Effectiveness of Gamification in Undergraduate Education

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Abstract: What is the quantitative effect of gamified learning/teaching on the performance of students? This basic question has not received as much attention as it deserves in the related literature, despite the many works that analyze the benefits and design principles of gamified activities across many domains. We present in this paper an analysis of this question focused on identifying the network structure variables that quantitatively explain the improvements reported when using gamification integrated in the course design. We compare the results with those from a group that does not follow gamification at all, hence we are able to ascertain the strength and impact that gamification has on numerical grades or scores.

1 INTRODUCTION

This paper is an attempt to clarify the following research question: how effective is the use of gamified activities and learning strategies for students? As an educational approach, gamified learning (GL) exhibits a number of clear advantages related to the dynamics of the learning process (Aldemir et al., 2018; Cakirogli et al., 2017), for instance in creating stronger and longer engagement from the students, and in improving their perceived learning experience. However, when in comes to a quantitative analysis of the real benefits of using technology-mediated gamified activities in a course, the picture extracted from the related research literature is less clear or systematic. Whereas some studies (Buckley and Doyle, 2017; Davis et al., 2018; Kyewski and Kramer, 2018) adopt the point of view of students, their attitudes and personal traits as one of the factors that may impact on the effectiveness of GL, another line of work is focused on less subjective experiments, and attempts to determine how much improvement in academic achievement is possible through a comprehensive embedding of GL into traditional teaching styles (Yildirim, 2017).

Our previous work in this area has been focused on identifying the network properties of the dynamics induced by the GL activities designed for undergraduates in engineering (Sousa et al., 2017). The main finding has been not only that the networked relations formed amongst the students in the online social realm can be exploited as robust predictors of final learning success (Sousa et al., 2018), but also that there exist significant statistical correlation between basic structural properties in the network and the graded performance of students (Ferreira et al., 2020a). In this paper, we take one step further and make a statistical comparison between groups of students exposed to GL and students taught without GL with respect to different types of GL activities. Our aim is to estimate the quantitative measure that a given GL teaching tool may have on the academic performance, so as to guide in the selection of the GL tools suitable for a given course.

The rest of the paper is organized as follows. Section 2 summarizes some recent related work. The methodology employed in the course under study is reported in Section 3. Section 4 contains the main results of the analysis applied to the datasets. Finally, some concluding remarks are included in Section 5.

2 RELATED WORK

Gamification is defined as the use of game design elements in non-game contexts (Kapp, 2012). It can be applied in several situations to influence the behaviors of individuals, mainly to increase engagement, to motivate action or to promote learning. Due to the fact that all these are major issues faced by teachers of all educational levels, in recent years multiple implementations of gamification in educational contexts have emerged. In this section, we present a literature review of those focused on higher education. Again, a more extensive compilation can be found in (Subhash and Cudney, 2018; Zainuddin et al., 2020). Table 1 summarizes, of the game design elements used in our case study, those mentioned in each paper.

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The work (Landers and Landers, 2014) studies the effect of a gamified version of an online wiki-based project in an industrial/organizational psychology course, showing an increase of the interactions. Moreover, results indicate that time-on-tasks predicts learning outcomes. The results explained in (Ibáñez et al., 2014) show positive effects on the engagement of C-programming students toward gamified learning activities and a moderate improvement in learning outcomes. In (Strmecki et al., 2015), authors conduct an experimental study to investigate the effectiveness of gamification of an online informatics course on computer graphics. Results show that students enrolled in the gamified version of the course achieved greater learning success. The article (Kuo and Chuang, 2016), reports the application of gamification to an online context for academic promotion and dissemination. Both quantitative and qualitative data were collected and analyzed, revealing that gamification has the potential to attract, motivate, engage and retain users. The research addressed in (Buckley and Doyle, 2017) examines the impact of different learning styles and personality traits on students' perceptions of engagement and overall performance in a gamified business course. Findings suggest that students who are oriented towards active or global learning as well as extroverted students have a positive impression of gamification. The effect of gamified instructional process to ICT students engagement and academic performance is studied in (Cakirogli et al., 2017). Conclusions show that using the proposed combination of elements provided a positive motivational impact on engagement and indirectly affected the academic results. Similar results are observed in (de Marcos et al., 2017), where authors found evidence that gamification can be used to improve the overall academic performance in practical assignments and to promote social interaction in a qualification for ICT users course. The work (Dias, 2017) describes the application of gamification in an operations research/management science course, where it was possible to observe an increase of participation in class, better results and a good assessment of the course made by the students. In the study (Sailer et al., 2017) authors vary different configurations of game design elements and analyze them in regard to their effect on the fulfillment of basic psychological needs. The article (Sánchez et al., 2017) presents a gamification experience within prospective primary teachers in a general science course. In an effort for promoting collaborative dynamics rather than competitive ones, a new variable called game index, that takes into account the scoring of the whole class, was introduced. A positive correlation among scoring and academic marks was confirmed. The experiment described in (Yildirim, 2017) was conducted to determine the effect of gamification-based teaching practices on achievements and attitudes towards learning, in a course about teaching principles and methods. The results show positive attitudes towards the lessons and a moderate effect on achievements. Although there was not difference between the final grades of the gamified and the control groups, students regard wiki and gamified activities positively.

