Gamification: A Motivation Metric Based in a Markov Model

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Abstract—The current situation in the world with the COVID-19 pandemic has reinforced a pre-existing trend based on increasing the use of gamification tools in education to motivate students. In this work, a study based on a Markov model is proposed to assess motivation during the training process in higher education. The evolution of Faculty of Business Administration graduates when using a gamified smartphone application (HEgameApp) has been measured. The behavior of graduates is assessed through collaboration in fora created by HegameApp, and the recognition given by their classmates. A utility function is defined to obtain a statistical estimator used in the assignment of motivational states of the study participants. In addition, a decrement function is assigned to the value of the components of the utility function to estimate the time variation of motivation during the process of knowledge assimilation. The proposed solution shows that when graduates are involved in using the app, they significantly increase their academic outcomes and satisfaction while receiving the lectures. In addition, the positive feedback perceived through the application fora has a measurable effect on their motivation.

Keywords—mobile learning, gamification, Markov model, higher education

1 Introduction

Gamification is generally considered a valuable strategy to increase student performance and satisfaction: (i) improve their tendency to collaborate in the learning process and (ii) intensify their motivation. In addition, gamification contributes to obtaining relevant information that can be exploited in other settings to enrich the educational process, be it face-to-face, remote, or in a hybrid format, ensuring the attention of all students [1].

The search for motivational strategies for the lessons, which encouraged the participation and satisfaction of the university students, has been a continuous task since teaching ceased to be individual. Currently, immersed in implementing digital technologies, it is still a generalized question since it is common to find students who systematically use smartphones with objectives other than those studying during lectures. Besides, banning mobile phones during lectures or applying any punitive measures has proven to be ineffective [2]. Furthermore, information and communication technologies, particularly smartphone-based applications, provide several instruments that can be used to increase students' motivation while they carry out their duties.

Gamification is a motivational strategy that uses components of the structures of games in a non-playful environment. It has been used extensively in recent times to increase the integration of students in their training procedures (especially in higher education), making them pleasant, more attractive, and productive [3]. Motivation, established as the aspiration or inclination to get involved and persevere in a task, can be declared to be the central axis of gamification [4,5]. Studies of educational process researchers have analyzed motivation from a static perspective, assuming it as a photo at a given sampling instant. However, other investigations, more adapted to reality, warn that the contribution models of the students show an important variable component, that is, motivation evolves with time. If these oscillations are not considered, motivation research may conclude erroneously [6]. Therefore, a dynamic perspective makes possible to study incentives or time-dependent variables, which can be intrinsic or extrinsic and affect changes in motivation states. From this perspective, the objective of this analysis is to study the variability of user motivation [7].

This study aims to generate a measuring instrument prepared to forecast the situations of motivation of users in a higher education framework based on incentives from gamification tools. This forecast is made by analyzing an online university class for which a tool is designed based on a gamified application called HEgameApp, built as a program whose objective is to exchange information that serves their learning strategies. This tool makes possible to identify the state of motivation of a student or a group of students during an academic year using a Bayesian Markov Model (from now on MM). HEgameApp tries to get students to acquire helpful study habits from the behaviors caused by gamification. For this, it is necessary to know the dynamics of motivation of the students. In this way, state changes in this process can be identified in real-time. Therefore, while it is observed that the motivation of the students declines, it is possible to incorporate motivators (actions performed by agents) to recover the high states of motivation, which, as it has been verified, coincides with the increase in the scores of the students in subjects.

The proposed tool, based on managing the evolution of motivation over time, classifies the created online community concerning the motivation measures. This segmentation enables the teacher to find the ideal occasion, in a certain period, in which it is necessary to make a decision that increases motivation and changes students' behavior. For this target, a MM has been proposed. Data from an online community feed the model, and through a utility function made up of the attributes from the contributions or evaluations of the students. Moreover, a decay function has been applied, considering that student motivation tends to decline over time [8].

