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Driving Student Motivation in MOOCs through a Conceptual Activity-Motivation Framework

Abstract

Massive Open Online Courses (MOOCs) require students' commitment and engagement to earn the completion, certified or passing status. This study presents a conceptual Learning Analytics Activity-Motivation framework that looks into increasing students' activity in MOOCs. The proposed framework followed an empirical data analysis from MOOC variables using different case studies. The results of this analysis show that students who are more active within the offered environment are more likely to complete MOOCs. The framework strongly relies on a direct gamified feedback that seeks driving students' inner motivation of competency.

Keywords

Learning Analytics, Massive Open Online Courses (MOOCs), Motivation, Activity, Framework

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1 Introduction

Distance learning in the form of Massive Open Online Courses (MOOCs) has experienced a quantum leap in the development of open educational resources and educational technology. The main advantage of such courses is that hundreds or even thousands of students can enrol in one course, which normally impossible in a regular classroom setting. The story of MOOCs started with Siemens and Downes' first course in 2008 and reached an early peak with Sebastian Thrun's "Introduction to Artificial Intelligence" course, which attracted more than 160,000 students from all over the world (YUAN & POWELL, 2013). Since then, MOOCs have received significant attention from the media and educationalists for their potential to extend the reach of education via technology.

MOOCs allow anyone to learn and interact through available learning technology-enhanced learning materials and tools such as video lectures, recommended articles, content downloads, discussion forums, assessments, etc. The two popular MOOC models, cMOOCs (connectivism MOOC) and xMOOCs (extended MOOCs), deliver courses at a remarkably large scale in terms of enrollments, diversity of topics and geographical reach. In addition, the characteristics of the open environment of MOOCs bring a distinct range of motivations and beliefs among students (LITTLEJOHN et al., 2016). Assuming the direct interaction between teachers and students does not reach the level of traditional face-to-face classroom lectures, students are forced to organize their own learning. Furthermore, MOOCs differ from the traditional settings in which student engagement varies in objectives. As a result, the need for students to self-regulate their learning, maintain their personal motivation (ZIMMERMAN, 2000), and actively interact with online learning objects (KHALIL, KASTL & EBNER, 2016) becomes crucial.

To increase great learning activities, newly adopted technologies in MOOCs allow researchers to track students' behavior (i.e. what they do and how they learn) by examining stored information about student engagement with different digital learning activities (e.g. videos, discussion forums, and quizzes). The collection of such a high volume of student data transforms the conventional data analytics into so-called "Big Data" analytics. Examining large data sets of student interactions and activities with online learning platforms provides a valuable opportunity to discover patterns and understand student behavior. To that end, there are two approaches for examining data in educational settings: Educational Data Mining (EDM) and Learning Analytics (PAPAMITSIOU & ECONOMIDES, 2014). Relying on data analytics, both approaches share common goals of improving education and optimizing learning environments.

Despite the fact that MOOCs have great benefits, there are corresponding challenges that affect their growth, especially in higher education courses. For instance, keeping students engaged and motivated (KHALIL, TARAGHI & EBNER, 2016; XU & YANG, 2016), the high attrition rate, the boring pedagogical design (STACEY, 2014). Being on the same track, Learning Analytics shows great potential when meets MOOCs (KNOX, 2014). The key benefits of Learning Analytics in connection with MOOCs are embodied in predicting, visualizing, recommending, personalizing, saving costs, and improving students' engagement (SIEMENS & BAKER, 2012; KHALIL, TARAGHI & EBNER, 2016).

In this research study, we aim at preserving students' engagement (and participation) within the MOOC sphere. Based on the empirical data from the Austrian MOOC platform, iMooX (http://www.imoox.at), this study proposes a framework to improve students' activity by examining various MOOC indicators. The article is outlined along the following hypothesis and research question:

- Hypothesis: *There is a relation between MOOC learning activities a student performs and his/her retention till the end of the MOOC.*
- RQ: *How could we motivate MOOC students to stay active during the MOOC?*

The paper begins with a literature review on Learning Analytics and Learning Analytics of MOOCs as well as the related topics of students' motivation and activity. After that, we describe the used methodology to validate the hypothesis and answer the research question with a description of the investigated dataset and its analysis. Further, the proposed Activity-Motivation module that describes our scheme of motivating students is discussed. At the end of the article, the key findings are summarized.

