When Teachers and Machines Achieve the Best Combination: A National Comparative Study of Face-to-face and Blended Teaching and Learning

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***Abstract*—This paper analyzes a national technology and education program in Uruguay known as Plan Ceibal. This work studies a sample of over 105,000 students from 4th, 5th, and 6th grade of public primary education in that country. This work aims to assess the impact of technology on teaching and learning of English. The method adopted is based on log-file data to compare two different modalities of English teaching (a face-to-face and a blended model). Additionally, we explored the correlation between a common measure of online engagement when using the Learning Management System (LMS) and an adaptive English assessment. We examined the impact of the teaching modalities on the students engagement and to what extent the engagement can contribute to enhance the student learning of English. This work documents the steps followed to elaborate the common measure of engagement to ensure transparency and its replicability (or improvement). A strength of this work, in comparison with previous studies, is the number of cases analyzed as well as the age of the target population (primary school students). The results indicate that engagement is affected by at least three key factors: socio-cultural context, teaching modality, and the role that teachers play. In fact, the higher the engagement level, the larger the proportion of students who achieve a better learning outcome in the assessment. This study shows that the use of LMS enhanced the learning experience when this tool is integrated within the ecosystem of the teaching and learning process. The findings of this study are consistent with previous works in the field, for instance: the relevance of the context as well as the role of teaching. Although the measurement of engagement can help to understand students performance noteworthy that as a stand-alone dimension it is a poor predictor of performance. To consider additional factors associated with learning is still necessary.**

***Keywords*—Plan Ceibal; Online learning; LMS Engagement; Learning Analytics; Adaptive test**

I. Introduction

This study analyzes a national technology and education program in Uruguay known as Plan Ceibal. In particular, this work aims to assess the impact of technology on teaching and learning of English in public primary schools. Previous research works have shown that the deployment of educational technology as such, can not necessarily be translated into better learning outcomes [1]. So, it is critical to consider associated factors such as the context, the teachers training, the pedagogical strategies among other factors which can play a relevant role during learning [2].

Since the Plan Ceibal works at a national level, it must manage and analyze large-scale platforms and datasets gathered from the whole public educational system. This wealth of data becomes a unique opportunity for conducting data analytics exploration. For instance, it opens the opportunity for combining and analyzing dimensions such as: access to technology, type of use of the devices in different modalities of teaching, frequency of use, among others [3] [4]. All these dimensions are relevant, but, as previous research shows, in order to play a meaningful role during the educational process, it is critical that students are engaged in the use of the technology during their learning experience. That is why our work aims to analyze students engagement during their learning experience [5]. It is relevant for our work to build a common measure of online engagement. This measure can be particularly useful to analyze from a comparative perspective how the different teaching modalities of English (a face-to-face and a blended one) have an impact on students engagement and to what extent this measure of engagement when using the LMS can contribute to enhance the student learning of English. This analysis focuses on the online interactions with the LMS platform, which includes over 13.7 million records, of 4th, 5th, and 6th grade students in two teaching modalities of English from the public educational system of Uruguay during 2015.

The study is structured as follows. Sections II describes the two different modalities of teaching English and the national evaluation. Sections III presents the methodological aspects of this work. Section IV includes the results and a discussion of the results obtained. Finally, Section V summarizes the conclusions and and suggests further work.

II. Educational context

In Uruguay, the teaching of English in primary schools is conducted under two different modalities. We are comparing

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two EFL (English as a Foreign Language) programs. One is delivered entirely face-to-face and the other uses a blended modality.

A. Face-to-Face modality

The Second Language Program runs a face to face teaching program. This modality consists of 3 hours per week for 4th, 5th and 6th graders. The pedagogical activities of the class are defined by each teacher. In this modality, there is no prescriptive definition regarding the use of technology (face-to-face classes can be enhanced by the use of LMS or other platforms).

B. Blended modality

”Ceibal en Inglés” is a program conducted since 2012 in partnership between Plan Ceibal and British Council to overcome the shortage of qualified EFL teachers in Uruguay. It offers a blended approach integrating remote teaching via video conference, LMS and traditional face-to-face instruction. It was designed for primary school learners in 4th, 5th and 6th grades, who have English lessons three times a week [6]. This blended model enabled to conduct multidimensional data analysis, offering useful information for both the academic community and the policy makers.