This work is organized as follows. In this section, the theoretical foundations of the link between gamification and education are presented, besides Markov Chain applied to education and, the last, motivation as a gamification strategy. Section 2 shows how the proposed gamification experimentation was developed and describes in detail the mathematical modeling of the proposed Bayesian approach to mobility management and the basis of its performance for the assessment of motivation. Next, section 3 presents the results of the recommended motivation measurement tool using the database with the gamification behaviors derived from the test. In section 4, there is a discussion and reflection on the results. Finally, section 5 presents the conclusions and future work.

1.1 Education and gamification

Technological advances and their continuous progress have transformed the way educational activities, especially those related to learning, are carried out; educators have the opportunity to introduce and integrate learning activities based on play through technology in learning processes. Incorporating ludic tools in this process has emerged a particular concept of game-based learning [9]. Play-based learning or educational gamification is based on the experimental nature of these tools that allow students to fully participate in the learning cycle. Also, design principles grant greater engagement and fun during the learning process. The engagement and fun factors of game-based learning have been shown to increase student motivation and maintain retention. There is also strong evidence showing a relationship between play and increased motivation, as well as the persistence of learning behaviors [9,10].

Tools like HEgameApp can increase motivation and commitment (which promotes learning), and they are also helpful for evaluating students' understanding of a topic. Most significantly, gamification develops students' metacognitive abilities, fosters empathy and teamwork skills. On the other hand, Wang [11] found that gamification tools can affect concentration, engagement, enjoyment, motivation, and classroom dynamics in a significant and positive way.

In short, gamification supposedly offers many benefits and allows educators to be creative and students to be intrinsically and extrinsically motivated. Game-based learning provides an emotion of the ordinary, an emotion that is absent from traditional education. These apps can make students enjoy and persist in doing tasks that they would not normally do. In his commentary on gamification, McGonigal [12] asserted, quite rightly, that the real world does not offer with the same ease the carefully designed places, the exciting challenges, and the powerful social bond that virtual environments provide. Furthermore, says the researcher, the reality is not motivated as effectively, nor is it designed to maximize people's potential.

Therefore, the study of student motivation and engagement classifiers, such as Markov Chains (from now on MC), seems relevant to know the influence of motivation on learning. In the context of higher education, this study aims to assess whether these tools would be helpful to university students [13].

1.2 Markov chains applied to education

If it considered the studies of recent years, an increase in the use of MC could be found in the analysis of educational processes applied to different elements of the field of education. One of these applications is the use of MCs to analyze academic performance and progress. Students' progression towards completing their higher education degrees has stochastic characteristics and can therefore be modeled as MC. Such an application would have a high practical value for the estimation and continuous monitoring of various indicators of quality and effectiveness of a given higher education study program [14]. In terms of quality, MC have also been used to improve the teaching of graduate physical education in schools using machine learning technology [15].

On the other hand, recent research has influenced the study of tutors' strategies to model their interventions where they present information and define activities, and strategies that promote students' will and motivation. Following the research trend of discovering new ways of evaluating teachers' approaches, physiological sensors are used based on student performance (successful completion of tasks). And, consequently, motivational strategies implemented through serious games are studied to support students' performance and motivation. For this, hidden Markov models based on Keller's ARCS model of motivation (Attention, Relevance, Confidence, and Satisfaction) and together with electrophysiological data (HR heart rate, SC skin conductance, and EEG electrocardiograms) have been used [16]. These analyses have identified physiological patterns correlated with different motivational strategies [17].

In the same way, the categorizations that label university students as full-time or part-time students have been studied with Markov models. Since student enrollment patterns at many colleges can be very complicated, it is not uncommon for students to alternate between full-time and part-time enrollment each semester based on finances, scheduling, or family needs. This effort to categorize is helpful to correlate it with variables such as academic performance [18].

Likewise, quality education is a fundamental element in any country's economic, political, and social development. Therefore, enrollment forecasting is necessary for higher education to assist universities in preparing their educational frameworks and budget, providing all the required facilities, and planning the general objectives in the short and long term. The evaluation pattern of students and their academic performance can be defined based on a Markov chain model (from now on MCM), where students' absorption, retention, and repetition rates in the different academic programs are analyzed [19].