2 Related Work

In order to provide the context of this study, this section gives a brief literature review of Learning Analytics and Learning Analytics of MOOCs, and reads previous studies of motivation and activity in online learning environments.

2.1 Learning Analytics

The prominent field of Learning Analytics has been widely discussed since the first international conference on Learning Analytics and Knowledge in 2011 (LAK'11). While there were a plethora of definitions describing its objectives, the Learning Analytics community has agreed to finally define it as "*…the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs*" (SIEMENS ET AL., 2011). Learning Analytics uses the generated data from students in order to discover patterns and develop insights into their behaviors. The borderless Internet and the increasing demand to reduce attrition as well as enhance learning environments and learning are considered to be the major driving factors behind the emergence expansion of this field (SIEMENS et al., 2011; PAPAMITSIOU & ECONOMIDES, 2014; KHALIL & EBNER, 2016a).

Acquiring and analyzing students' data are no more than two stages that open an iteration loop in the holistic Learning Analytics lifecycle. According to Doug Clow (2013) paper "*The Learning Analytics Cycle: Closing the loop effectively*", Learning Analytics loop should be closed in a way to invest the analysis phase outcome with proper action(s). Provided that, Learning Analytics encompasses four main phases (KHALIL & EBNER, 2015): a) learners generate data, b) data gets processed, c) results get interpreted, and finally d) actions are optimized.

2.2 Learning Analytics of MOOCs

Software and online platforms are usually supported by event recording systems, called log files. MOOC platforms are online approaches that are set up using Internet programming languages such as HTML or JavaScript. MOOCs' log files record every event happening on the platform and on that basis, Learning Analytics applications of MOOCs are developed to mine and interpret such data in order to intervene or predict actions (KHALIL & EBNER, 2016a).

Despite their great advantages in online learning, MOOCs face challenges of dropout, disengagement, and lack of motivation (KHALIL & EBNER, 2016b). For such purposes, researchers were looking into finding adequate algorithms, tools, or elements to surpass MOOC issues. There are various research studies and topics regarding Learning Analytics and MOOCs. For example, Kizilcec and his colleagues focused on engagement among students in MOOCs (KIZILCEC, PIECH & SCHNEIDER, 2013). They developed a classification model to identify a small number of longitudinal engagement trajectories. Another study about engagement is based on the examination of assignments and video lecture views (ANDERSON et al., 2014). The authors clustered MOOC students into five subpopulations: Viewers, Solvers, All-Rounders, Collectors, and Bystanders.

Other research studies utilized Learning Analytics to detect and intervene before a student drops out of the course. For instance, a recent study by XING et al. (2016) developed a mechanism to detect at-risk students through their activity in discussion forums. The researchers used the decision tree as an Educational Data Mining technique for building the at-risk detection algorithm. Researchers from HTW Berlin were able to predict students' success based on MOOC discussion forum by building student profiles (KLÜSENER & FORTENBACHER, 2015).

2.3 Student Activity and Motivation

Recent work on MOOCs revealed a high attrition scale in activities in the first two weeks (BALAKRISHNAN & COETZEE, 2013). The authors reported a 50% dropout at the end of the second week. Some researchers suggested cutting course duration in half (LACKNER, EBNER & KHALIL, 2015). Others pushed the concept of grabbing students' attention by looking into boosting the extrinsic factors such as offering badges, certificates and honor awards (WÜSTER & EBNER, 2016). Researchers from Northeastern University of China have noticed that the activities performed by students in the MOOC platform reflect their motivation (XU & YANG, 2016). The authors concluded a strong relation between someone's behavior and his/her evaluation of excitation. From there, they tried to find a relation between grade prediction and certification ratio along with their activities in the MOOC through a developed classification model. While such prediction might be hard to examine because of the complex nature of the predictive models (KLÜSENER & FORTENBACHER, 2015), others used online surveys and semi-structured interviews to identify learners' motivation (LITTLEJOHN et al., 2016). Further research about understanding the motivation of online learners in MOOCs can be found in the article by Stanford University researchers who listed 13 factors that could captivate learners' motivation (KIZILCEC & SCHNEIDER, 2015). Despite their benefits, online surveys lack the proper target group and might provide inaccurate results.