C. National evaluation of both modalities

Since 2014, the National Educational System (ANEP, by its Spanish acronym), Plan Ceibal and the British Council implemented an annual EFL adaptive test applied to children in both teaching modalities (face-to-face and blended). Performance levels were designed in accordance with the standards defined by the The Common European Framework of Reference for Languages: Learning, Teaching, Assessment (CEFR) for the teaching and learning of Foreign Languages [7]. The students' EFL learning is assessed through an adaptive online test, including the following domains: Vocabulary, Reading, Grammar (VRG), Listening and Writing. The assessment adapts to the level of knowledge of the test taker. Depending on the accuracy of the student answers to previous questions, the assessment displays either a more difficult or an easier question as subsequent test items.

The scores patterns indicate that the best results are obtained by students from higher socio-cultural contexts, as defined by ANEP. In addition, the higher the student grade level, the better the results [8]. A subset of the sample of 21.989 students who completed both 2014 and 2015 tests was analyzed. The results showed significant improvements from 2014 to 2015, across all three grades, regardless of students socio-cultural contexts. However, the learning outcomes gap between students from high and low socio-cultural context remain throughout these years.

III. Methodological aspects

In this section, we present the objectives of this study, a summary of the state of the art and the different methodological steps implemented to reach our goals. Particularly, we present our proposal of an engagement index and the characteristics of our dataset.

A. Key questions

The main question of this study is: what is the effect of the teaching modality (blended vs face-to-face) on the level of LMS engagement. We also considered a subsidiary question: to what extent the use of this technology contributes to enhance the learning outcomes of learners?

B. Previous research

Using LMS data is often at the heart of learning analytics studies. It is also one of the most popular research orientations due to its ubiquity in many educational institutions [9]. Although the expectation is that students' use of the LMS features have a positive effect on student performance, previous research works show mixed results: basic LMS data does not predict student academic performance [10]. LMS usage is at best a poor proxy for actual user-behaviour of students. The challenge is to build a more comprehensive understanding of online practices. Previous works indicate that a combination of LMS data with data from assessments can be a better predictor for students learning outcome or engagement [11] [12]. More and more studies of online education have begun to focus on student engagement, noting that engagement is also influenced by the learning context and by the instructor who plays a significant influence in online (or blended) education [13] [14] [15] [16]. Student engagement can be represented by the time and effort students devote to their learning experience, but also based on the activities conducted online [17] [18]. When analyzing student engagement in the online learning environment, it is necessary to select the indicators to measure online engagement [19] [20]. As previous studies have explored [21], the integration of LMS into an English language course can offer a flexible and convenient space for learning, also called a “third space” for education. Likewise, recent works have examined different styles on the engagement patterns [22]. As Wintrup et al. report, previous studies have analyzed how learners engagement online varies according to their learning experience [23]. Previous works present an alternative methodology based on latent class models instead of computing a single index score [5] [24]. Having revised and analyzed the existing literature in the field [5] [6] [7] [8], this article develops a methodological approach grounded on data mining strategies using log-file data. One of the key contributions found in the literature is the measurement of students engagement using log data which is both minimally disruptive and highly scalable [8].

C. Data sources, sample and index computation

In order to answer our key questions, we used data from different sources. Our main dataset was the data from the logs of the LMS platform, 13.7 million records of events of the students activity during 2015. Administrative information was collected and merged from Ceibal (grade, school, classroom and the socio-cultural context of the school). In addition, for each student, we added the achieved score from the annual EFL adaptive online test. The test was applied to 4th, 5th and 6th grade students from primary education who attended either one of the two modalities of English teaching (blended and face-to-face). The assessment was not universal, although it reached 62% (65,699 students) of the total number of students [8]. This subset included members of all the socio-cultural contexts and grade levels. The proportion of students in each grade and in each socio-cultural level in this subsample were similar to the values of the total population.

The universe considered in this study are students from 4th, 5th and 6th grade of public primary education (105,715 students: 76,752 blended students, and 28,963 face-to-face students) from all (942) urban schools. Despite the large number of students and events registered, we managed the volume of the data with the standard libraries in R (base, stats) [25]. The original data was read using the library RODBC [26] to connect to Structured Query Language (SQL) Server.