Other research focuses on modeling the flow of students in the educational system with a stochastic process that depends mainly on Markov chains to predict the number of students graduating for the following years [20]. Markov chains have even been used to design more reliable piano teaching methods [21].

Similarly, it has been investigated whether it is possible to classify the time series data from a gamified learning management system in such a way that teacher supervision could be distributed more efficiently among students who are more likely to fail, that motivates the possibility of increasing the retention and completion rate of students [22].

In another vein and starting from the idea that most gamified learning systems were designed without considering the personalities of the different students, other researchers combine gamification, classification, and adaptation techniques to increase the effectiveness of e-learning by classifying students into different types of players based on their interaction with the gamified system [23].

Finally, regarding the measurement of motivation derived from gamification in the university education environment, there is not much research beyond the research team that proposes this study [24]. However, previous research has been conducted applying models based on Markov chains to study the change in the learning capacity of the students, a hidden Markov model is used that analyzes the continuous learning process of the MOOC students where it characterizes the high and low learning capacity of the students [25].

1.3 Motivation: Gamification strategies

Gamification and motivation go hand in hand, and they are intimately linked. Starting from a theoretical basis, the foundations of gamification instruments have their origin in individual reasons since it requires the game's resources to promote behavior change [26,27]. This study uses of the theory of self-determination (SDT) that bases its propositions on the division of motivation into two categories: extrinsic and intrinsic motivation. Extrinsic motivation is made up of agents external to the subject that elicit the behavior through tangible rewards, and the intrinsic one is formed from internal agents such as one's longings, values, self-determination, or the sense of being part of a group [28]. In addition, these two subdivisions are compounded by internalized extrinsic motivation [29], which, although it arises from external influences, such as prestige, achieves self-regulated behavior from the subjects. There is a phenomenon of internalization of these external influences.

It can be observed that performance throughout the students' training and achievements are influenced by factors originating from knowledge and emotions [30,31]. Motivation, therefore, affects performance throughout the training but also the consequences of that training. Researchers in this field have dealt with motivation by considering different points of view, but there seems to be an agreement that intrinsic factors have the most significant impact on motivation. Some of them believe that the particularities of each student are the elements that most influence motivation [32,33], and others deduce from their research that intrinsically motivated students not only progress in their studies but also obtain higher outcomes than those who are extrinsically motivated [34]. However, university students often must study subjects that they do not find suggestive or attractive but essential to their instruction. When this situation occurs, the use of a punishment or reward structure is the only tool left to educators to promote those behaviors that facilitate the educational performance of university students. In this sense, the use of strategies based on the game, in addition to the tactic based on rewards and punishments, offers an added stimulus to teaching that turns training tasks into fun and enjoyable hobbies [12]. In this way, the use of game elements in learning activities favors creating a stimulating environment in a teaching environment, something that gamification strategies such as those used by HEgameApp in this study allow to fulfill and, therefore, facilitate the creating motivating environments. Since it has been shown that motivation influences different learning styles, knowing the student's state of motivation seems essential in teaching processes [35].

2 Materials and methods

2.1 Development of the gamified app

This research addresses the analysis of the evolution of student motivation in a temporary way. An MM-based strategy is developed to identify the impact of motivational processes in a scenario of optional participation. This central archetype establishes the mechanics of student contributions and the jumps between the different categories of motivation. In this study, a MM has been implemented with the information generated during the use of HEgameApp. It refers to a gamification web application that was developed for three purposes: (i) to make students aware of the appropriate use of smartphones in face-to-face teaching, (ii) to exchange information, and (iii) to provide references to the teacher on the student's evolution in the subject.

