An Analysis of Engineering Students in Virtual Learning Environments

Darío J. Delgado, PhD, Pablo Munevar-Garcia, PhD, C. González, MEd, and Diego F. Aranda, PhD
Universidad Nacional Abierta y a Distanca, Colombia
dario.delgado@unad.edu.co, pavlo.munevar@unad.edu.co, caludio.gonzalez@unad.edu.co, diego.aranda@unad.edu.co

Abstract– ***In this work, we present an analysis for a sample of 896 undergraduate engineering students in virtual learning mode, using the LOGS that come from a Learning Management System to contrast institutional policies and beliefs. We use a characterization approach to translate LOGS into academic information and statistical analysis to verify the policies and beliefs. We found some trends to be analyzed in future work in order to reformulate some policies, especially those related to the student's commitments, and use the Learning Management System student's behavior as a strategic asset to define new policies.***

I. Introduction

Interactions between teachers and students traditionally happen in physical spaces. However, education, as well as other disciplines approach the digital transformation changing its educational model [1]. Today, virtual education and its educational model it's trending in higher education [2], However, an inconvenient in this kind of educational model, even in blending learning (B-Learning) approach [3] are the difficulties that educational institution and teachers have in relation with identifying and understand students behavior in courses or virtual programs. In a traditional educational model, in which students and teachers coexist in a classroom, there are many conditions and information that teachers could use to obtain feedback and realize corrective actions in their educational strategies in order of obtaining the best results for their students.

In this work, we approach the engineering undergraduate student's behavior understanding in a full virtual learning environment, in particular, we analyzed the student's interactions with Learning Management System (LOGS) and use this information to contrast some educational policies and institutional beliefs.

II. Context

In this work, we use a sample of 896 engineering undergraduate students in the b-learning model from 8 different engineering programs. On average, each student was enrolled in 4 academic courses deployed in 16 weeks. Each engineering program is usually composed on average by 60 courses that have between 150 and 180 academic credits deployed in a Virtual Learning Environment (Moodle).

We use a subset of academic policies and beliefs used to define the ideal behavior of teachers and students in the Learning Management System (LMS) according to quality conditions to interact with its academic courses [4,5].

- Students must participate actively, pertinently, and opportune according to parameters in each activity.
- Students must review the course general forums and participate in a pertinent way according to the instructions and utility of each forum.
- Students should check in an opportune way the course forums.
- To ensure feedback of teachers in forums, especially in collaborative work, students must participate in activities until three days before activities end.
- Students prefer to use the VLE at night hours and weekends.
- Per academic credit, a student must have 16 hours of direct advising and 32 hours of independent work.

To articulate the educational policies and the impact on engineering students, we collected LOGS information from the LMS [6] in order of corroborating the impact of policy definition and its operationalization.

III. Information analysis

In a Learning Management System (LMS), A LOG is a sequential file with temporal records associated with all events in an academic course product of the student's interactions with the LMS. For finalized courses, we can obtain a set of records of the students' and tutors' behavior in a specific configuration of the LMS [7].

For this work, the LMS configuration is defined as follows. The set of activities, $A = \{a_1, a_2, \dots, a_n\}$ where n is the number of activities, to performing during the course. The set of forums $F = \{f_1, f_2, \dots, f_n\}$ defined for each activity, the schedule (interval time) $T = \{[t_1, t_2], [t_3, t_4], \dots., [t_{n-k}, t_n]\}$ defined for each activity, the evaluative weight $P = \{p_1, p_2, \dots_{p_n}\}$ for each activity where $\sum_{i=1}^{n} p_i = 500$, the course materials $M = \{m_1, m_2, \dots, m_w\}$ where w is the number of folders (folders for each activity with books, articles, videos, etc, …), the students enrolled in the course $E = \{e_1, e_2, \dots, e_m\}$ where m is the number of students, and the academic ponderation $N = \{n_1, n_2, \ldots, n_m\}$ for each student. According to the VLE configuration, a course is defined as the function $C(A, F, T, P, M, E) \rightarrow N$.

The LOG list $L = \{l_1, l_2, \ldots, l_m\} \in C$ for each student where $l_i = \{f_i, u_i, ua_i, ec_i, c_i, en_i, o_i, ip_i\} \in e_i$ contains the temporal records of each student, see *TABLE I*.

TABLE I
LOGS STRUCTURE

Component	Description
f_i	LOG date and time
u_i	Username
ua_i	Interaction with the user
ec_i	Event Context
c_i	Course Component accessed
en_i	Event name
o_i	Access origin (mobile, web)
ip_i	IP address

Standard LOGS representation is not enough to contextualize this information in academic terms [7,8]. To transform the LOGS into academic relevant information we realize a characterization process to measure a set of variables that allows realizing an academic interpretation of the students and teacher behavior in the VLE. We propose a set of variables measured using the logs $l_i \in e_i$ for each student, see *TABLE II*.