Recently, the article (Aldemir et al., 2018) presents the gamification process, iterations made into the game elements and their features and students' perceptions in a gamified teacher education course. The study (Davis et al., 2018) investigates college students' experiences of a gamified informatics course, showing positive trends with respect to students' perceptions of gamification's impact on their learning, achievement, and engagement in the course material. The authors of (Ding et al., 2018) explore the effects of gamification on students' engagement in online discussions. Conclusions and interviews with students and teachers suggest a positive effect of the game-related features of the platform. The focus of the study reported in (Huang and Hew, 2018) is to explore whether gamification could be a good strategy to motivate students to participate in more out-of-class activities without decreasing the quality of work. Results from two experiments conducted in two master level courses on statistics reveal that the gamified classes completed significantly more activities and produced higher quality work. In (Jo et al., 2018), authors test the effectiveness of adding educational gaming elements into the online lecture system of a flipped classroom, as a method to increase interest in online preparation before class, obtaining good results and better academic achievements of mid-upper level students. The work (Jurgelaitis et al., 2018) analyses the effect of using gamification elements in a course related to software development. The study confirms that students' grades and motivation can increase as a result of applying gamification to their learning process. In the experiment described in (Kyewski and Kramer, 2018) students were randomly assigned to three different conditions: no badges, badges visible to peers and badges only visible to students themselves. Contrarily to expectations, the last one was evaluated more positively than the second one. The effects of using gamification elements in courses that make use of a wiki environment on the participation rates as well as on student academic success is addressed in (Ozdener, 2018). In (Roy and Zaman, 2018), authors measure the possible evolution of motivational levels in response to the interaction with the game elements used in a university course. The findings illustrate the significance of the individual nature of motivational processes, the importance of sensitive longitudinal motivation measurements and the relevance of the implemented game elements' design characteristics. The work addressed in (Tsay et al., 2018) indicates, from a cohort of undergraduate business students, that course performance was significantly higher among those students who participated in the proposed gamified system than in those who engaged with the traditional delivery. The article (Zatarain et al., 2018) describes an advanced learning environment that detects and responds to computer programming students' emotions by using ML techniques, and incorporates motivation strategies by using gamification methods. In (Baydas and Cicek, 2019), authors develop a scale to measure the factors that may affect the gamification process via kahoot in a pre-service teachers undergraduate course. The study presented in (Ortiz et al., 2019) describes the positive effect of gamification, based on leaderboards, on learning performance in an introductory computer programming course. Finally, in (Toda et al., 2019) authors propose a solution to help instructors to plan and deploy gamification concepts with social network features in learning environments. A case study over a programming course reveals that the implemented gamified strategies achieved positive acceptance among teachers and students.

Related to our prior work in this area, (Sousa et al., 2017) focused on the quantitative characterization of non-formal learning methodologies. To this end, we used one custom software platform for discovering what factors or variables have statistically significant correlation with the students' academic achievements. The dataset was collected along several consecutive editions of an undergraduate course. Next, in (Sousa et al., 2018) we compare and combine the power of different classifiers for success/failure learning prediction, using as inputs some of the features discovered in previous works that have measurable correlation with the students' performance. Finally, in (Ferreira et al., 2020b) we focused on the analysis of forums engagement, modeling forums' interactions as social graphs. It was the first time that we encourage and reward quality participation in this activity in the undergraduate and master level courses under study. In (Ferreira et al., 2020a) we extended this analysis and we showed the power of some of the graphs properties for success/failure learning prediction. In this work, as the last step of this longitudinal study, we allow the following-up of the gamification methodology to be optional and we compare the results obtained with each one of the two learning paths.

3 EDUCATIONAL CONTEXT & DATASET

We have taken as our educational environment the 2019/2020 edition of a course on Computer Networks directed to undergraduates of the second year of the Telecommunications Technologies Engineering degree. This course has a weekly schedule that spans 14 weeks (between January and May). The classroom activities are organized as follows:

- Lectures, that blend the presentation of concepts, techniques and algorithms with the practice of problem-solving skills and discussion of theoretical questions.
- Laboratory sessions, where the students design and analyze different network scenarios with different protocols, using real or simulated networking equipment. Moreover, in some of these sessions students make a programming assignment.

In both editions the activities are supported by a tailored Moodle site to which the students and teachers belong, and wherein general communication about the topics covered takes place. To encourage networked learning and collaborative work, different activities are planned and carried out in the platform. The students may gain different kinds of recognition by completing or participating in these activities. In the editions analyzed in this work, these online activities were proposed:

1. Homework tasks, to be worked out before the in-class or the laboratory sessions. With this activity teachers encourage the students to prepare some of the material in advance.
2. Quizzes, proposed before the midterm exams for self-training.
3. Collaborative participation in forums. Several forums were created in Moodle to allow the students to post questions, doubts or puzzles related to the organization of the course, the content of the in-class lectures or the laboratory sessions and the programming assignments.
4. Optional activities, such as games, peer assessment of tasks, etc.

