Chatti, and U. Schroeder, "Supporting action research with learning analytics," *Proc. Third International Conference on Learning Analytics and Knowledge*, pp. 220-229, 2013

[2] T. Sitzman and K. Ely, "A Meta-Analysis of Self-Regulated Learning in Work-Related Training and Educational Attainment: What We Know and Where We Need to Go," *Psychological Bulletin*, vol. 137, no. 3, pp. 421-442, 2011

[3] R. Carneiro, P. Lefrere, K. Steffens, J. Underwood. *Self-Regulated Learning in Technology Enhanced Learning Environments. A European Perspective*. TECHNOLOGY ENHANCED LEARNING Vol. 5, Sense Publishers, Rotterdam, 2011

[4] S.B. Follows and B. Scott, "Virtual Learning Environments," *THE Journal, Technological Horizons In Education* vol. 27, no. 4, pp. 2011

[5] H.F. O'Neil and R.S. Perez. *Web-Based Learning: Theory, Research, and Practice*. Routledge, 2006

[6] M. Keppell, K. Souter and M. Riddle. *Physical and Virtual Learning Spaces in Higher Education: Concepts for the Modern Learning Environment*. Hershey, PA: IGI Global, 2011

[7] S. Ryan, B. Scott, H. Freeman and D. Patel. *The Virtual University: The Internet and Resource-Based Learning*. Routledge, 2012

[8] B.J. Zimmerman and D.H. Schunk. *Self-regulated learning and academic achievement: Theory, research, and practice*. New York: Springer, 1989

[9] B.J. Zimmerman and D.H. Schunk. *Self-regulated learning and academic achievement: Theoretical perspectives* (2nd ed.). Mahwah, NJ: Erlbaum, 2001

[10] B.J. Zimmerman and D.H. Schunk. *Handbook of Self- Regulation of Learning and Performance*. NY: Routledge, 2011.

[11] M. Boekaerts, P.R. Pintrich and M. Zeidner. *Handbook of Self-Regulation*. San Diego, CA: Academic Press, 2000

[12] P.H. Winne, "A cognitive and metacognitive analysis of self-regulated learning". In B. J. Zimmerman & D.H. Schunk (Eds.), *Handbook of self-regulation of learning and performance* (pp. 15–32). New York: Routledge, 2011.

[13] P.H. Winne, "Self-regulated learning". In J. D. Wright (Ed.), *International encyclopedia of social & behavioral sciences (Vol. 2)*. Oxford: Elsevier, 2014.

[14] P.H. Winne and R.S.J.D. Baker, "The Potentials of Educational Data Mining for Researching Metacognition, Motivation and Self-Regulated Learning," *Journal of Educational Data Mining* vol. 5, no. 1, pp. 1-8, 2013

[15] J. Kay, "Learner control," *User Modeling and User-Adapted Interaction*, vol. 11, pp. 111-127, 2001

[16] K. Steffens, "Self-Regulated Learning in Technology-Enhanced Learning Environments: lessons of a European peer review,"

European Journal of Education, vol. 41, no. 3/4, pp. 353-379, 2006

[17] P.R. Pintrich, "A conceptual framework for assessing motivation and self-regulated learning in college students," *Educational Psychology Review*, vol. 16, pp. 385-407, 2004

[18] P.R. Pintrich, "The role of goal orientation in self-regulated learning". In M. Boekaerts, P.R. Pintrich and M. Zeidner (Eds.), *Handbook of Self-regulation*. San Diego, CA: Academic Press, 2000

[19] D. Schön. *The reflective practitioner: How professional think in action*. London, UK: Temple Smith, 1983

[20] G. Bolton. *Reflective practice: Writing & professional development (3rd ed.)* London, UK: Sage, 2010

[21] J.A. Greene, D.C. Moos, R. Azevedo, "Self-Regulation of Learning with Computer-Based Learning Environments," *New Directions for Teaching and Learning*, vol. 2011, no. 126, pp. 107-115, 2011

[22] L. Kyriakides, C. Christoforou and C. Charalambous, "What matters for student learning outcomes: A meta-analysis of studies exploring factors of effective teaching," *Teaching and Teacher Education*, vol. 36, pp. 143-152, 2013

[23] C. Hart, "Factors Associated With Student Persistence in an Online Program of Study: A Review of the Literature," *Journal of Interactive Online Learning*, vol 11, no. 1, pp. 19-42, 2012

[24] C. Wankel and P. Blessinger. *Increasing Student Engagement and Retention using Online Learning Activities: Wikis, Blogs and Webquests*. Emerald Group Publishing, 2012

