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Can Feedback based on Predictive Data Improve Learners' Passing rates in MOOCs? A Preliminary Analysis

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ABSTRACT
This work in progress paper investigates if timely feedback increases learners' passing rate in a MOOC. An experiment conducted with 2,421 learners in the Coursera platform tests if weekly messages sent to groups of learners with the same probability of dropping out the course can improve retention. These messages can contain information about: (1) the average time spent in the course, or (2) the average time per learning session, or (3) the exercises performed, or (4) the video-lectures completed. Preliminary results show that the completion rate increased 12% with the intervention compared with data from 1,445 learners that participated in the same course in a previous session without the intervention. We discuss the limitations of these preliminary results and the future research derived from them.

Author Keywords
MOOC; Self-regulated Learning; Feedback; Prediction.

CSS CONCEPTS
Applied computing: Education: e-Learning; Applied computing: Education: Distance Learning

INTRODUCTION
Although the number of learners in Massive Open Online Courses (MOOCs) grows daily [1], many committed learners still struggle to complete them and achieve their learning goals [6]. One of the main reasons is related to the openness and flexible nature of these courses, where learners do not necessarily receive the guidance and support from teachers, unlike other online traditional settings [17]. This is why MOOC learners need self-regulated skills for planning, developing, and monitoring their learning process autonomously [10][11].

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However, recent work shows that most learners experience several difficulties for engaging the course, including those learners with high intrinsic motivation in the course and good self-regulated skills [2]. Among the most common difficulties, studies refer to the lack of time [2, 3, 4] and the lack of timely support [3, 5]. Prior studies show that timely feedback is one of the key elements to assist students [7], proving them with support to persist in their learning process [8]. According to Shute [9], feedback should be used to reduce the gap between learners' current performance and the desired performance level or learning goal. Further planning strategies and timely feedback are, therefore, necessarily to reduce the intention-action gap that affects students' persistence beyond the first weeks of a MOOC. However, providing personalized and timely feedback throughout a MOOC could be challenging due to its large-scale [10] [20].

Researchers in learning analytics have been investigating the use of models and tools for providing timely and goal-oriented feedback. Most of these interventions use dashboards with descriptive analytics showing students' activity in the course. For students, their activity is compared with others for promoting better behaviors, such as Learning Tracker [10] or NoteMyProgress [11], while for teaching staff the dashboards are designed to facilitate teachers' interventions, such as adapting the course design [12][13]. Experimental results with dashboards show that learners exposed to this type of intervention were more successful in the course [10, 11], having managed their time better to accomplish the assessment activities of the course [10].

Other interventions use predictive analytics to propose models that forecast learners' future behavior based on previous data [15] and trigger actions accordingly. However, very few propose interventions using these models [14]. One of these is the study by Cobos et al. [13], which proposes a widget for edX that uses a predictive model for classifying students into cohorts and sends automatic weekly messages to each group. A study evaluated this with 43 students, showing that weekly messages increase learners' interaction with course content and their success rates when comparting with a pre-intervention group of 41 students. The results of this study suggest that messages based on risk predictive models could help students succeed in a MOOC-based environment, but the small data sample does not allow extracting conclusions for further educational settings.

This prior work suggests that some forms of timely feedback improve learners' persistence in MOOCs: (1) the use of dashboards is good approach to facilitate teachers' interventions at scale, (2) providing learners with indicators related with their time management and their course activity improve engagement and success, and (3) predictive models grouping learners according to their risk of abandoning helps scaling up the feedback in large scale situations. In this paper, we evaluate a solution based on this prior work for providing timely feedback in a MOOC.

PILOT STUDY

A pilot study was conducted for assessing the following hypothesis: *H1. Prompting learners with similar drop-out risk in the course with specific feedback improves MOOC passing rate in a (self-paced) MOOC.*

The pilot study was conducted in a 6-week self-paced MOOC about programming in Python of the Universidad Católica de Chile deployed in Coursera. The intervention lasted 7 weeks from 2nd July to 20th August 2020. Two teachers and 2,421 students registered in the running version of the course during the pilot, and they were the main participants. This course was subject to a European Project starting in 2010 focused on using learning analytics in higher education, so data collection protocols were already in place and all participants signed a consent informing that their data could potentially be used for scientific analysis.