The score of tasks (and their peer assessment) and quizzes is measured in so-called merit points, and represents the total score gained for accomplishment of these activities in the modality B of the continuous assessment (a 10% of the final grade). It is possible to obtain extra merit points by doing the optional activities in order to compensate for low scores or late

Table 1: Game design elements used in the selected papers.

	Badges	Boards	Levels	Points	Rewards
(Landers and Landers, 2014)		✓			
(Ibáñez et al., 2014)	✓	✓		✓	✓
(Strmecki et al., 2015)	✓	✓		✓	✓
(Kuo and Chuang, 2016)	✓	✓	✓	✓	✓
(Buckley and Doyle, 2017)	✓	✓	✓	✓	✓
(Cakirogli et al., 2017)		✓		✓	✓
(de Marcos et al., 2017)	✓	✓		✓	
(Dias, 2017)	✓	✓		✓	
(Sailer et al., 2017)	✓	✓	✓		
(Sánchez et al., 2017)				✓	
(Yildirim, 2017)	✓	✓	✓	✓	
(Aldemir et al., 2018)	✓	✓	✓	✓	✓
(Davis et al., 2018)	✓	✓	✓	✓	
(Ding et al., 2018)	✓	✓	✓	✓	✓
(Huang and Hew, 2018)	✓	✓	✓	✓	✓
(Jo et al., 2018)		✓		✓	
(Jurgelaitis et al., 2018)	✓	✓	✓	✓	✓
(Kyewski and Kramer, 2018)	✓	✓			
(Ozdener, 2018)	✓	✓	✓	✓	✓
(Roy and Zaman, 2018)	✓	✓			
(Tsay et al., 2018)	✓	✓			
(Zatarain et al., 2018)	✓	✓		✓	
(Baydas and Cicek, 2019)	✓	✓	✓	✓	✓
(Ortiz et al., 2019)		✓			
(Toda et al., 2019)		✓	✓		✓

submissions of some of the tasks or quizzes. Well-done peer assessments and the best scores in tasks and quizzess are rewarded with coins and badges.

Participation in forums, solving doubts or sharing resources, is also valued with points or votes granted by the teachers or the classmates. As new points or votes are obtained, the so-called karma level of each student increases, depending on different factors that take into account the quality of the student's actions and the comparison with that of his/her classmates. As the karma level increases, students can get coins.

The use of the virtual classroom is also rewarded by the automatic scoring of different actions carried out in the platform related to the normal activity unfolded along the term, like posting or viewing resources, posting new threads, replying to posts, completing tasks, etc. The so-called experience points are organized into levels and are awarded in a controlled environment with maximum values and their frequency set by the teachers. When students level up, they get coins.

At any time, a student can check his/her accumulated merit points, karma level and accumulated experience points and level. Moreover, students can check their positions in the global rankings and the averages values of the course. And occasionally, the best students of a ranking can be made public to the group.

The coins accumulated at the end of the course can be converted into the following benefits helpful to pass the subject (the final exam consist of 6 exercises; each exercise scores 2 points and the maximun score is 10 points).

- 32 coins can be changed by the *extra exercise wildcard*: the 6 exercises of the exam are corrected and their mark is added up to a maximum of 10 points.
- 22 coins can be changed by the *remove worse exercise wildcard*: the 6 exercises of the exam are corrected and the worse is not taken into account.
- 16 coins can be changed by the *remove exercise wildcard*: students choose the exercise whose score is not taken into account.
- 4 or 6 coins can be converted into one or two pages of notes for the final exam.
- 3 coins can be changed by 5 bonus merit points up to a maximum of 25.

For students who do not have a wildcard, the 6 exercises are corrected and the score of each one is scaled by $10/6$. It is clear that the students that follow the modality B of the continuous assessment can get more benefit from the gamification strategy.

Students may pass the course after a single final examination covering all the material (provided the programming assignment meets the minimum requirements), but they are encouraged to follow the continuous assessment. In continuous assessment we allow two modalities, A and B. We weigh 40% the final exam, but the rest is split as follows: 36% in modality A and 24% in modality B from the midterm exams, 24% from the programming assignment and 12% (only in modality B) coming out from the merit points obtained by accomplishing the online activities (task, quizzes and optional tasks) described previously, devised as a tool to increase the level of participation. Students have two opportunities to pass the exam (non-exclusive), May and July.

To finish our description, among all students enrolled in this course, 121 students did not drop out (i.e. they attendend the final exam). Among these 121 students, of the 114 students who followed the continuous assessment (18 in modality A and 96 in modality B), 84 finally passed the course (13 (72%) in modality A, almost all second-taking students, and 71 (74%) in modality B). And none of the 7 students not engaged in continuous assessment was able to pass. Related to the rate of success in the final exam, it was 0% for the single final examination modality, 22% for the continuous assessment modality A and 32% for the continuous assessment modality B.

At this point, it is important to highlight that the adaptation of this subject to the lockdown caused by the pandemic, that affected the second part of the term, was fast and without incidents for the vast majority of students, because they were already used to the platform and the blended learning methodology since January. In fact, among the students who followed the continuous assessment, the dropout rate of the students in modality A was 1.5 times higher than that of the students modality B.