[25] J. Hattie. *Visible Learning: A Synthesis of Over 800 Meta-Analyses Relating to Achievement*. Routledge, 2008

[26] V. Aleven, B.M. McLaren, I. Roll, and K.R. Koedinger, "Toward Meta-cognitive Tutoring: A Model of Help Seeking with a Cognitive Tutor," International Journal of Artificial Intelligence in Education, vol. 16, no. 2, pp. 101–128, 2006

[27] P. J. Muñoz Merino, C. Delgado Kloos, R. Seepold, and R. M. Crespo García, "Rating the importance of different LMS functionalities," *Proc. Frontiers in Education Conference, FIE*, 2006, pp. 13–18.

[28] K.R. Koedinger, J. Kim, J.Z. Jia, E.A. McLaughlin, N.L. Bier, "Learning ist Not a Spectator Sport: Doing is Better than Watching for Learning from a MOOC," *Proc. of the the second annual meeting of the ACM Conference on Learning at Scale (L@S '15)*. ACM, 2015.

[29] J. L. Santos, J. Klerkx, E. Duval, D. Gago and L. Rodríguez, "Success, activity and drop-outs in MOOCs an exploratory study on the UNED COMA courses," *Proc. Fourth Int. Conf. Learn. Anal. Knowl.*, pp. 98–102, 2014.

[30] C.K. Cheng, D.E. Par, L.M. Collimore and S. Joordens, "Assessing the effectiveness of a voluntary online discussion forum on improving students course performance," Computers & Education, vol. 56, no. 1, pp 253-261, 2011

[31] D. Gašević, N. Mirriahi, and S. Dawson, "Analytics of the effects of video use and instruction to support reflective learning," *Proc. of the Fourth International Conference on Learning Analytics And Knowledge - LAK '14*, pp. 123–132, 2014

[32] D. Coetzee, A. Fox, M. a. Hearst, and B. Hartmann, "Should your MOOC forum use a reputation system?," *Proc. of the 17th ACM conference on Computer supported cooperative work & social computing - CSCW '14*, pp. 1176–1187, 2014

[33] J. Davies and M. Graff, "Performance in e-learning: online participation and student grades," *Br. J. Educ. Technol.*, vol. 36, no. 4, pp. 657–663, 2005.

[34] M. Munoz-Organero, P. J. Muñoz-Merino, and C. Delgado Kloos, "Student behavior and interaction patterns with an LMS as motivation predictors in e-learning settings," *IEEE Trans. Educ.*, vol. 53, no. 3, pp. 463–470, 2010.

[35] K. Brandl, K., "Effects of required and optional exchange tasks in online language learning environments," *ReCALL*, vol. 24 pp. 85-107, 2012

[36] M. J. Lage, G. J. Platt, and M. Treglia, "Inverting the Classroom : A Gateway to Creating an Inclusive Learning Environment Inverting the Classroom : A Gateway to Creating an Inclusive Learning Environment," *J. Econ. Educ.*, vol. 3, no. 1, pp. 30–43, 2000

[37] J. A. Ruipérez-Valiente, P. J. Muñoz-Merino, D. Leony, and C. Delgado Kloos, "ALAS-KA: A learning analytics extension for better understanding the learning process in the Khan Academy platform," *Comput. Human Behav.*, vol. 47, no. Learning Analytics, Educational Data Mining and data-driven Educational Decision Making, pp. 139–148, 2015

[38] P. J. Muñoz-Merino, J. A. Ruipérez Valiente, and C. D. Kloos, "Inferring higher level learning information from low level data for the Khan Academy platform," *Proc. of the Third International Conference on Learning Analytics and Knowledge* - pp. 112–116, 2013

[39] V. Aleven, B. M. Mclaren, O. Roll, and K. Koedinger, "Toward Tutoring Help Seeking ; Applying Cognitive Modeling to Meta-Cognitive Skills," *Proc. Seventh International Conference on Intelligent Tutoring Systems*, pp. 227–239, 2004

[40] A. Caspi, E. Chajut, and K. Saporta, "Participation in class and in online discussions: Gender differences," *Comput. Educ.*, vol. 50, no. 3, pp. 718–724, Apr. 2008

[41] P.J. Muñoz-Merino, M. Fernández-Molina, M. Muñoz-Organero, C. Delgado Kloos, "Motivation and Emotions in Competition Systems for Education: An empirical study," *IEEE Transactions on Education*, vol. 57, no. 3, pp. 182-187, 2014

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