The goal of integrating HEgameApp into the class is to provide students with the opportunity to be fully engaged in their learning processes. User engagement is achieved by utilizing the benefits of gamification through a combination of points-based rewards. Research by Robson et al. [36] defines a gamified practice as employing the MDA fundamentals (mechanics, dynamics, and aesthetics) based on the peculiarities of the learners involved in the game practice. Thus, the structure of the HEgameApp pursues a game orientation towards a uniform set of undergraduates with a similar degree of education and age. Despite this orientation, the gamified experience of this app favors more those socializing university students who are inclined to exchange the information they have in their possession. This development is adapted to a website (WebApp), which is platform-agnostic. It offers enough flexibility for the user to have at his disposal a wide range of devices on which to use the app.

The development of HEgameApp follows the MDA framework [37,38] with the following layered design: the first layer (the mechanics) involves data representation and programming; the second layer (the dynamics) alludes to the behaviors that manifest themselves as a result of the students' action on the mechanics selected for the development of the application; the third layer (the aesthetic) is linked to the fundamental purpose of the game which is to induce an emotional replica of the student. In the developed experimentation, three essential strategies were used: the self-satisfaction that makes students aware of the importance of exchanging information, the tangible prize measured in points, and, finally, the achievement of prestige before the teacher that materializes as a plus in the grade at the end of the study of the subject.

HEgameApp includes five parallel themed channels (knowledge sharing venues) in which students can neatly insert their contributions: Questions, Resources, Presentations, News, and Others. It should note that contributions with the "Others" theme are not considered for counting points since this channel accepts contributions unrelated to the course's contents. For enrollment, a username and password are required to access the application, which ensures student privacy. The reward structure based on obtaining points includes the following inputs:

1. The number of contributions by thematic channel
2. The number of classmates' evaluations: each student values the contributions of other colleagues
3. The quality of the contributions according to the peers' evaluations (other university students), in an evaluation range from 1 to 5, with five being the highest and one the lowest.

The equation to estimate the total value through the structure of rewards for evaluations is the following (these coefficients were proposed by a panel of motivation experts using the DELPHI method):

$$Score = contributions\ \times 0.3 + performed\ assessments\ \times 0.2 + received\ assesements\ \times 0.1 \quad (1)$$

Additionally, HEgameApp rewards the evolution of students through badges, which are awarded for each thematic channel, scalable in three possible categories according to the value achieved: bronze, silver, and gold. The bronze reward is obtained after five contributions, the silver one after 10, and the golden one after 20. Also, when a student has achieved the awards of all thematic channels, they will obtain a diamond award. The gamification experimentation carried out throughout the 2018-2019 academic year is explained below when the disciplines of "Organizational Behavior" and "Leadership Skills" were taught at the Faculty of Economics and Business Administration of the University of Las Palmas de Gran Canaria, Spain.

2.2 A mathematical model for estimating motivation

The mathematical model that has been developed assesses and classifies motivation, analyzed as a value that changes over time in the students' learning process.

Utility function (UF). A multivariate has been proposed to quantify the variation in student motivation throughout the training process. The purpose was to shape the attributes of this question using the originated data when the community of students used the application.

Let $I_{A_K}^{C}(x)$ be an indicator function such that if x belongs to the set $A_K^{(c)}$, the set comprising all contributions of the learner k in the interaction topic channel c, then $I_{A_K}^{c}(x) = 1$ otherwise $I_{A_K}^{C}(x) = 0$. If it is employed the above relationship, the first attribute of the posed UF can be established as follows:

$$A(t) = \sum_X I_{A_K}^{c}(x)e^{-\lambda t} \quad (2)$$

Where x is set as the input made in the online classroom. When a specific time elapses, gamification incentives need to be reactivated; student motivation decreases during learning procedures. For this reason, it becomes necessary to model the change in motivation originating from an input or assessment when it moves along the timeline.