4 ANALYSIS OF THE DATASETS

4.1 MERIT POINTS

Figure 1 displays the points obtained by some representative students that followed modality B of the continuous assessment. These points include the merit points obtained in the tasks and tests proposed, the extra merit points and the bonus points. In these figures we represent the accumulated number of merit points earned by each student along the term. Students are identified by his/her position in the ordered list of final grades (we represent the first 8 students with the best final grades and the 8 students with the worst final grades among the 96 students that followed the modality B of the continuous assessment and did not drop out the course). As we can see, the pattern of accomplishment of all the students represented in the figure on the top is similar, reaching all or almost all the possible points. And although the activity of the students represented in the figure on the bottom is more irregular, almost all of them reached more than 80% of all the possible points.

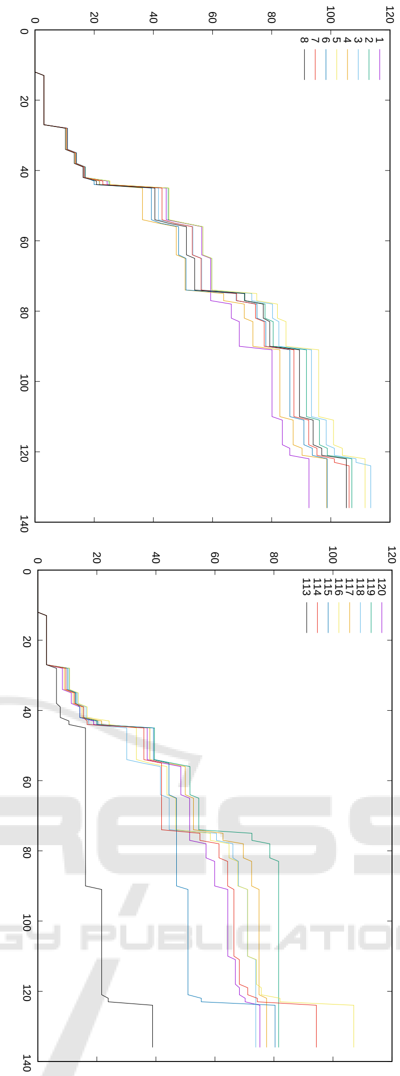

Figure 1: Accumulated merit points. First positions in the ordered list of final grades (top) and last positions (bottom).

Table 2: Individual merit points.

	$\hat{\mu}$	$\hat{\sigma}$
tqmp	58.5253	18.1286
emp	13.8074	6.1131
tmp	75.8786	21.5459
tmps	0.7023	0.2013

Table 2 shows the estimated mean value and standard deviation of the individual merit points (merit points form tasks and quizzes(tqmp), extra merit points (emp) and total merit points (tmp)) and the slope of total merit points (tmps), that is, the coefficient of a linear regression model of the total merit points per time graph, of all the students that followed the modality B of the continuous assessment.

Table 3: Correlation between individual merit points and student's performance in the final exam.

	$\hat{\rho}$	$(\hat{\beta}, t, \mathbb{P}(>\lvert t\rvert))$
tqmp	0.4783	$(0.0689, 5.3112, 7.21 \cdot 10^{-7})$
emp	0.1677	$(0.0559, 1.6591, 1.01 \cdot 10^{-1})$
tmp	0.3654	$(0.0483, 3.8261, 2.33 \cdot 10^{-4})$
tmps	0.3944	$(5.2706, 4.1831, 6.41 \cdot 10^{-5})$

In order to check the relationship among the patterns of engagement along the term and knowledge acquisition, we have measured the statistical correlations between the individual merit points and the performance in the final exam (taking into account the sum of the scores of the 6 exercises before applying wildcards) of the students that followed the continuous assessment and did not drop out the course. For this purpose, the sample correlations $\hat{\rho}$ were computed and the linear regression statistical test was used to quantify such correlations. The estimated linear coefficient is denoted by $\hat{\beta}$. Under the null hypothesis (meaning that there is not such linear dependence) the test statistic follows a t-distribution and high values are very unlikely to be observed empirically (James et al., 2013). In Table 3 we can see statistically significant positive dependences.

4.2 Forums Activity

We have applied standard SNA techniques (Newman, 2018) to mine the data collected in forums. For such purpose, we have recorded the events that took place in each forum, users who posted new threads, users who replied and the average valuations they received. This information is represented as a graph where two nodes, the users, are connected by an edge if one has given a reply to an entry posted by the other. Moreover, self-edges represent new threads. The weight of each edge is related to the points or votes obtained by the reply or the new thread post. Orange edges identify replies marked as useful by the owner of the question and green edges identify the best replies based on the opinion of the owner of the question and/or the teachers. An illustration of the graphs related to each forum is given in Figure 2, where every node is a student identified by his/her position in the ordered list of final grades. The node with label 0 corresponds to the instructors.