The second step was to generate an index in order to systematize the students performance in the LMS, the Engagement Index (IEG, in Spanish). This index provided a combined indicator of key activities: students access, type of usage in the LMS and intensity of use. This index is used to establish a common measure to compare both English teaching modalities.

The properties considered during the elaboration of the index were (a) it should be increasing with higher level of engagement, (b) it must be bounded, preferably between 0 and 1, and (c) it should be on a logarithmic or relative scale.

In order to summarize the students activity on the platform, a subset of 13 variables were selected from the dataset. These variables computed the number of times that a certain task was done (logging in, uploading files, etc.) and the number of different days when those tasks were done. Since some of these variables were highly correlate, we selected those that showed less correlation (less than 0.8) in order to represent the various aspects of the multivariate analysis. The variables used in the index were: x_1 = number of assignments submitted, x_2 = number of files uploaded, x_3 = number of comments, x_4 = number of comments on submissions, x_5 = number of days in which comments on submissions are made, and x_6 = number of days in which some activity took place.

The computation of the IEG includes two steps: aggregation of the six variables involved, and re- scaling and smoothing of the result. First, we computed $\pi = \prod_{i=1}^{6}(1 + x_i)$, which takes a minimum value of 1 when all variables are zero. Then, we transform the product of the six functions of the variables:

$$IEG = (\delta + 1)/\delta \times [(\pi/(\delta + \pi) - 1/(\delta + 1)],$$

where δ is a smoothing parameter (after some calibration we set $\delta = 90$ for the IEG). It can be seen that $IEG = 0$ if $\pi = 1$ and $IEG \to 1$ as $\pi \to \infty$. After having obtained the index, the following step was to analyze the behavior of the IEG at different levels of analysis (student-level vs classroom-level) according to the English teaching modalities.

Finally, in order to answer the second research question, we explored the correlation between IEG and the adaptive English test scores. From the total number of students (65,699) who completed the computerized adaptive test, 46,776 were blended students enrolled in the LMS, so our correlational analysis focused particularly on this subset.

IV. Results and Discussion

The findings of this study are structured in two sections, in order to answer the questions, followed by a discussion. First, we conduct a comparative analysis to explore to what extent the teaching modality (blended vs face-to-face) defines the level of engagement in the use of the LMS. Second, we present to what extent the use of the LMS enhances the learning outcomes of learners. Finally, we discuss the results.

A. Relation between engagement and teaching modalities

Based on a comparative analysis of the coverage rate for access to the platforms done by learners according to the modality of English teaching, it was observed that blended students registered the highest student coverage rates (82% blended versus 52% face-to-face). We interpret that these results, in addition to the proportion of blended students (76,752) in the total number (105,715), indicate that the access to the LMS can be explained mostly by the role the platform plays in the remote teaching of English. It was also observed that the coverage rate increases with the student grade level: 65.7%, 67.5% and 73.3% for 4th, 5th and 6th, respectively.

The differences identified in the coverage rate according to the modality of English teaching can be also observed in terms of the intensity of use of the platform. Figure 1 shows the engagement index obtained per student for the two teaching modalities. The engagement index reflects a higher participation and interaction of blended students, with an average of 0.5 and a median of 0.5, whereas for the face-to-face students the average is 0,3 and the median is 0. Furthermore, as seen in other studies [27], we found a positive correlation between students engagement and the socio-cultural context. The medians for the IEG for each one of the socio-cultural quintiles are: $Q_1 = 0.11, Q_2 = 0.22, Q_3 = 0.41, Q_4 = 0.57$, and $Q_5 = 0.85$, where Q_1 is the most critical and Q_5 is the least critical context.

Figure 1 shows that for approximately 30% of the blended students the interaction with the LMS is zero or very low. These low values at the beginning of the curve are notably extended in the graphic corresponding to face-to-face students; more than half of them have zero or very low levels of IEG. It can be seen that the proportion of students with higher engagement is more relevant in the case of the blended students. Finally, the index illustrates that, in the case of the blended students, the distribution between the students with high and low engagement is very similar, while in the case of the face-to-face students the largest proportion of the students register a very low engagement index. For illustrative purposes, a student with a IEG greater than 0.985 is a student who does at least 12 comments in 3 differents days, has 24

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assignments submitted, 12 files uploaded, 4.2 comments on submissions and the standard activity frequency is 32 days per year when some activity took place.