In this mathematical modeling in (2), a well-known general function was selected with an exponential decay factor λ, a positive constant that sets the decay rate, which can be estimated based on the average duration of an input. If the independent variable (time) is quantified in days, the average duration would therefore be:

$$t = 14 = -(\log 0.5)/\lambda;\ \lambda = 0.05 \tag{3}$$

Similarly, the second UF attribute quantifies the feedback received from other learners on the learner's contributions k in the subject channel c, i.e.:

$$B(t) = \sum_x I^c_{B_K}(x)e^{-\lambda t}, \tag{4}$$

where $B_K^{(C)}$ indicates the set of ratings received by the k-th student in the interaction topic channel c. Finally, a quality attribute is added to quantify the effect of student contributions k, which is represented as:

$$C(t) = \sum_{x_l} I^c_{C_K}(x_l) * l * e^{-\lambda t} \tag{5}$$

where x_l is the rating made on the contribution x with a rating of $l \in 1, 2, 3, 4, 5$. According to the peer ratings, the quality score of the contribution's ranges from l=1 to 5.

Thus, the multivariate UF for the k-th student in one of the thematic channels of interaction is specified as:

$$U_c t = \alpha * A(t) + \beta * B(t) + \gamma * C(t) \tag{6}$$

Therefore, the overall UF over the four thematic interaction channels for the *k-th* learner can be quantified as follows

$$U(t) = \sum_{C=1}^{4} U_c\, t \tag{7}$$

Markov Model (MM). The evolutionary model used measures and studies the point-based reward combination developed to encourage students' contributions to their training process. Its fundamental particularity is its dynamism. This characteristic entails constituting a model that allows the quantification of the students' contributions and their evaluation over time. For this, a strategy based on a MM is proposed that establishes a transition matrix of motivation levels for each student, and derived from this matrix, a vector state of stationary probability is formed that serves to classify students into three different degrees of motivation.

The proposed strategy is based on a homogeneous evolutionary Markov model, which uses the contributions and ratings of each student to feed the points-based reward system. This information is measurable by the UF of (7). To pin down the evolutionary behavior of the MM, one must determine not only its configuration but also the transition probabilities. The design of the proposed MM is depicted in Figure 1. There, the tree states S_1, S_2, S_3 are contemplated, which correspond to the degrees of motivation (from lower to higher) and which are achievable with a change probability $P_{i,j}$ for i, j=1, 2, 3, assigned to every arc. Those values refer to the conditional probability $P(S_j/S_i)$ of moving to state S_j given that the current one is in state S_i.

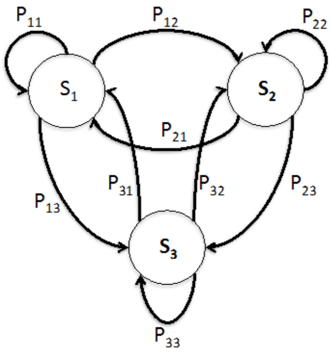

Fig. 1. MC diagram

To determine the transition probabilities, the degree of motivation of all undergraduates must be available daily and for a specific period of time using the UF $U(t)$ (see equation 7). Figure 2 shows an example of this function, in which the values of U are represented for a specific student during a time interval of one semester (120 days). It is possible to appreciate some periods of decay time; this behavior occurs because the values of the UF are given by the period quantified in days from the date on which the contribution occurred. The following procedure was proposed to characterize this model:

1. A normalized histogram was composed with each of the UFs of the university students who participated in the experimentation.
2. Then a soft classification was performed using a Gaussian mixture model (GMM) composed of a trio of distributions (low, medium, and high motivation).
3. Finally, a student's level of motivation was determined by evaluating the utility function $U(t)$ each day and then estimating the maximum likelihood of the three quantities of probabilities provided by the GMM.

A sample of these histograms and Gaussian mixture for four months is observed in Figure 3, where each distribution appears with different coloration.