TABLE II
LOGS CHARACTERIZATION FOR EACH STUDENT (AVERAGE PER WEEK)

Variable	Description
Tp	Total time spend by student in the VLE
Vm	Number of visits to the course materials
Ls	Number of weekdays generated LOGS
Lf	Number of weekend generated LOGS
Le	Number of LOGS generated early morning
Lm	Number of LOGS generated in the morning
La	Number of LOGS generated in the afternoon
Ln	Number of LOGS generated in the night
Pa	IP ratio
Fa	Access frequency
L_{Monday}	Number of LOGS generated the Monday
$L_{Tuesday}$	Number of LOGS generated the Tuesday
$L_{Wednesday}$	Number of LOGS generated the Wednesday
$L_{Thursday}$	Number of LOGS generated the Thursday
L_{Friday}	Number of LOGS generated the Friday
$L_{Saturday}$	Number of LOGS generated the Saturday
L_{Sunday}	Number of LOGS generated the Sunday
Ne	Number of events that system modifies
Nc	Number of courses that student access in the VLE

In a first approximation, $\forall e_i \in E$ we can characterize each student as $g(l_i) \rightarrow x_i | x_i = \{Tp_i,\ Vm_i,\ Ls_i,\ Lf_i,\ Lm_i,\ La_i,\ Ln_i,\ Le_i,\ Pa_i,\ Fa_i,\ L_{Monday},\ L_{Tuesday},\ L_{Wednesday},\ L_{Thursday},\ L_{Friday},\ L_{Saturday},\ L_{Sunday},\ Ne_i,\ Nc_i\}$.

IV. DATA ANALYSIS

A preliminary analysis of courses deployment using the VLE LOGS, we can appreciate some general and also relevant information about the student's behavior. In the first analysis, we can observe in Fig. 1, a heatmap that represents 112 days in 16 weeks against the 24 days hours, showing the interactions of students in activities forums (Posts) in the LMS. Most of the courses, with 3 academic credits on average, are composed of five activities in three moments, an initial moment developed in two weeks, and an intermediate moment developed in 12 weeks, and a final moment developed two weeks.

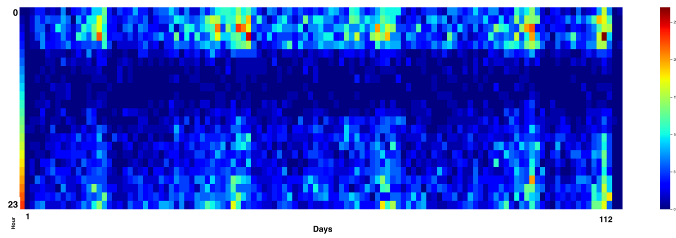

Fig. 1 Students participation in virtual courses in a period of 112 day

In Fig. 1 we can observe some general tendencies follow by the majority of engineering students like i) Participation in activities happens just a few days before the activities end, ii) Interactions with teachers by the use of forums happen mainly early-morning, from 0:00 hours to 2:00 hours in the morning, iii) from 5:00 hours in the morning, until 3:00 hours in the afternoon, forums activity in the LMS is almost null.

In a weekly analysis, having in account variables defined in *TABLE II*, and a statistical description of the characterized variables. See *TABLE III*, It's possible to analyze the engineering student's behavior since a LMS interaction context, having into account its work patterns.

TABLE III
STATISTICAL DESCRIPTION FOR CHARACTERIZED VARIABLES STUDENT (AVERAGE PER WEEK)

Variable	Average	Deviation	Max	Min	Units
Tp	319	220	1539	0	Seconds
Vm	4.034	2,241	15	0	Visits
Ls	100	61	513	0	Records
Lf	27	19	160	0	Records
Le	10.51	12.8	145	0	Records
Lm	21.21	22.47	164	0	Records
La	36.81	28.65	208	0	Records
Ln	58.47	39.36	351	0	Records
Pa	2,67	1.78	14	0	IPs
Fa	21	15	120	0	Accesses
L_{Monday}	20	13	103	0	Records
$L_{Tuesday}$	22	14	107	0	Records
$L_{Wednesday}$	24	16	115	0	Records
$L_{Thursday}$	19	13	108	0	Records
L_{Friday}	14	12	145	0	Records
$L_{Saturday}$	13	10	80	0	Records
L_{Sunday}	15	11	80	0	Records
Ne	19.59	20.67	355	0	Events
Nc	3.93	1.57	8	0	Courses