This study was further influenced by a couple of Learning Analytics applications, which were considered in our proposed framework. One of these tools was Course Signals (ARNOLD & PISTILLI, 2012). It is an application that provides feedback according to the traffic light system. Whenever a green light is shown, it means that the student is on track, whereas the orange and the red lights imply at-risk situations and intervention(s) by either a teacher or an institution would be required.

The literature review described previously is strongly related to our research. By examining engagement and activity either in the discussion forums or video events, this research study leverages the data from MOOC variables to preserve students' activities and motivate them to stay engaged. The existing literature, however, provides very little research in regards to direct Learning Analytics feedback for students on MOOC platforms. Despite the fact that showing statistics or gamification elements to students is usually obtainable in most online environments as a motivation factor, to the best of our knowledge, we could rarely find a module that looks at preserving students' activity in MOOCs and providing them a direct feedback.

3 Methodology

Our methodology focused on obtaining data from the following MOOC variables: watching video lectures, login frequency, posts in forum, reading of forum posts, and quizzes in order to identify a *competent activity level*. Henceforth, an analysis that includes finding patterns in visualizations and an examination using exploratory analysis on empirical data was conducted. Data collection was performed using the iMooX Learning Analytics Prototype (iLAP). iLAP is a Learning Analytics application developed to track students on the iMooX MOOC-platform to improve online learning and to provide a rich repository of data for research purposes (KHALIL & EBNER, 2016a). When students log into the MOOC platform, the database starts to be filled with low-level data related to students' performance and behavior. Every action performed is recorded, saved and filtered for a large scale processing phase. We followed the content analysis methodology (NEUENDORF, 2002), in which these variables were measured and referenced to answer the research questions. The study also employed WANG and HANNAFIN's (2005) design-based research methodology that depends on identifying goals, collecting data during the whole design process, and refining according to the required goals.

3.1 Dataset Description

iMooX MOOC-platform offers various courses which target people from German speaking countries from secondary school level to Higher Education and beyond. As a case study, we have chosen a MOOC called "Gratis Online Lernen" which translates to "Free Online Learning", abbreviated in this article as GOL-2014 and GOL-2015 (EBNER, SCHÖN & KÄFMÜLLER, 2015). The course has been offered in a continued series in the years: 2014 and 2015, and educates people about using the Internet for learning. The MOOCs duration was set to be 8 weeks with a workload of 2 hours/week (in total, 16 hours). Students had to score 50% in every weekly quiz in order to pass. The MOOC platform offers self-assessment quizzes in which every test can be repeated up to five times with a systematic approach to consider the highest grade out of the attempts.

The main content of the courses were video lectures with an average duration of 5 minutes per video. Students were rewarded with certificates after they successfully passed all the quizzes.

4 Dataset Analysis

In this section, we try to validate the questioned hypothesis by examining whether the certified students show more activity using MOOC variables (forums and videos). For this purpose, we chose to analyse the following three MOOC variables: posts in forum, views in forum and video lectures for MOOCs GOL-2014 and GOL-2015. We split the students into two categories: *certified* and *non-certified*. The first group includes those who completed a MOOC and therefore received a certificate at the end of the course, while the second group includes the students who dropped out of the MOOC at any time during the course. The certified students in GOL-2014 and GOL-2015 were (*N*= 193, *N*= 117) respectively, while the non-certified students in GOL-2014 and GOL-2015 were (*N*= 810, *N*= 359). The analysis results in the following subsections proved that learning activities have quite an impact on students to persist in a massive open online course.