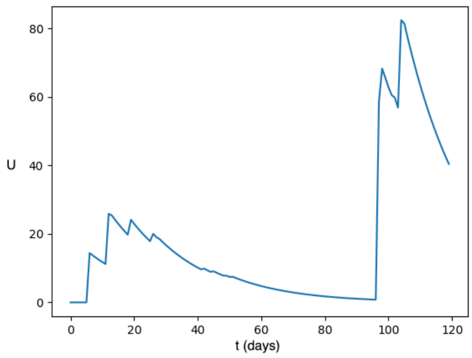

Fig. 2. Sample of changes in a UF for a single student

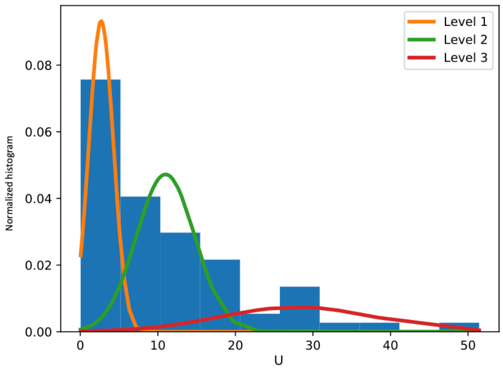

Fig. 3. Histogram and Gaussian mixture model of the UF proposed for the whole set of students studied

It is established a 3×3 change matrix for everyone to define probabilities. This matrix is set as follows: for each day, a state is fixed using the maximum likelihood of the GMM as previously mentioned, and it is analyzed whether there is a variation in the state compared to the preceding day (Markovian process), and one is added to the corresponding marker (remaining or changing) to consider it in the change matrix. The derived matrix is normalized, so the summed total of each row is 1; thus, a 3 × 3 matrix is obtained in which the element (i, j) quantifies the change probability $P_{i,j}$. Then, employing the change matrix, one can determine the likelihood of being in each state of motivation S_i after many days. If a person begins in the state $S1$, its state-vector can be established as $\boldsymbol{p}T = 100$. Then, the probability of being in any of the states on the second day can be calculated with the function

$$\boldsymbol{p}^{(2)} = \boldsymbol{p}^{\boldsymbol{T}}\boldsymbol{M}, \tag{8}$$

where $\boldsymbol{M}$ is the change matrix, and $\boldsymbol{p}^T$ is the vector transposed on the first day ($\boldsymbol{p}^{(1)}$). Then, after n days, it is obtained

$$\boldsymbol{\pi} = \boldsymbol{p}^{(n)} = \boldsymbol{p}^T\boldsymbol{MMM} \cdots \boldsymbol{M} = \boldsymbol{p}^T\boldsymbol{M}^{n\text{-}1}. \tag{9}$$

Equation (9) is convenient since the probability of being in any of the states after a period of n days could be quantified. Thus, in the limit (when $n \rightarrow \infty$), it is possible to calculate a stationary matrix of rank one and choose some row as $\boldsymbol{\pi}$, regardless of the initial state $\boldsymbol{p}^{(1)}$. Practically, there are very effective ways to avoid lifting power matrices with these characteristics, such as the eigenvector-eigenvalue decomposition used in this work [39].

A complicated element of the presented methodology was using the vector $\boldsymbol{\pi}$ in $\boldsymbol{R}^3$ of all the students to concentrate them in three global clusters representing the degrees of motivation and, thus, assessing and examining the point-based reward system. To this end, a hard clustering scheme was implemented using k-means with k=3 [40]. It should be noted that each $\boldsymbol{\pi}$ vector is in the x+y+z=1 plane, where the xyz axis refers to the probability of being part of the S_1, S_2, and S_3 states, respectively; furthermore, the centroids the three clusters must lie in this plane. Figure 4 shows an example of this representation in which the blue spheres and pyramidal markers close to coordinate 1,0,0 refer to the individuals that are part of state S_1 (low motivation class), those marked in red, close to 0,1,0, to state S_2 (medium motivation class), and the green ones close to 0,0,1 to state S_3 (high motivation class). This representation is adequate as it presents the predisposition from a probabilistic optic for the three degrees of motivation posed rather than a strict taxonomy. It is necessary to emphasize that this work is strictly modeling, not intervention.