In terms of student's interaction with LMS in a weekly context, see Fig. 2, using an ANOVA [8] test to verify a significant difference between the use of platforms at weekends and during the week, in which we obtain a $p - value$ of 2.2×10^{-6}, that's mean that exists a significant difference between the students' interaction during the week in contrast with the interaction with the platform during the weekends. Additionally, with a hypothesis test, in which the null hypothesis $H_0: \bar{X}_{week} > \bar{X}_{Weekend}$, and an alternative hypothesis $H_1: \bar{X}_{week} \leq \bar{X}_{Weekend}$. that as a result, with $\frac{\alpha}{2} = 0.025$, it's impossible to reject the null hypothesis, engineering students in virtual education interact and work in the LMS during the weekdays more than at weekends.

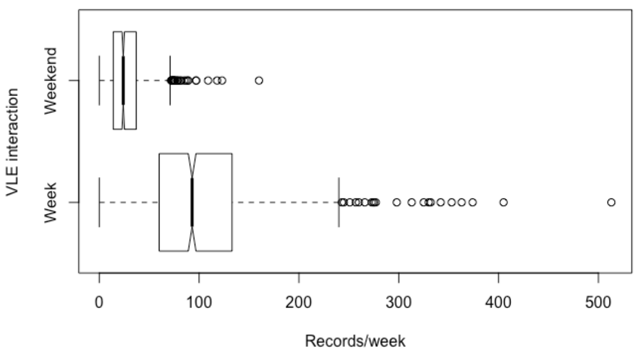

Fig. 2 Students interaction in virtual courses according to the day of the week

Contrasting, the hours in which the students interact in a general way with the LMS, see Fig. 3, with the principal moments in which they interact in forums with his partners and teachers, see Fig. 1, we can observe that exist a latency between the platform observation and interaction and its effective participation in forums with his partners and teacher, exists a high activity in the platform by the students in the nights but, his participation in forums primarily happens early-morning.

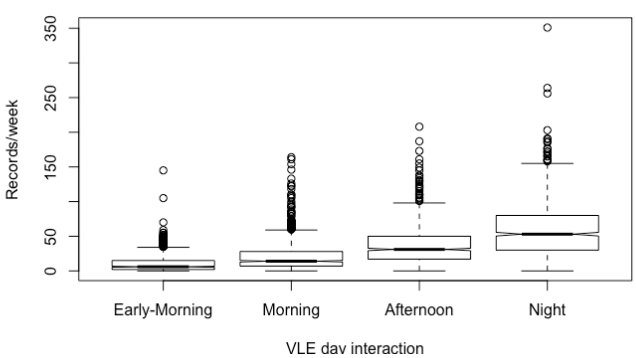

Fig. 3 Students interaction in virtual courses according to the hour of the day

Concerning the access spots to the LMS, in terms of access IPs (Pa), Students mostly use on average 3 access spots, perhaps in-home, at work, and probably on his mobile. Also, they access the platform, 5.31 minutes on average during the week in almost 4 courses, which means that on average an engineering student in the platform is giving to each course less than 1.32 minutes per course.

Analysis and Conclusions

In contrast with some policies defined, students as an active part in the learning process [10], to ensure quality in the teaching and learning process are breaking the quality requirements about the opportune moments of its contributions in courses, leaving for the last days of activities the interaction with teachers and partners. And also, they spend less time on the platform, which the defined for each course according to the academic credits, an important remark in relation to time in the platform is related to students' academic work, which could happen outside of LMS and we must have in account the diversity in learning styles present in virtual students, learning styles that could not follow institutional policies but could conduct to effective learning processes. However, an average of 1.32 minutes per course is not enough to read and analyze the contributions of other students in forums and could also affect the quality of teaching and learning processes in terms of the defined policies. In addition to the data that shows students spend more time on the platform just a few days before activities end.

Concerning institutional believing, the assumption of students uses mainly the LMS on weekends and nights it's partially true but needs a more deeply analysis. In relation to the use of platforms during the weekends, data reflects that this affirmation it's It is not entirely true, showing a mayor interaction during the weekdays, this difference between weekdays and weekends could be explained by the facility to internet access, urban centers with complete internet access, in contrast with the student's in a rural region with limitation of connectivity that must mobilize to an urban center, principally weekends. However, in relation to the interaction in the platform during the night, we can affirm that students use the platform especially during nigh, but interaction with partners and teachers happens during early-morning.

With this data, for future work, we propose a behavior characterization of students, perhaps using artificial intelligence approaches, to define a policy-making framework that allows an institutional capability related to the use of students' behavior as a strategical asset, routed to personalize learning approaches.

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