A Virtual Environment to Support Classroom Face-to-Face Teaching of Engineering Courses

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Abstract: The objective of our study is to answer three questions: a) How to build a low cost online teaching tool to support face-to-face classrooms of introductory engineering disciplines? b) What is the effectiveness of the use of virtual environment in promoting learning? c) Does the number of accesses by the students onto the virtual environment increases their grades and reduces their failure in introductory engineering disciplines? The online teaching tool was developed in Moodle environment, being composed by three components for each discipline: a) video lectures, b) video lessons explaining how to solve proposed exercises, c) a list of unsolved exercises. To evaluate the effectiveness of the virtual environment we collected data during Jan-Dec/2016, amongst engineer students. The main predictor variable, the number of access to the online support tool, was firstly evaluated in univariate analysis. Multiple linear regression was used to assess how the outcome of "final grade" were influenced by all predictors variables together, in a multivariate way. The number of accesses by the students onto the virtual environment increases their grades and reduces their failure in introductory engineering disciplines, especially for General Chemistry, Differential Calculus, Physics Electricity and Algorithms.

1 INTRODUCTION

Any country that intends to be serious about building a strong economy and be successful through the 21th century must produce hundreds of thousands of engineers during the next decade. How can we get there if the majority of students give up their bachelor courses right after beginning? The first two years of engineering are hard and, in essence, do not inspire any student! Actually, high-performing students frequently cite uninspiring introductory courses as a factor in their choice to quit (PCAST, 2012). In this paper we present a virtual environment to support face-to-face teaching in introductory disciplines of engineering courses.

Many initiatives to improve the first years of engineering education and courses other than engineering have been developed recently (Greenhalgh, 2001). Most initiatives proposed lately are based on computer supported tools and active learning methods as case studies, problem-based learning, problem sets in groups, concept mapping, peer instruction, analytical challenge before lecture, computer simulations and games dynamics (Saxe, Braddy, Bailer, 2015; Sim, 2015; Boada, Soler, Prados, Poch, 2004). Success of active teaching practices and intelligent tutoring system has been validated (Roll, Aleven, McLaren, Koedinger, 2011). For example, students in traditional lecture courses are twice as likely to leave engineering and three times as likely to drop out of college entirely compared with students taught using active learning techniques. Besides, students in a face-to-face class that used active learning methods learned twice as much as those taught in a traditional class, as measured by test results (PCAST, 2012).

Unfortunately, in spite of all evidences in favor of active learning methods, we have not yet achieved to broadly apply such teaching practice to engineering courses. Some isolated initiatives are underway in a private higher education institution from Brazil, with about ten thousand engineering

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students. However, the majority of our students are enrolled in traditional lecture courses. In fact, this is the reality of most engineering courses in Brazil and in other countries as well. Face-to-face engineering courses still need support environment to help students to improve their learning processes in such classrooms.

The objective of our study is to answer three questions: a) How to build a low cost online teaching/learning tool to support face-to-face classrooms of introductory engineering disciplines? b) What is the effectiveness of the use of virtual environment in promoting learning? c) The number of accesses by the students onto the virtual environment increases their grades and reduces their failure in introductory engineering disciplines?

2 METHODS

The online teaching tool to support face-to-face classrooms was developed in Moodle environment (https://moodle.org/). The objective was to build an online tutoring system based on the idea of passive tutoring, understood as a way of self-regulated learning. For each discipline involved, chosen among those introductory to engineering, an asynchronous learning course was developed, free and not obligatory (Haslam, 2014). Students were encouraged to access the environment that is available through the Internet, 24 hours a day, 7 days a week, being composed by three components:

a) video lectures with the theories of the discipline,
b) video lessons that explain how to solve a representative list of exercises from the discipline, one video for each exercise chosen,
c) a list of unsolved exercises.