Measures

During the pilot, teachers had access to the course and to another web platform called DaP-MOOC specially designed for the study. This tool offers teachers with a dashboard that classifies students into three groups according to their risk of dropping out (Figure 1). The risk is calculated once a week with a model using Random Forest, and several variables are considered: learners' activity (number of active days, total time in the platform and number of sessions), interactions with videos (number and proportion of started, completed and reviewed videos) and interactions with exercises (number and proportion of attempted, completed and passes, and reviewed exercises). The latter group of variables were calculated separately for formative and summative activities. These variables and algorithm were selected based on their high performance in a previous work on dropout prediction [16]. Notice that in this model, students are considered as dropouts when they have a period of inactivity greater than four weeks. The model changed once a week, for accumulating the data collected during the past week.

In addition to the number of students in each group, teachers had also information about their activity in the course through indicators of four types: (Type 1) the average time spent in the platform per learning session (a new learning session is stablished when no activity is detected for a learner for 45 minutes), (Type 2) the percentage of video-lectures completed, (Type 3) the percentage of exercises completed, and (Type 4) total time devoted to the course.

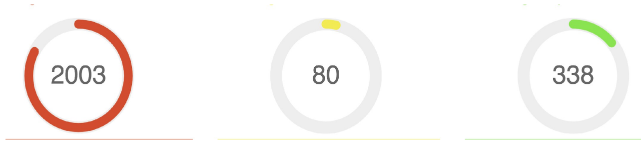

Figure 1: Dap-MOOC Tool showing the distribution of students in group risks of dropping out for the last week of the intervention (Red: High risk; Yellow: Medium Risk; and Green: Low risk).

Teachers also had the possibility of downloading the list of students' IDs in each group and 4 messages templates. The template messages were designed using the recommendations about directive feedback from Shute [9]. A total of 16 messages were proposed, four for each risk group, one per each type of indicator. For students in the high and medium risk groups, the messages included: (1) An explanation of the problem using one of the four indicators depending on the Type of Indicator; (2) A recommendation of how to improve the indicators; and (3) an encouragement sentence to keep going. For students in the low-risk group, four messages of encouragement including indicators about their good performance were included. Details for each message can be found at: https://www.dropbox.com/s/jqxmca09f3xvfl1/FeedbackMessageTemplates-ENG.pdf?dl=0

During the pilot study, one of the two teachers was in charge of sending a message to each group of students following the proposed templates. In total, 18 feedback messages were sent during the pilot (3 per week and per group, except for week 7, in which teachers did not send any message). In total, teachers sent 2 messages of Type 1, 2 (Weeks 1 and 6) messages of Type 2 (Weeks 2 and 7), 1 message of Type 3 (Week 3) and 1 message of Type 4 (Week 5).

Analytical approach

For analyzing the impact of the feedback provided during the pilot study, we compared the trace-data of the participants in the pilot (intervention group, IG) with those participating in the same course at the same period the year before, from 2nd July to 20th August 2019 (pre-intervention group, P-IG). Learners in the P-IG were not exposed to any feedback message from the teachers. We collected information from 2,421 learners for the IG, and 1,454 for the P-IG. In both cases, we selected those participants starting the course the week of the intervention. No information about gender or background was provided by the platform for these learners.

We conducted three preliminary analysis. First, we analyzed the percentage of students passing and dropping out in each group and verified that there was a statistically significant difference between both groups applying a chi-square test. Second, we evaluated and compared the evolution of the different group risks every week for both the IG and the P-IG. For calculating the risk groups each week, we applied the predictive model used by DaP-MOOC for informing the teachers about students' evolution. Finally, using a Markov Model, we computed the probability of transitioning between risk groups from one week to another in each condition.

Students Groups	Dropout	Pass
P-IG (n=1,455)	1,339 (92%)	116 (8%)
IG (=2,421)	2,084 (86%)	337 (14%)

Table 1. Students passing and dropping out in each condition.

PRELIMINARY RESULTS

Two main results were obtained. First, we observe that the percentage of students passing the course in the IG (14%) is higher than in the IG (8%) (with a p-value of 2.39e-08) (see Table 1). Also, we observe the percentage of students who passed the course and were labelled as medium-risk in week 1 was higher in the IG (13%) than in the P-IG (7%), as well as those labelled as high risk (8% in IG and 2% in P-IG).

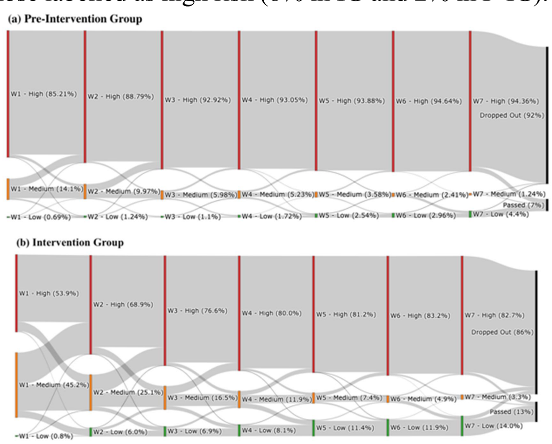

Figure 1: Sankey diagram of the students' flow between risk groups per week: (a) P-IG and (b) IG.