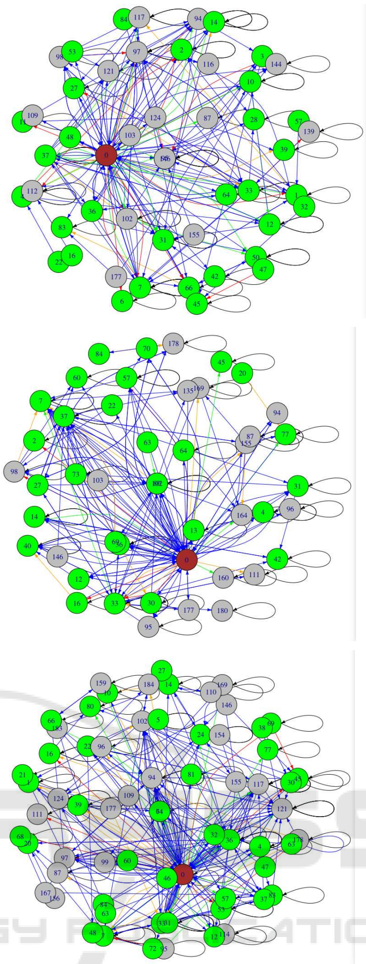

Figure 2: Forums activity graphs. Lessons graph (top), programming graph (middle) and organization graph (bottom).

4.3 Measures

Next, we report some of the typical measures of a graph that can be obtained globally or individually for each node, and their values in our datasets. Notice that for some measures we consider simplified versions of the graphs, where the weight of each edge is the sum of the weights of all the edges between the underlying pair of nodes. Moreover, including self-edges means including the opening of new forum threads in the analysis.

For the case of degree centrality, we considered separately the in-degree and out-degree centralities. In this application, considering the simplified version of the graphs, the in-degree centrality is the number of neighbors whose replies a student receives, and the out-degree centrality is the number of neighbors that receive the replies given by a student. The results in Tables 4-6 reveal that the in-degree centrality values

Table 4: Summary of parameters of the lessons graph.

degree	in	0.2136
	out	0.6244
closeness		0.6026
betweenness		0.6716
eigenvector		0.8454
# cliques	Size	
	2	110
	3	68
	4	15
number new threads (μ-σ)	0.4608	0.9485
number new threads (mod. B) (μ-σ)	0.5	0.9765
number replies (μ-σ)	0.9043	2.0475
number replies (mod. B) (μ-σ)	1.0408	2.1821
points new threads (μ-σ)	9.0591	27.5874
points new threads (mod. B) (μ-σ)	14.2755	27.9704
points replies (μ-σ)	20.5652	46.1802
points replies (mod. B) (μ-σ)	24	49.2351

Table 5: Summary of parameters of the programming graph.

degree	in	0.3298
	out	0.7161
closeness		0.6827
betweenness		0.7489
eigenvector		0.8425
# cliques	Size	
	2	84
	3	43
	4	4
number new threads (μ-σ)	0.3217	0.7199
number new threads (mod. B) (μ-σ)	0.3673	0.7651
number replies (μ-σ)	0.7304	1.8746
number replies (mod. B) (μ-σ)	0.8163	2.0017
points new threads (μ-σ)	8.5478	19.1532
points new threads (mod. B) (μ-σ)	9.7857	20.3734
points replies (μ-σ)	14.2434	33.9929
points replies (mod. B) (μ-σ)	15.6531	35.9713

are moderate, but the out-degree centrality is noticeable, indicating a non-homogeneous distribution of the number of neighbors that receive the replies submitted by the participants. A subset of few nodes act as very active participants in forums (among them the teachers). Nevertheless, more nodes act as generators of new threads and recipients of information.

For the closeness centrality, that measures how easily a node can reach other nodes computing the inverse of the average length of the shortest paths to all the other nodes in the graph, the high values shown in Tables 4-6 are again indicative of the existence of few very active contributors.

In the case of the betweenness centrality, that tries to capture the importance of a node in terms of its role in connecting other nodes, computing the ratio between the number of shortest paths that a node lies on and the total number of possible shortest paths between two nodes, the high values observed in Tables 4-6 suggest that few nodes act as bridges between different parts of the graph.

Eigenvector centrality is a measure based on the premise that a node's importance is determined by how important or influential its neighbors are. The scores arise from a reciprocal process in which the centrality of each node is proportional to the sum of the centralities of the nodes it is connected to. Considering the version of the graph with self-edges, Tables 4-6 show that the measured eigenvector centrality values are noticeable. Again, this clearly means that there are substantial differences among the nodes in their patterns of participation in this activity.

Table 6: Summary of parameters of the organization graph.

degree	in	0.2185
	out	0.5832
closeness		0.6071
betweenness		0.6417
eigenvector		0.8721
# cliques	Size	
	2	141
	3	99
	4	42
	5	12
	6	1
number new threads (μ-σ)	0.6086	1.2333
number new threads (mod. B) (μ-σ)	0.6428	1.2701
number replies (μ-σ)	1.2696	2.7859
number replies (mod. B) (μ-σ)	1.3061	2.6879
points new threads (μ-σ)	16.1391	32.3066
points new threads (mod. B) (μ-σ)	16.7959	33.0713
points replies (μ-σ)	27.9304	58.5248
points replies (mod. B) (μ-σ)	28.1428	54.4638

Table 7: Correlation between individual features and student's performance in the final exam (lessons graph).