The way in which the Moodle was introduced to the students was not directly integrated with the face-to-face teaching. Actually, we made a kind of marketing using email to introduce the environment to all students and professors. To evaluate the effectiveness of the virtual environment in promoting learning, we collected data during January and December, 2016, amongst engineer students in a private university from Belo Horizonte, Brazil. Two outcome variables were chosen for analysis: the final grade of the student, varying from zero to 100 points, and a categorical variable, the final result in the discipline (approved versus not-approved). Predictors or independent variables evaluated: the number of accesses by students onto the specific online discipline environment, varying from zero to “n” accesses, student age (years), student gender (male versus female), percentage of missed face-to-face class, from a specific discipline (0 to 100%), number of disciplines per semester, varying from one to “k” disciplines, course schedule or course shift (day versus night), and type of high school background of the student before he enters university (private school versus public school). If the discipline involved had one or more online class, the type of course (face-to-face versus distance learning), was analyzed as a categorical variable also. The main predictor variable, the number of access to the online support tool, was firstly evaluated in univariate analysis by Mann-Whitney two-sample test. Multiple linear regression was used to assess how the outcome “final grade” were influenced by all predictors variables together, in a multivariate way (Altman, 1991). All analysis were done by bilateral statistical hypothesis testing with a significance level of 5% ($\alpha = 0.05$).

3 RESULTS

Presently, the virtual environment developed allows support for seven disciplines: Geometry, General chemistry, Differential calculus, Physics (mechanics), Algorithms, Integral calculus, and Physics (electricity). It is available for all students and professors after user authentication in the link www.una.br. Data from January to December 2016, during two academic semesters, were used to investigate the effectiveness of the online supporting tool. We gathered information about all students that participated at least in one class of any of the seven disciplines elected, during the first or the second semester or both. A total of 3,056 different students could use the environment in one year. The cost for teachers to the implementation of the educational resources was about EUR 1,000 per discipline, totaling €7,000 which gives a cost of €2.30 per student. It was necessary about four months to produce all materials. After that, there is almost no cost to maintain the services. The number of students per discipline varied from 1,170 in Physics (mechanics) to 657 in General chemistry (Table 1). Students’ behavior in regarding to the access of the virtual tool varied greatly among the disciplines: standard deviation was much higher than its respective mean from all seven disciplines (Table 1). Despite all the campaign encouraging students to use the environment, the majority did not access the online tool anytime during both semesters. Actually, for all disciplines the majority of student did not access the virtual tool anytime. Percentage for each discipline of students that did not use the online tool are: 63% (Geometry), 64% (Differential calculus), 65% (Physics electricity), 70% (Integral calculus), 71% (General chemistry), 74% (Physics mechanics), and 75% (Algorithms).

Table 1: Number of access by each discipline during 2016 (n - total of students, mean access and standard deviation): results present very high variability in this predictor, suggesting students that behave completely different in terms of use of the virtual environment.

Discipline	n	Mean	Std Dev
Physics (mechanics)	1,170	4.4	10.9
General chemistry	657	5.8	14.4
Integral calculus	1052	6.0	16.3
Algorithms	710	6.1	17.3
Physics (electricity)	828	13.7	30.4
Differential calculus	828	13.8	30.5
Geometry	835	14.7	36.1

Note: standard deviation quantify the variability of the number of access by each discipline. Standard deviation higher than the mean indicates that the data are spread out over a wider range of values.

Figure 1 and 2 represent graphical analysis of the profile of access to the virtual environment as a protective factor against failure in each discipline. From the seven disciplines, four suggest good effectiveness of the online tool and three showed unsuccessful. In a univariate analysis (Table 2), access for Physics (electricity) it was not significantly associated with the student's success.

Tables 3.1 to 3.7 contain multivariate analysis for the seven disciplines. By using this analysis we can evaluate the joined effects of all predictors as possible protective factors, that rising the students' final grade, and risk factors, which decrease the final grade of each discipline. Similar to other studies (Senior, 2008), the most important risk factor for all the seven face-to-face classes is the percentage of missed classes. Surprisingly, when night course shift was significantly associated with final grade, it was identified as a protective factor for failure on Physics mechanics (Table 3.4), Differential calculus (Table 3.6) and Algorithms (Table 3.7).

The more disciplines to which a student attends along the semester, the better tends to be their final grades in Geometry (Table 3.2), Physics mechanics (Table 3.4), Integral calculus (Table 3.5), and Algorithms (Table 3.7). To attend more disciplines during a semester seems to force the student to dedicate more to achieve success during that semester! The virtual environment is a significantly support system for classroom face-to-face teaching of four disciplines: General chemistry (Table 3.1), Physics electricity Table 3.3), Differential calculus (Table 3.6) and Algorithms (Table 3.7). Unfortunately, the online support tool did not work very well on three distinct situations: Geometry (Table 3.2), Physics mechanics (Table 3.4) and Integral calculus (Table 3.5).