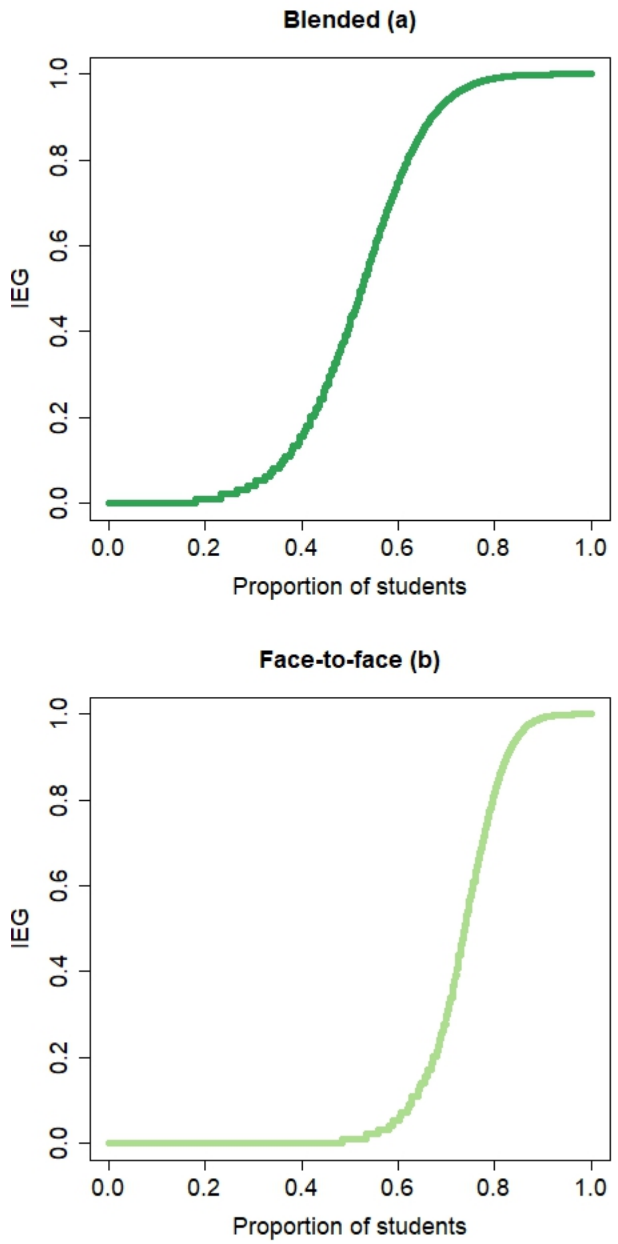

Figure 1. Blended (a) and Face-to-face (b): IEG distribution by modality of English teaching.

In the field of education, the data from schools have typically been considered as well-defined units with students "nested" or grouped within schools. The same happens at the classroom-level. The analysis at the classroom level contributes to examine what role do the teachers play in the engagement of their students.

For each student, an indicator was computed showing if they submitted any assignments. The new indicator, $y_1 = 1$ if $x_1 > 0$ and $y_1 = 0$ otherwise, was aggregated at the classroom level by computing its average for all the students in each classroom. A classroom with an average of 0.50 would mean that half of the students submitted at least one assignment and the rest of the students did not submit any. Figure 2 shows for each classroom the percentage of students with at least one assignment submitted. It can be seen that in both histograms, for the students in blended classrooms and for the ones in face-to-face classrooms, a U-shaped graph appears. The U-shaped graph shows that the average of y_1 for the classrooms do concentrate either near 0% or 100% suggesting the teachers effect on the level of students engagement. There are some teachers who do use the LMS, and therefore almost all of their students use it, and there are some teachers who do not use the LMS and neither do their students.

The engagement on the LMS is influenced by the modality of English teaching: more groups from blended than face-to-face registered a higher engagement (IEG). This indicates that the students' activity is not only determined by the teaching modality but also by the role played by the classroom teacher.