4.1 Forum Readings Analysis

During the 8 weeks of forum discussions, there were 22,565 views of forum threads in GOL-2014 and 8,214 views of forum threads in GOL-2015. Figure 1a and figure 1b show the average number of thread views for both MOOCs. The difference between the reading activity of the two groups is quite obvious. Figure 1a depicts a maximum number of reads in week 1 for both groups, which rapidly drops until week 4. This follows the condition that attrition rate becomes more stable after the first four weeks of a MOOC (LACKNER, EBNER & KHALIL, 2015). However, in figure 1b, we realized that certified students' forum views escalated in week 5 and then dropped to around 4 views per user till the end of the MOOC. A study by Wong and his colleagues recorded similar student behavior (WONG et al., 2015). The authors unveiled that active users showed higher activity after the first weeks of the MOOC.

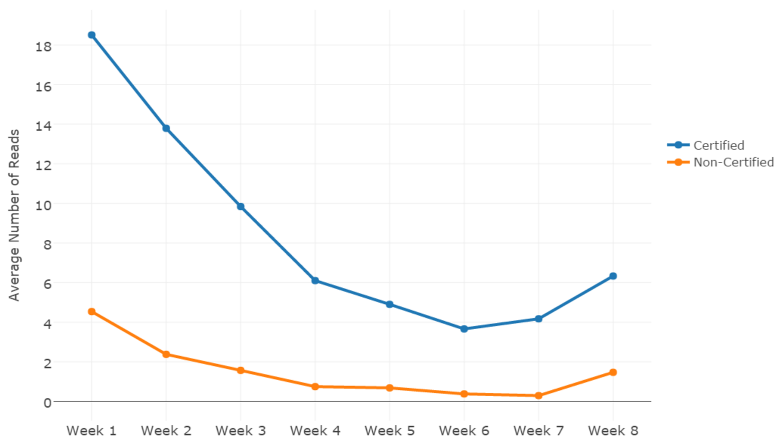

Figure 1a: The average number of discussion forum views in GOL-2014 MOOC

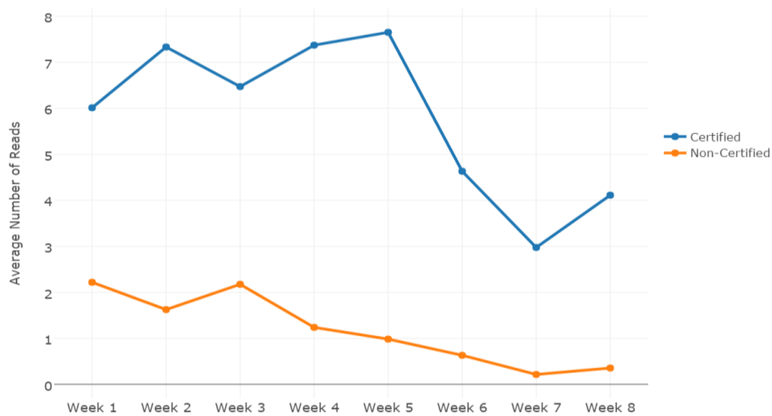

Figure 1b: The average number of discussion forum views in GOL-2015 MOOC

4.2 Forum Posts Analysis

In total, in GOL-2014 there were 828 and in GOL-2015 there were 408 posts written in the respective forum. These posts took the forms of comments, threads, and replies. Figure 2a and Figure 2b illustrate the average number of written posts in both MOOCs forums.