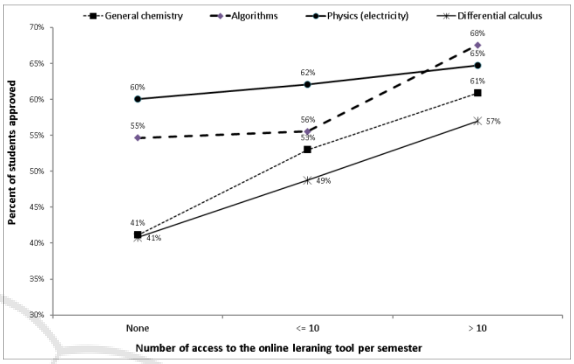

Figure 1: Results of the profile of number of access and rate of approval in each discipline suggest effectiveness of the environment to prevent failure in General chemistry, Differential calculus, Algorithms, and Physics (electricity).

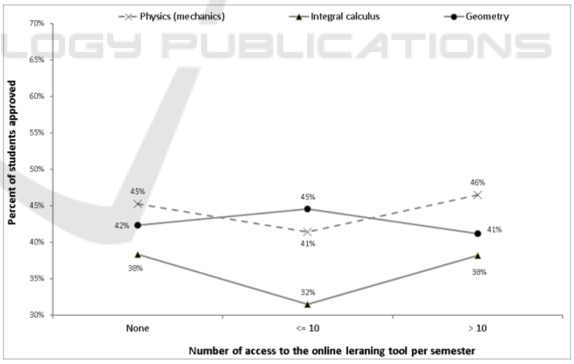

Figure 2: Three disciplines seem to be not affected by the number of access to the online tool: rate of approval in Integral calculus, Physics (mechanics) and Geometry were constant, independently of the use of the virtual environment.

Table 2: Impact of number of access to the online tool by each discipline against the outcome "final result" (approved versus not approved): in a univariate analysis, this predictor was significantly protective factor against failure in three disciplines (General chemistry, Algorithms and Differential calculus).

Discipline	Final result: approved?	N	Mean	s	p value
Physics mechanics	No	644	4	11	0.916
	Yes	526	4	11	
General chemistry	No	355	4	12	<0.01
	Yes	302	7	17	
Integral calculus	No	659	6	15	0.474
	Yes	393	7	18	
Algorithms	No	307	4	12	0.029
	Yes	403	8	20	
Physics electricity	No	319	11	25	0.128
	Yes	509	15	33	
Differential calculus	No	448	9	23	< 0.01
	Yes	380	19	37	
Geometry	No	482	13	35	0.611
	Yes	353	17	38	

Obs.: s = standard deviation.
p value by Mann-Whitney two-sample test
p value < 0.05 = statistically significantly results.

Table 3.1: Multiple linear regression model for multivariate analysis of the influence of all predictors together onto the outcome "final grade": analysis of General chemistry. Number of access to the virtual environment and number of disciplines per semester are significantly protective factors, raising final grade of General chemistry. Student's age and, mainly, the percentage of face-to-face missed classes are significantly risk factors for the final grade.

Predictor	b	s.e.	p value
Constant	60.81	5.2	
Chemistry: #accesses	0.21	0.1	0.000
High school in private school	0.49	1.9	0.801
#disciplines per semester	2.77	0.6	0.000
Age (years)	-0.35	0.1	0.013
Gender = female	-0.97	1.7	0.577
Night course	-2.99	1.8	0.105
Missed classes (%)	-206	11.1	0.000

Obs.: b = regression coefficients; s.e. = standard error.
p value < 0.05 = statistically significantly results.

Table 3.2: Multiple linear regression model for multivariate analysis of the influence of all predictors together onto the outcome "final grade": analysis of Geometry. Number of access to the virtual environment does not affect the students' final grade. Number of disciplines per semester and private high school are significantly protective factors, raising final grade of Geometry. Student's age and, mainly, the percentage of face-to-face missed classes are significantly risk factors for the final grade.

Predictor	b	s.e.	p value
Constant	64.15	4.4	
Geometry: #accesses	0.03	0.0	0.111
High school in private school	3.56	1.6	0.025
#disciplines per semester	1.49	0.6	0.013
Age (years)	-0.26	0.1	0.044
Gender = female	0.56	1.5	0.702
Night course	2.59	1.7	0.125
Missed classes (%)	-116	3.9	0.000

Obs.: b = regression coefficients;
s.e. = standard error.