B. Relationship between engagement and performance levels

The correlation was computed between IEG and the adaptive online EFL test score. Performance levels of the test are designed in accordance to those of CEFR. The analysis was done with 46,776 blended students.We found a moderate correlations, namely, the Pearson correlation was 0.24 for all students. We compared the distribution of the levels reached by the students in the English assessment according to their level of IEG (see Table I). The analysis shows that the higher the IEG level, the larger the proportion of students that reach the highest levels of the test results. Only 32% of the blended students who have no activity in the LMS (IEG = 0) achieve the A2 level in the EFL test, whereas this percentage increases to 62% when we consider the students with a high level of engagement (IEG greater than 0.985).

The results obtained are observed in the comparison of the different estimated density functions of the obtained score for each IEG level. Figure 3 represents the blended students grouped based on their engagement performance. As mentioned before, the higher the IEG the higher their VRG score. The range of the score of the adaptive test is from 0 to 1500. The score was standardized with an average of 500 and a standard deviation of 100. After that, cut-off points were established to determine the levels in accordance to the CEFR. Figure 3 shows a shift to the right of the curves that represent a higher level of IEG.

TABLE I. ADAPTIVE EFL TEST (VRG) LEVELS OBTAINED BY LEVELS OF IEG.

	A0	*A1-*	*A1+*	*A2-*	*A2+*	*Total*
$IEG = 0$	1%	32%	35%	31%	1%	100%
$0 < IEG \leq 0.3$	1%	26%	32%	41%	1%	100%
$0.3 < IEG \leq 0.8$	0%	19%	28%	50%	2%	100%
$0.8 < IEG \leq 0.985$	0%	16%	27%	54%	3%	100%
$IEG \geq 0.985$	0%	10%	23%	62%	5%	100%

In order to compare the distribution of the VRG scores according to their level of IEG, we run Kolmogorov-Smirnov

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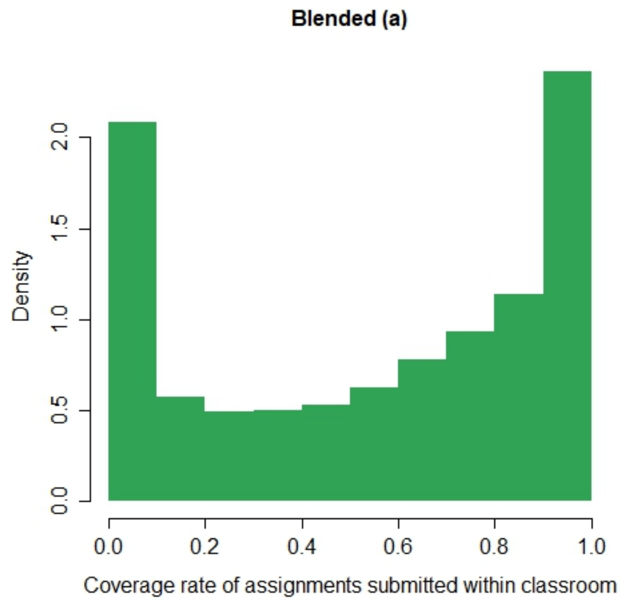

Figure 2. Blended (a) and Face-to-face (b): Percentage of students within a classroom with at least one submission by modality of English teaching.

tests in R for each pair of densities. The five distributions are significantly different (all of the *p-values* are less than 10^{-13}).

V. Discussion

The modality of teaching plays a relevant role during the learning of English. The results are consistent with previous works which suggest that online engagement is enabled or influenced by the role played by teachers or tutors [28] [29]. In other words, it is not only the deployment or access to the educational technology but the human factor which enables students participation or engagement. This study illustrates the advantages of an appropriate integration between the use of

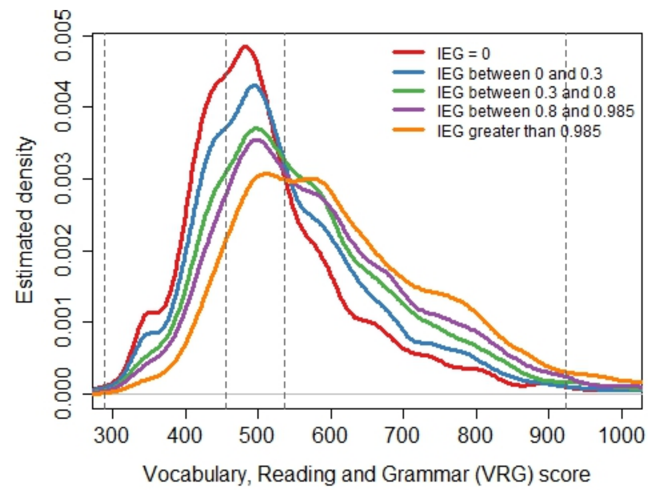

Figure 3. Blended students: estimated VRG score density by levels of IEG.