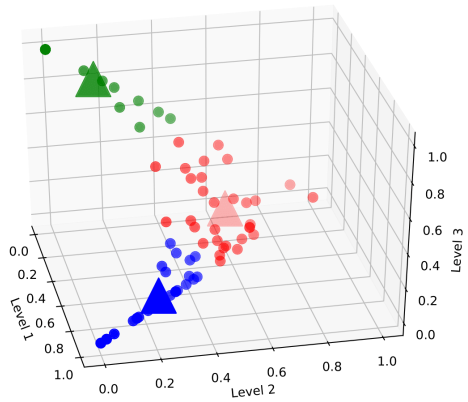

Fig. 4. Clusterization and centroids of the set of students for the three degrees of motivation: (1) Low, blue markers; (2) Medium, red markers; (3) High, green markers

3 Results

The proposed points-based reward structure pattern was tested on a set of 69 students of the Faculty of Business Administration, Economics and Tourism of the University of Las Palmas de Gran Canaria, Spain, in the disciplines of Organizational Behavior and Leadership Skills, when using HEgameApp, a gamified WebApp, throughout four months (during February to May 2019). Then, the method specified in the epigraph on methodology was applied, where the k-means clustering procedure was able to determine three centroids that have been used to label each student's initial motivation state: Low (set 1), Medium (set 2), and High (set 3); it is equivalent to the 3D polytope (plane $x+y+z=1$) in Figure 4. It is possible to notice that the centroids are also placed in the polytope, indicating that probability density functions appear clustered in the same way as the distributions being classified. At the end of the experiment, the students' final assessments in each classroom were obtained; Figure 5 presents the boxplot of these ratings clustered by the degree of motivation. It is possible to appreciate that the median of set 1 is less than 6, while set 2 is 6.62 and finally that of set 3 is 7.62. Similarly, it is even more interesting to note that the dispersion of set 1 is much higher than that of the other sets, which shows that the taxonomy derived from the proposed methodology appropriately divides the groupings with a high degree of motivation, which is reflected in the final ratings. To corroborate this result, Table 1 presents the quantification of the median shown in the graphs, but in addition, some statistical measures such as the mean, the standard deviation, and the maximum value of the final grades are presented.

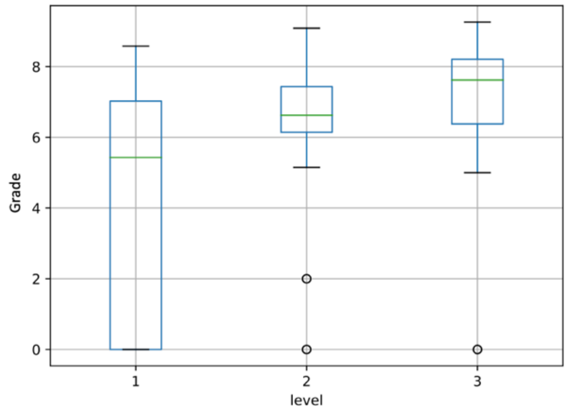

Fig. 5. BoxPlots of the final ratings clustered by the three degrees of motivation

Table 1. Mean and variance for each of the sets

Set	Mean	Standard deviation	Maximum value
1	4,54	3,15	8,58
2	6,57	1,82	9,09
3	6,88	2,28	9,26

4 Discussion

This paper assumes that, apart from the initial surge of community launch, the number of new contributions will be relatively stable over time. Similarly, the trends should be regular about the number of badges and positive votes. This stability suggests that those who contribute to the community should consider the responses' quality and consistency. Likewise, the quality of the answers must be stable, except for a decrease in the initial period.

If it is studied over time, significant heterogeneity in user contributions should be observed. However, the contribution at the individual level should show a different, decreasing pattern, although it seems that some individuals remain active throughout the study period. Understanding the behaviors and motivations of those individuals who contribute the most over the experiment's lifetime may help create sustainable communities and elucidate what type of gamification tools will be most efficient for student academic success.

In addition, one could drill down to the individual level and plot the contribution of several representative users in the sample. According to [7], even relatively active users should show substantial fluctuation in their contributions during their tenure in the online community. These would contribute actively during some periods, while in other periods, they would be inactive. The objective of this work was to model the fluctuation of user contributions (dynamics) and, in the future, to study the influences of different motivational mechanisms leading to such dynamics of active contribution or lack of them.