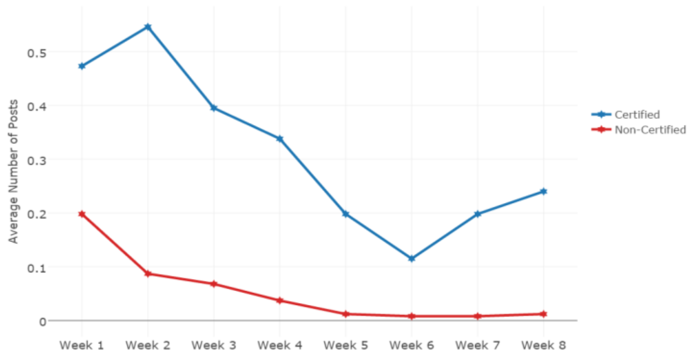

Figure 2a: The average number of discussion forum posts in GOL-2014 MOOC

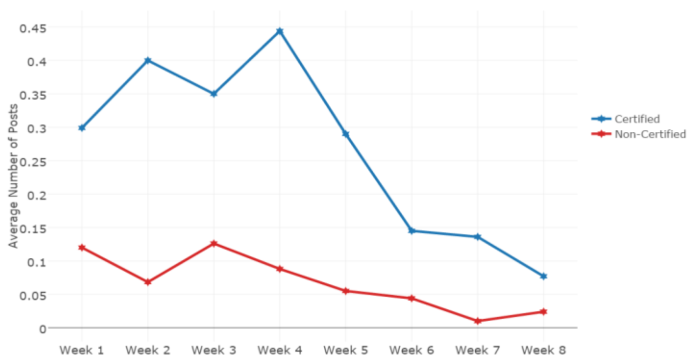

Figure 2b: The average number of discussion forum posts in GOL-2015 MOOC

In fact, it is apparent that certified students are more active in posting and commenting in MOOC forums. In Figure 2a, the average number of contributions is very low after the fourth week. There are various reasons for this, such as the steep drop out rate after the first weeks (see Figure 3), or the low motivation to contribute and comment (MANNING & SANDERS, 2013).

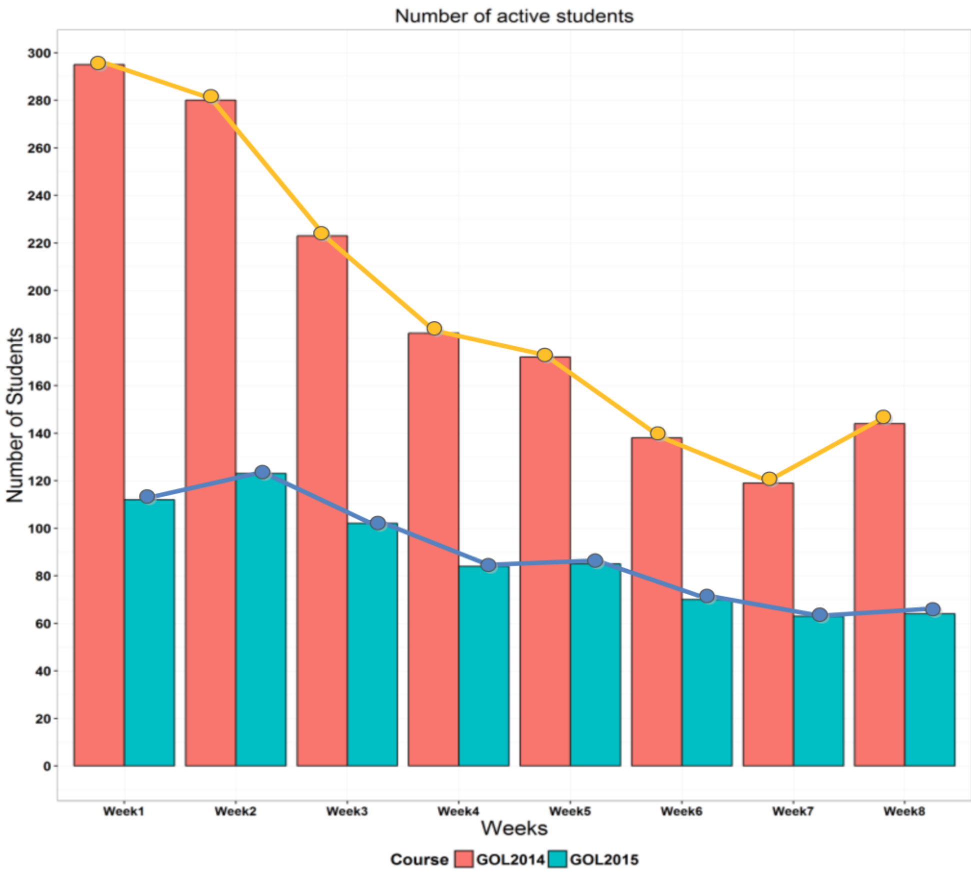

Figure 3: Remarkable activities attrition after the first weeks of the GOL-2014 and GOL-2015 MOOCs