educational technology and face-to-face practices in primary level education. The majority of research works we reviewed address higher levels of education. However, in this case the analysis focused on K-12 students and the results showed to be consistent with the results of more advanced levels of education. Additionally, previous works have indicated that only small, positive relationship was identified between engagement and performance at the student's level [30]. In our work, we tested these results but aimed for a larger sample (national scale outside of the context of Massive Open Online Course) in order to explore the replicability of this trend. We identified low to moderate correlation between the use of the LMS (based on the engagement index) and the students performance on the adaptive test. This is aligned with what Gašević et al. (2016) [10] suggest that under specific circumstances engagement can be correlated with student performance, when measuring the use of LMS. However, engagement can not be understood as a unequivocal predictor of performance. In that sense, it is important to state that our results do not indicate causality on student performance but they suggest the usefulness of the LMS during the learning experience.

This study follows guidelines of previous works which have focused on engagement as a critical dimension to study students learning and/or participation [5] [23] [24] . One contribution of this study has been to document the elaboration of the engagement index. The input that our work provides is to document the steps followed during the selection of different variables as well as the weight that these values have in the elaboration of the IEG. This was done with two major purposes in mind: to ensure the transparency of the indexs elaboration, and to simplify the replicability (or improvement) of the IEG in future works.

VI. Conclusion and Further Work

This study aimed to analyze a large sample of 4th, 5th, and 6th grade primary students in Uruguay.We elaborated an Engagement Index to compare two different teaching modalities for learning English. One of them, more traditional based on face-to-face interaction where the teachers deliver the lessons in dialogue with learners. The other is conducted under a blended model, combining remote video conference, the use of a LMS and face-to-face interaction.

One of the findings that arises from the comparative analysis is that socio-cultural context and teaching modality are correlated with engagement. Students from higher socio-cultural contexts present higher levels of engagement. We identified that engagement increases with student grade level. In other words, the higher the students grade, the higher their LMS participation. Blended students registered a higher index of engagement in comparison to the face-to-face students. This could indicate that, when technological resources are well embedded in the design of the program, students engagement increases. The contribution of technology was registered even when the English proficiency of teachers was not high.

Regarding the learning outcome (test results) and the Engagement Index, we identified a consistent correlation in all groups analyzed, between frequency of use of the LMS and the English learning outcome. Although this result does not indicate causality, it suggests the usefulness of the platform. Engagement can help to understand students performance; however, as a stand-alone dimension, it is a poor predictor of performance. It is still necessary to consider additional factors associated with learning.

As shown in the analysis, IEG tries to capture the effect of the teaching modality (face-to face vs blended) in the integration of the LMS during the teaching practices. The results indicate that the use of LMS by 4th, 5th, and 6th grade students enhanced the learning experience when this tool is integrated within the ecosystem of the teaching and learning process.

Based on the findings, we present some reflections regarding the introduction of technology in educational practices with students in primary education. Although this study is exploratory based on data analysis, it is important to emphasize the role of teachers in relation to the use of the platforms at the primary level. Academic work exploring the impact of technology in education has usually studied large scale interventions in secondary and tertiary education, e.g., Massive Open Online Courses. It is expected that this study can contribute to future research in the field when exploring the role of technology with students in primary level.

One limitation of this research is that we can not claim that the sample is representative of the population. Although this study included a high number of students, the participants were self-selected (the ones assessed in the national adaptive test).

Future research can also revise the analysis of log data (optimizing the engagement index) in order to improve student outcomes. Additional studies could explore if it is possible to optimize the IEG measurement by capturing non-structured data, e.g., contents of the comments, quality of assignments from the LMS as well as using social network analysis. Further research can investigate the possibility to replicate the analysis using the 2016 log-data in order to verify the consistency of the patterns found. Finally, it would be interesting to identify the critical variables which explain and/or predict learning performance.

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