	$\hat{\rho}$	$(\hat{\beta}, t, \mathbb{P}(>\lvert t\rvert))$
in degree	0.2218	$(0.2441, 2.4192, 1.72\cdot10^{-2})$
out degree	0.1181	$(0.1298, 1.2643, 2.09\cdot10^{-1})$
betweenness	0.1151	$(0.0082, 1.2332, 2.22\cdot10^{-1})$
closeness	0.1593	$(1.4924, 1.7153, 8.91\cdot10^{-2})$
eigenvector	0.1918	$(2.9671, 2.0719, 3.99\cdot10^{-2})$
crossclique number	0.1473	$(0.0401, 1.5831, 1.16\cdot10^{-1})$
number new threads	0.1728	$(0.3498, 1.8652, 6.47\cdot10^{-2})$
number replies	0.0974	$(0.0913, 1.0404, 3.01\cdot10^{-1})$
points new threads	0.1427	$(0.0099, 1.5332, 1.28\cdot10^{-1})$
points replies	0.1156	$(0.0048, 1.2376, 1.77\cdot10^{-1})$

A clique is a completely connected subgraph of a given graph. So, cliques represent strongly tied subcommunities where each member interacts with any other member. And the crossclique number accounts for the number of cliques a node belongs to. Tables 4-6 list the number of cliques in the graphs by their size.

Finally, if we consider the non-simplified version of the graphs, the in-degree centrality is the number of replies a student receives, and the out-degree centrality is the number of replies given by a student. Moreover, the number of self-edges accounts for the number of new threads opened by each student. In addition to the intensity of interactions, another important factor is their quality that can be measured taking into account the weights of the edges. The results in Tables 4-6 show the mean value and the standard deviation of this measures for all the students that did not drop out the course and for the students that followed the modality B of the continuous assessment. We can observe higher values for these, mainly in the lessons forum.

Table 8: Correlation between individual features and student's performance in the course (lessons graph).

	$\hat{\rho}$	$(\hat{\beta}, t, \mathbb{P}(>\lvert t\rvert))$
in degree	0.1654	$(0.1951, 1.7832, 7.72 \cdot 10^{-2})$
out degree	0.1244	$(0.1466, 1.3331, 1.85 \cdot 10^{-1})$
betweenness	0.1526	$(0.0116, 1.6424, 1.03 \cdot 10^{-1})$
closeness	0.1072	$(1.0054, 1.3943, 1.66 \cdot 10^{-1})$
eigenvector	0.1201	$(1.9893, 1.2851, 2.01 \cdot 10^{-1})$
crossclique number	0.1249	$(0.0363, 1.3381, 1.83 \cdot 10^{-1})$
number new threads	0.1286	$(0.2791, 1.3791, 6.47 \cdot 10^{-2})$
number replies	0.1064	$(0.1071, 1.1385, 2.57 \cdot 10^{-1})$
points new threads	0.1279	$(0.0095, 1.3711, 1.73 \cdot 10^{-1})$
points replies	0.1268	$(0.0056, 1.3591, 1.77 \cdot 10^{-1})$

Table 9: Correlation between individual features and student's performance in the final exam (programming graph).

	$\hat{\rho}$	$(\hat{\beta}, t, \mathbb{P}(>\lvert t\rvert))$
in degree	0.0461	$(0.0575, 0.4908, 6.25 \cdot 10^{-1})$
out degree	0.0233	$(0.1101, 0.2481, 8.05 \cdot 10^{-1})$
betweenness	−0.0005	$(-0.0004, -0.0001, 9.99 \cdot 10^{-1}$
closeness	0.1162	$(1.0895, 1.2442, 2.16 \cdot 10^{-1})$
eigenvector	0.0567	$(0.9791, 0.6041, 0.54 \cdot 10^{-1})$
crossclique number	0.0598	$(0.0242, 0.6381, 5.25 \cdot 10^{-1})$
number new threads	0.1042	$(0.2781, 1.1142, 2.68 \cdot 10^{-1})$
number replies	0.0408	$(0.0417, 0.4342, 6.65 \cdot 10^{-1})$
points new threads	0.0644	$(0.0064, 0.6861, 4.94 \cdot 10^{-1})$
points replies	0.0055	$(0.0003, 0.0591, 9.53 \cdot 10^{-1})$

Table 10: Correlation between individual features and student's performance in the course (programming graph).

	$\hat{\rho}$	$(\hat{\beta}, t, \mathbb{P}(>\lvert t\rvert))$
in degree	0.0921	$(0.1232, 0.9832, 3.27 \cdot 10^{-1})$
out degree	0.0785	$(0.1101, 0.8381, 4.04 \cdot 10^{-1})$
betweenness	0.0361	$(0.0037, 0.3857, 7.01 \cdot 10^{-1})$
closeness	0.1012	$(1.5546, 1.6656, 9.88 \cdot 10^{-2})$
eigenvector	0.1098	$(2.0321, 1.1742, 0.24 \cdot 10^{-1})$
crossclique number	0.1835	$(0.0435, 1.0751, 2.85 \cdot 10^{-1})$
number new threads	0.1555	$(0.4446, 1.6743, 9.69 \cdot 10^{-2})$
number replies	0.0948	$(0.1041, 1.0132, 3.13 \cdot 10^{-1})$
points new threads	0.1211	$(0.0231, 1.2976, 1.97 \cdot 10^{-1})$
points replies	0.0794	$(0.0048, 0.8472, 3.99 \cdot 10^{-1})$

4.4 Correlations with Final Results

In order to check the relationship among the patterns of participation in the forums and the achievements of the course, we have measured the statistical correlations between the features under study in this section and the final grades in the final exam (taking into account the sum of the scores of the 6 exercises before applying wildcards) and in the course of the students that followed the continuous assessment and did not drop out the course.