4.3 Video Lectures Analysis

The third MOOC variable we analyzed was video lectures. Video content was hosted on YouTube; however, the iLAP can only mine events of participants using play and pause/stop that happen on the iMooX platform. We summed up the total number of video interactions and showed the average number of events (play, pause, and full-watch) per week. There were 17,384 video events in GOL-2014 and 8,102 video events in GOL-2015. Figure 4a and Figure 4b show a graph line of learner interactions in GOL-2014 and GOL-2015.

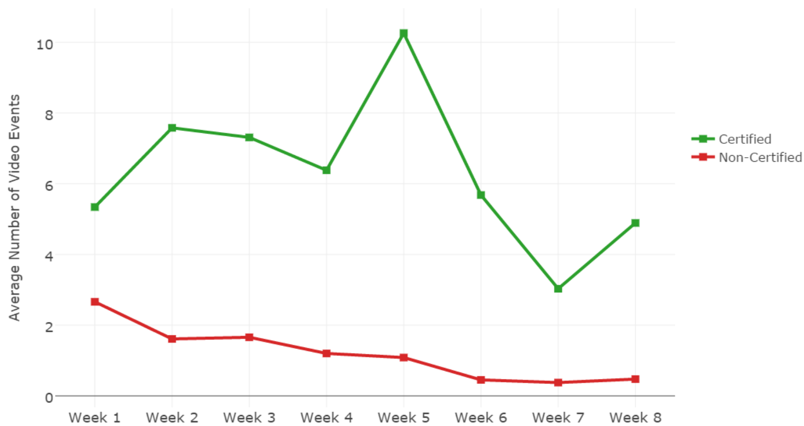

Figure 4a: The average number of video events in GOL-2014 MOOC

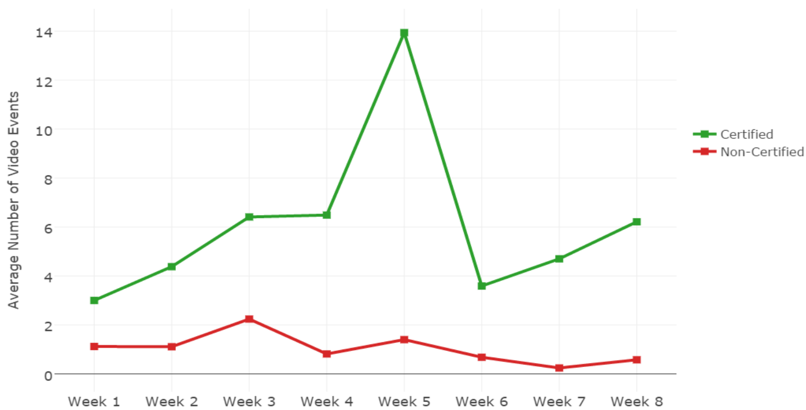

Figure 4b: The average number of video events in GOL-2015 MOOC

The figures displayed above show that the average number of video events of certified students is undoubtedly higher than non-certified students. Non-certified students show weak video lectures activity.

4.4 Data Analysis summary

The seven figures in the previous subsections showed that the active users demonstrated higher activity during the MOOC weeks. With regards to students' forum activities, we found there was an obvious gap between certified and non-certified students that made us consider the first hypothesis. Motivated students are more likely to engage in discussion forums (LACKNER, EBNER & KHALIL, 2015). Gilly Salmon identified four learner strategies in online discussions: (1) "Some do not try to read all messages." (2) "Some remove themselves from conferences of little or no interest to them, and save or download others." (3) "Others try to read everything and spend considerable time happily online, responding where appropriate." (4) "Yet others try to read everything but rarely respond." (SALMON, 2007). The data presented in sections 4.1 and 4.2 corresponds to Salmon's learner types 1, 2 and 4. Non-active students do not ask questions or comment in the forums. Presumably, certified students are more likely to post questions to ask a teacher or colleague for help which means they are more active in forums.