Table 3.3: Multiple linear regression model for multivariate analysis of the influence of all predictors together onto the outcome "final grade": analysis of Physics (electricity). Number of access to the virtual environment is a significantly protective factor, raising final grade of Physics electricity. Only the percentage of face-to-face missed classes is a significantly risk factor for the final grade.

Predictor	b	s.e.	p value
Constant	74.77	4.3	
Physics electricity: #accesses	0.04	0.0	0.017
High school in private school	1.65	1.3	0.212
#disciplines per semester	0.24	0.5	0.633
Age (years)	-0.19	0.1	0.118
Gender = female	0.27	1.2	0.814
Night course	-2.92	1.6	0.068
Missed classes (%)	-134	8.1	0.000

Obs.: b = regression coefficients; s.e. = standard error.
p value < 0.05 = statistically significantly results.

Besides using the access to the online tool as a predictor for the student final grade, we collected data from six more variables that were used to build the multiple linear regression models. Coefficients of determination (R^2) were calculated for the linear models. Low value of R^2 indicates poor model. All seven models built did not properly predict future values of any final grade (Table 4): R^2 varied from

26% to 52%. This result strongly suggests that is necessary to find more predictors in an attempt to fit the final grade data.

Table 3.4: Multiple linear regression model for multivariate analysis of the influence of all predictors together onto the outcome “final grade”: analysis of Physics (mechanics). Number of access to the virtual environment does not affect the students’ final grade. Number of disciplines per semester and, surprisingly, night shift course are significantly protective factors, raising final grade of Physics mechanics. Only the percentage of face-to-face missed classes is a significantly risk factor for the final grade.

Predictor	**b**	**s.e.**	**p value**
Constant	49.86	4.1	
Physics mechanics: #accesses	0.08	0.1	0.163
High school in private school	2.00	1.5	0.170
#disciplines per semester	3.75	0.5	0.000
Age (years)	-0.22	0.1	0.071
Gender = female	-0.45	1.3	0.738
Night course	3.18	1.5	0.040
Missed classes (%)	-131	5.8	0.000

Obs.: b = regression coefficients; s.e. = standard error.
p value < 0.05 = statistically significantly results.

Table 3.5: Multiple linear regression model for multivariate analysis of the influence of all predictors together onto the outcome “final grade”: analysis of Integral calculus. Number of access to the virtual environment does not influence the students’ final grade. Only the number of disciplines per semester is a significantly protective factor, raising the final grade of Integral calculus. The percentage of face-to-face missed classes is significantly risk factor for the final grade.

Predictor	**b**	**s.e.**	**p value**
Constant	41.48	4.74	
Integral calculus: #accesses	0.05	0.04	0.305
High school in private school	-1.39	1.69	0.412
#disciplines per semester	3.65	0.61	0.000
Age (years)	-0.04	0.13	0.766
Gender = female	1.55	1.58	0.326
Night course	-0.78	1.71	0.649
Missed classes (%)	-90	4.61	0.000

Obs.: b = regression coefficients; s.e. = standard error.
p value < 0.05 = statistically significantly results.

Table 3.6: Multiple linear regression model for multivariate analysis of the influence of all predictors together onto the outcome “final grade”: analysis of Differential calculus. Number of access to the virtual environment and, surprisingly, night shift course are significantly protective factors, raising final grade of Differential calculus. Student’s age and, mainly, the percentage of face-to-face missed classes are significantly risk factor for the final grade.

Predictor	**b**	**s.e.**	**p value**
Constant	63.06	4.93	
Differential calculus: #access	0.07	0.02	0.008
High school in private school	2.26	1.89	0.231
#disciplines per semester	0.63	0.54	0.249
Age (years)	-0.33	0.13	0.013
Gender = female	1.15	1.63	0.480
Night course	4.53	1.60	0.005
Missed classes (%)	-103	4.81	0.000

Obs.: b = regression coefficients; s.e. = standard error.
p value < 0.05 = statistically significantly results.

Table 3.7: Multiple linear regression model for multivariate analysis of the influence of all predictors together onto the outcome “final grade”: analysis of Algorithms. Number of access to the virtual environment, number of disciplines per semester and, surprisingly, night shift course are significantly protective factors, raising final grade of Algorithms. Student’s age and, mainly, the percentage of face-to-face missed classes are significantly risk factor for the final grade. When the course is offered as a distance learning class is also a risk factor for the final grade of Algorithms, reducing students’ grade.