Second, the evolution of the risk groups shows those that were more affected by the intervention were the Medium Risk and Low Risk groups. If we analyze the Sankey diagrams in Figure 1, we observe that, the percentage of students in the Medium Risk group is much higher in the IG (45,2%) than in P-IG (14,1%). However, the fluctuation between groups varies similarly in the P-IG and the IG, with some differences. Both groups have in common that, the Medium High Risk group decreases, while the High and Low risk increases. However, in the IG we observe that the decrease of the Medium Risk group is lower than in the P-IG, week by week. Also, one of the main differences is that the IG starts with a higher number of students in the Medium Risk (45,23%) compared with the same students in the P-IG (14,1%). One reason for that could be the periods in which the data was collected. The intervention was conducted during the COVID-19 pandemic, in which all online courses in Coursera experienced a registration increment compared with other periods A similar case occurs with students in the Low-Risk group. While in both cases, the number of students increases, the increment in the IG is higher for these students than those in the P-IG.

These results are also supported by the probabilistic models in Figure 2, showing the accumulated probability of transition between the different risks groups for the P-IG and the IG. In this case, we observe the following. (1) Students' probability of staying in High-Risk Group in the P-IG (0.991) is higher than in the IG (0.96). (2) Students in the High-Risk Group have a higher probability of moving to the Low-Risk group in the IG (0.037) than in the P-IG (0.009). And (3) Students in the Low-Risk Group have a higher probability of remaining there in the IG (0.889) than the P-IG (0.752). All these differences are statistically significant ($p<0.05$), even when comparing the Marcok matrices as proposed by Bickenbach, F., & Bode [21]. In summary, results suggest that the intervention could have had an impact in high and medium risk students.

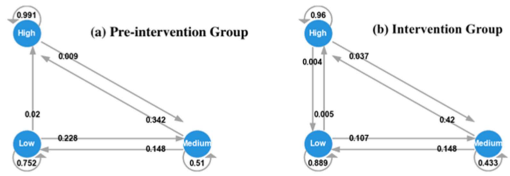

Figure 2: Probability of participants on moving from one risk group to another for the two conditions: (a) P-IG and (b) IG.

DISCUSSION & FUTURE WORK

This paper presents the preliminary results of an intervention for improving learners' completion rates in MOOCs. Based on prior work, this intervention provides teachers with a dashboard with information about learners' risks of dropping out and a set of feedback messages to encourage learners to continue on the course based on different indicators. For informing the teachers, we used learners' activities in the course to define the predictive model of dropout risk that we evaluated in prior work [16].

Preliminary results obtained are encouraging since, so far self-regulation interventions have raised students' engagement in the first weeks but not in the passing rates [18]. However, students in the IG could have some differences from students in P-IG that could also explain the results. First, the number of enrolled students in each group is quite different which can be an indicator of some changes of conditions. Second, no data about students' demographic is available, which makes it difficult to run analysis according to students' prior knowledge and see if this has an impact on passing rates as shown in previous studies. Third, students in the IG did the course during COVID-19 pandemic, while students in the P-IG were pre-pandemic. According to data provided by Coursera, during the pandemic, registrations in the course raised significantly, and especially those of students belonging to the institution. We know that this course was never mandatory for students in the organization, but some teachers might have used it as a complement to their course, which could have increased the passing rate. In this work, we decided to compare the students' activity in the same period in two different years to keep it as similar as possible, but future analysis should perform a complete analysis including different periods along the 2020 and 2021 and compare the average passing rates. In addition, no distinction in the analysis was made per type of message sent and, therefore, we could not isolate the impact in the students' engagement per type of message.

Future work would include further analysis of the data available in order to isolate the factors that affect the effectiveness of this intervention, as suggested by Kizilcec et al. (2020) [18]. Different actions are planned: (1) ask for demographic data to make comparable groups of students and analyze their activity; (2) analyze data from different periods of the year, before and after the pandemic; (3) run analyses to isolate factors such as the type of message sent and to check what indicators and messages are more useful in increasing learners' passing rate; and (4) include as predictors variables related not only to activity within the platform, but also to the self-regulated behavior of students.

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