The video analysis also showed the difference between certified and non-certified students. As MOOCs rely on videos, students need to watch them in order to pass quizzes. Thus, active students who want to pass quizzes need to watch videos, except for some cases where students try to game the MOOC system (KHALIL & EBNER, 2016c).

5 Proposed Activity-Motivation Framework

According to the previous analysis results and the impact of activities on students' motivation to complete a MOOC, we propose an Activity-Motivation framework to motivate learners to do more activities. We designed this framework in correspondence to the iMooX MOOC-platform's potential of offering variables such as quiz attempts, logins, forum posts and views, and the tested empirical data in section 4. The Activity-Motivation framework intends to assist in increasing students' motivation and engagement.

Figure 5: The Activity-Motivation framework

The proposed model is shown above in Figure 5 and consists of four main dimensions. Each of the dimensions contributes with a portion to a gamification element. Our choice of such items was a battery as we believed it expresses a “filling up” animation. We thought that what happens to a battery is similar to what a student does with the MOOC activities. We aim to keep the students charged with activity, motivation, and incentive. Gamification elements have a positive impact on student motivation and learning (GONZALEZ, TOLEDO & MUNOZ, 2016).

The four dimensions of the proposed framework are: login, video, quiz, and forum. It is worth noting that these dimensions can be extended and are not exhaustive to the ones listed. For instance, extra dimensions involve readable content such as a downloadable article or assignments, can be included when required. The gamification element was divided into four segments based on the number of selected MOOC variables. The proposed Activity-Motivation model can be implemented as a plugin or as an independent tab on the MOOC page and would be updated on a weekly-basis. In the following paragraph, we will briefly elaborate on the model and describe its mechanism. As seen below, each element counts for a 25% charged portion in the battery:

- *Login:* When a student logs into the MOOC, he/she will reflect relatively on the gamification element (battery). The first segment of the battery will be 25% charged. Several logins will not increase the charged portion.
- *Video:* The second dimension is the video lecture. When a student interacts with the MOOC video lectures and completes a number of predefined events the battery is charged a bit further.
- *Quiz:* The battery will be filled with one extra portion when a student does a quiz. As previously described, iMooX MOOC-Platform allows each student to try the every weekly quiz up to five times. However, just one trial would be enough to indicate that the student is active. Identical to the previous dimensions, several attempts will not increase the battery's charged portion.
- *Forum:* The analysis in sections 4.1 and 4.2, showed the relation of discussion forums and student activity. Being engaged in the forums either by writing or reading threads will increase the battery charging portion.

6 Discussion and Conclusion

Massive Open Online Courses (MOOCs) are a new trend in the domain of Technology-Enhanced Learning. Higher Education institutions have come under pressure to adopt an accessible and open educational environment. MOOCs provide such an opportunity, yet, there are issues regarding drop-out rate, engagement with MOOC elements, the interaction between students and instructors as well as motivation. On the other hand, Learning Analytics offers techniques and tools to predict and intervene to enhance both the learning and the educational environment.

In this research study, we utilized analysis techniques on students' data in order to investigate the hypothesis of the relation between students' activities and retention in MOOCs. We found that certified students, who got certificates at the end of the course, participated in more activities than the non-certified students. Certified students engaged more in discussion forums; they viewed more forum posts and wrote more frequently than non-certified students. Additionally, they often interacted more with video lectures. In fact, the seven figures in section 4 show that the active users demonstrated higher activity during the MOOC weeks. As a result of that, we became quite certain of the hypothesis that the more activities are done, the more likely the students are to complete the MOOC.

Based on the validation of this hypothesis, we proposed an Activity-Motivation model with the aid of Learning Analytics techniques and a gamification element. The framework was built on the previous analysis results in this study using the inheritance of MOOC indicators. The proposed framework can be extended with extra MOOC indicators and is easy to implement and adopt in similar MOOC platforms. While we agree that the didactical approaches and the intrinsic factors of MOOCs can affect students' motivation, we also strongly believe in the need to develop such a model to stir students' motivation of competency.

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