Predictor	**b**	**s.e.**	**p value**
Constant	44.40	6.75	
Algorithms: #accesses	0.17	0.06	0.006
Distance education course	-17,6	3,80	0,000
High school in private school	1.98	2.29	0.388
#disciplines per semester	5.02	0.71	0.000
Age (years)	-0.34	0.17	0.050
Gender = female	-2.65	2.15	0.219
Night course	6.873	3.47	0.048
Missed classes (%)	-220	17.27	0.000

Obs.: b = regression coefficients; s.e. = standard error.
p value < 0.05 = statistically significantly results.

Table 4: Goodness-of-fit of the multiple linear regression models: statistic R^2, that assess crudely how well the model fits data overall, is poor for the seven models.

Discipline & Regression model	R^2
Geometry	52%
General chemistry	45%
Differential calculus	41%
Physics (mechanics)	33%
Algorithms	32%
Integral calculus	32%
Physics (electricity)	26%

4 CONCLUSIONS

Regarding the questions presented in this paper, we can promptly answer that is possible to build an effective low cost online teaching/learning tool to support face-to-face classrooms of introductory engineering disciplines. The number of accesses by the students onto the virtual environment increases their grades and reduces their failure in introductory engineering disciplines, especially for General chemistry, Differential calculus, Physics electricity and Algorithms. Unfortunately, the online tool does not support students of Geometry, Physics mechanics nor Integral calculus. For these disciplines, we understand that it is necessary to reformulate its online contents, i.e., we need to review all video lectures and the video lessons that explain how to solve exercises, specifically for these three disciplines. The main conclusion of this paper refers to the fact that it is really possible to use an online education support system in a way that students from face-to-face classes can improve their chances of success in introductory disciplines of engineering.

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REFERENCES

Altman, D.G., 1991. Practical statistics for medical research. *Chapman & Hall*, 610p.

Boada, I., Soler, J., Prados, F., Poch, J. 2004. A teaching/learning support tool for introductory programming courses. *In the Proceedings of the Fifth International Conference on Information Technology Based Higher Education and Training. ITHET*, 604-609. Retrieved from http://www.academia.edu/2952178/A_teaching_learning_support_tool_for_introductory_programming_courses.

Greenhalgh, T., 2001. Computer assisted learning in undergraduate medical education. *BMJ,* 322:40. Retrieved from http://www.bmj.com/content/322/7277/40.

Haslam, J., 2014. Synchronous vs. Asynchronous Classes. eLearners. Retrieved from https://www.elearners.com/education-resources/degrees-and-programs/synchronous-vs-asynchronous-classes/

PCAST - President's Council of Advisors on Science and Technology, 2012. Engage to Excel: Producing One Million Additional College Graduates with Degrees in Science, Technology, Engineering, and Mathematics. Washington, DC: White House Office of Science and Technology Policy. Retrieved from https://www.whitehouse.gov/sites/default/files/microsites/ostp/fact_sheet_final.pdf.

Roll, I., Aleven, V., McLaren, B. M., Koedinger, K. R., 2011. Improving students' help-seeking skills using metacognitive feedback in an intelligent tutoring system. *Learning and Instruction*, 21(2), 267-280. Retrieved from http://www.cs.cmu.edu/afs/cs.cmu.edu/Web/People/bmclaren/pubs/RollEtAl-ImprovingHelpSeekingWithITS-LandI2011.pdf.

Saxe, K., Braddy, L., Bailer, J., et al., 2015. A common vision for undergraduate mathematical sciences programs in 2025. *Mathematics Association of America.* Retrieved from http://www.maa.org/sites/default/files/pdf/CommonVisionFinal.pdf.

Senior, B.A., 2008. Correlation between absences and final grades in a college course. *Proceedings of the 44th Annual Conference of the Associated Schools of Construction, Auburn, Alabam.* Retrieved from http://ascpro0.ascweb.org/archives/cd/2008/paper/CEUE275002008.pdf.

Sim, T.Y., 2015. Exploration on the impact of online supported methods for novice programmers. *e-Learning e-Management and e-Services (IC3e) 2015 IEEE Conference.* 158-162. Retrieved from http://ieeexplore.ieee.org/abstract/document/7403505/