The results in Tables 7-12 show a statistically significant positive dependence between many of the considered factors and the students' performance in the lessons graph.

Table 11: Correlation between individual features and student's performance in the final exam (organization graph).

	$\hat{\rho}$	$(\hat{\beta}, t, \mathbb{P}(>\lvert t\rvert))$
in degree	−0.0203	$(-0.0156, -0.2176, 8.29 \cdot 10^{-1})$
out degree	−0.0279	$(-0.0252, -0.2971, 7.67 \cdot 10^{-1})$
betweenness	−0.0044	$(-0.0002, -0.0487, 9.62 \cdot 10^{-1})$
closeness	0.0362	$(0.3258, 0.3861, 7.01 \cdot 10^{-1})$
eigenvector	−0.0139	$(-0.2144, -1.4801, 8.83 \cdot 10^{-1})$
crossclique number	−0.0308	$(-0.0039, -0.3281, 7.43 \cdot 10^{-1})$
number new threads	−0.0347	$(-0.0541, -0.3691, 7.13 \cdot 10^{-1})$
number replies	−0.0795	$(-0.0547, -0.8487, 3.98 \cdot 10^{-1})$
points new threads	0.0017	$(0.0001, 0.0183, 9.85 \cdot 10^{-1})$
points replies	−0.0686	$(-0.0022, -0.7324, 7.95 \cdot 10^{-1})$

Table 12: Correlation between individual features and student's performance in the course (organization graph).

	$\hat{\rho}$	$(\hat{\beta}, t, \mathbb{P}(>\lvert t\rvert))$
in degree	−0.0065	$(-0.0053, -0.0692, 9.45 \cdot 10^{-1})$
out degree	0.0095	$(0.0092, 0.1021, 9.19 \cdot 10^{-1})$
betweenness	0.0301	$(0.0014, 0.3221, 7.56 \cdot 10^{-1})$
closeness	0.0432	$(0.8162, 0.9044, 3.68 \cdot 10^{-1})$
eigenvector	−0.0068	$(-0.1128, -0.0732, 9.42 \cdot 10^{-1})$
crossclique number	−0.0225	$(-0.0031, -0.3281, 8.11 \cdot 10^{-1})$
number new threads	−0.0129	$(-0.0216, -0.1381, 7.13 \cdot 10^{-1})$
number replies	−0.0519	$(-0.0383, -0.5522, 5.82 \cdot 10^{-1})$
points new threads	0.0175	$(0.0011, 0.1871, 8.52 \cdot 10^{-1})$
points replies	−0.0245	$(-0.0008, -0.2611, 7.95 \cdot 10^{-1})$

5 CONCLUSIONS

We presented in this paper a broad correlation study between individual features pertaining to the structutal properties of the network relations graph formed in an online social environment and final performance of students, both for individuals following the GL-based style and those who refuse this option. Consistently, our results show that positive correlations are present always between individuals in the GL group and better academic achievement, almost irrespective of the particular network feature studied. Thus, these students attain better grades and better success probability in the final exams, are much less prone to quit the course, and provide more frequent contributions and information to the forums, usually of high quality and better cr itical thinking.

A possible limitation of our study is that the split between the GL group and the non-GL group is not totally random nor blind, which might introduce some bias in our results. Nevertheless, we conjecture that, since for most students this is their *first* exposure to GL, their prior attitude toward gamification is inconsequential and little relevant as to the final outcomes. Therefore, our study contributes to the identification of the measurable variables that correlate positively and significantly with the students performance.

REFERENCES

Aldemir, T., Celik, B., and Kaplan, G. (2018). A qualitative investigation of student perceptions of game elements in a gamified course. *Computers in Human Behavior*, 78:235–254.

Baydas, O. and Cicek, M. (2019). The examination of the gamification process in undergraduate education: A scale development study. *Technology, Pedagogy and Education*, 18(3):269–285.

Buckley, P. and Doyle, E. (2017). Individualising gamification: An investigation of the impact of learning styles and personality traits on the efficacy of gamification using a prediction market. *Computers & Education*, 69:43–55.

Cakirogli, U., Basibuyuk, B., Guter, M., and Atabay, M. (2017). Gamifying an ICT course: Influences on engagement and academic performance. *Computers in Human Behavior*, 69:98–107.

Davis, K., Sridharan, H., Koepke, L., Singh, S., and Boiko, R. (2018). Learning and engagement in a gamified course: Investigating the effects of student characteristics. *Journal of Computer Assisted Learning*, 34(5):492–503.

de Marcos, L., García, A., and García, E. (2017). Towards the social gamification of e-learning: A practical experiment. *International Journal of Engineering Education*, 33(1):66–73.

Dias, J. (2017). Teaching operations research to undergraduate management students: The role of gamification. *The International Journal of Management Education*, 15:98–111.

Ding, L., Er, E., and Orey, M. (2018). An exploratory study of student engagement in gamified online discussions. *Computers & Education*, 120:213–226.

Ferreira, O., Sousa, M., López, J., and Fernández, M. (2020a). An assessment of statistically classification for socially oriented learning methodologies. In *CSEDU'20, 12th International Conference on Computer Supported Education*.

Ferreira, O., Sousa, M., López, J., and Fernández, M. (2020b). Studying relationships between network structure in educational forums and students' performance. In *Communications in Computer and Information Science. Computer Supported Education*. Springer.

Huang, B. and Hew, K. (2018). Implementing a theory-driven gamification model in higher education flipped courses: Effects on out-of-class activity completion and quality of artifacts. *Computers & Education*, 125:254–272.

Ibáñez, M., Di-Serio, A., and Delgado, C. (2014). Gamification for engaging computer science students in learning activities: A case study. *IEEE Transactions on Learning Technologies*, 7(3):291–301.

James, G., Witten, D., Hastie, T., and Tibshirani, R. (2013). *An introduction to statistical learning with applications in R*. Springer.

Jo, J., Jun, H., and Lim, H. (2018). A comparative study on gamification of the flipped classroom in engineering education to enhance the effects of learning. *Computer Application on Engineering Education*, 26(5):1626–1640.

Jurgelaitis, M., Ceponienè, L., Ceponis, J., and Drungilas, V. (2018). Implementing gamification in a university-level uml modeling course: A case study. *Computer Applications in Engineering Education*, 27(2):332–343.

Kapp, F. (2012). *The gamification of learning and instruction: Game-based methods and strategies for training and education*. Pfeiffer.

Kuo, M. and Chuang, T. (2016). How gamification motivates visits and engagement for online academic dissemination: An empirical study. *Computers in Human Behavior*, 55:16–27.

Kyewski, E. and Kramer, N. (2018). To gamify or not to gamify? an experimental field study of the influence of badges on motivation, activity and performance in an online learning course. *Computers & Education*, 118:25–37.

Landers, R. and Landers, A. (2014). An empirical test of the theory of gamified learning: The effect of leaderboards on time-on-task and academic performance. *Simulation & Gaming*, 45(6):769–785.

Newman, M. (2018). *Networks*. Oxford University Press.

Ortiz, M., Chiluiza, K., and Valcke, M. (2019). Gamification through leaderboards: An empirical study in engineering education. *Computer Applications in Engineering Education*, 27(4):777–788.

Ozdener, N. (2018). Gamification for enhancing web 2.0 based educational activities: The case of pre-service grade school teachers using educational wiki pages. *Telematics and Informatics*, 35(3):564–578.

Roy, R. and Zaman, B. (2018). Need-supporting gamification in education: An assessment of motivational effects over time. *Computers & Education*, 127:283–297.

Sailer, M., Ulrich, J., Mayr, S., and Mandl, H. (2017). How gamification motivates: An experimental study of the effects of specific game design elements on psychological need satisfaction. *Computers in Human Behavior*, 69:371–380.

Sánchez, J., Cañada, F., and Dávila, M. (2017). Just a game? gamifying a general science class at university. collaborative and competitive work implications. *Thinking Skills and Creativity*, 26:51–59.

Sousa, M., López, J., Fernández, M., Ferreira, O., Rodríguez, M., and Rodríguez, R. (2018). Prediction of learning success/failure via pace of events in a social learning network platform. *Computer Applications in Engineering Education*, 26(6):2047–2057.

Sousa, M., López, J., Fernández, M., Rodríguez, M., and López, C. (2017). Mining relations in learning-oriented social networks. *Computer Applications in Engineering Education*, 25(5):769–784.

Strmecki, D., Bernik, A., and Radosevic, D. (2015). Gamification in e-learning: Introducing gamified design elements into e-learning systems. *Journal of Computer Science*, 11(12):1108–1117.

Subhash, S. and Cudney, E. (2018). Gamified learning in higher education: A systematic review of the literature. *Computers in Human Behavior*, 87:192–206.

Toda, A., Carmo, R., Silva, A., Bittencourt, I., and Isotani, S. (2019). An approach for planning and deploying gamification concepts with social networks within educational contexts. *International Journal of Information Management*, 46:294–303.

Tsay, C., Kofinas, A., and Luo, J. (2018). Enhancing student learning experience with technology-mediated gamification: An empirical study. *Computers & Education*, 121:1–17.

Yildirim, I. (2017). The effects of gamification-based teaching practices on student achievement and students' attitudes toward lessons. *Internet and Higher Education*, 32:86–92.

Zainuddin, Z., Wah-Chu, S., Shujahat, M., and Perera, C. (2020). The impact of gamification on learning and instruction: A systematic review of empirical evidence. *Educational Research Review*, 30.

Zatarain, R., Barrón, M., Ríos, J., and Alor, G. (2018). A virtual environment for learning computer coding using gamification and emotion recognition. *Interactive Learning Environments*.