User contributions are public goods by nature in online communities since they are voluntary, free, and open. The critical issue in public goods is opportunism, which means that everyone can share the benefits, but only the contributor incurs the cost. The students who were part of this experiment are in those very circumstances. In this sense, lack of provision is a common problem in many models of pure altruism [41]. Consequently, online communities may eventually become exhausted, suffering from "the tragedy of public goods." But these models are not adequate to explain why some groups can attract substantial contributions from users. Such discrepancies between theoretical models and empirical phenomena can be reconciled by models of impure altruism [42,43], where individuals contribute because they derive utilities, not only from pure altruism but also get personal benefits of their own, such as highlighting their skills or the satisfaction of helping others.

The public goods framework and particularly models of impure altruism have been used to model user contributions in an online community. Each user chooses how much to contribute. The utility of a user network is made up of three parts:

1. Their valuation of the accumulated contribution in the community
2. Their valuation of their own contribution
3. Their contribution cost

The first part captures the benefit that the user could obtain from the community as suggested by the pure altruism literature. The second part captures impure altruism corresponding to the internalized extrinsic motivation reviewed in the literature. The third part indicates that making contributions is costly in terms of time and effort. However, this treatment of public goods theory is a convention used by this paper and is open to further contributions by other researchers. On the other hand, the distribution of motivation in three grades, low, medium, and high, also agrees with the findings of other researchers [44].

5 Conclusions

The doctrine implicit in these mathematical analyzes is the habit cycle. This theory exposes the formation of a habit based on behaviors derived from gamification strategies. These strategies convert extrinsic motivations into internalized extrinsic ones. It is also introduced a new concept of gamification. In this case, gamification is defined as a tool that transforms a repetitive behavior into a habit by internalizing extrinsic motivators, using external stimuli derived from gamification, such as the visibility of individual behaviors, the study process, or peer feedback [24]. In this work, gamification strategies are used to foster critical thinking and deep learning skills into successful habits and accentuate behaviors that reflect autonomy capabilities in students. It is intended that students can assimilate such behaviors so that, when the external incentives disappear, the attraction for gamification can also disappear, but maintaining the habits of critical thinking and deep learning.

The research presented here was based on the students' contributions to an online collective and the evaluations of their peers. It is inferred that the motivation categories correspond to the sets of students grouped by their qualification, as evidenced by the grouping of university students in the categories of medium and high motivation with a minimum standard deviation, increasing this standard deviation for the category of low motivation and showing no correspondence with the student's qualification.

Due to the COVID-19 pandemic, many higher education institutions closed their campuses and switched to online education. Some researchers [45] have found that staying at home affects students, especially their motivation. Students, in general, rated online education as less satisfying than on-campus education and defined their motivation as unfavorable. This fact was reflected in lower time investment: lectures and small group meetings were attended less frequently, and students' estimates of hours studied decreased. Lower motivation predicted this drop in effort. In general, students were not satisfied with online education; there was a decrease in motivation that could be due to the lack of means of most universities for this type of education and that they were used to a social interaction that did not occur [46]. Using gamification techniques to increase motivation also entails a point of online socialization through the exchange of knowledge and assessments to other students that can solve this demotivation.

The use of the tool that classifies students by their motivation at any point in the learning process, during the course in which their motivation is evaluated, can be used to prevent sudden decreases in motivation. Moreover, if this decrease is generalized, it is possible to investigate its causes. This tool can indicate both generalized and individual problems in periods such as those during the COVID-19 pandemic. In this way, the teacher can react as quickly as possible before the root problem becomes entrenched or give individual or generalized guidelines to the cause of the drop in motivation. However, it should be noted that the tool must be used frequently, and its results analyzed. This frequency depends on the teacher's criteria, but it is recommended that the data be analyzed weekly [47]. This solution proves the effectiveness of the application since the proposed MM has shown its capacity for future use in decisive situations during the learning process. It has been proven that, based on this classification, the introduction of stimuli from gamification corrects behaviors and optimizes the performance of the online lessons in a specified period. In addition, more efficient study progress is obtained with an immediate consequence on the students' final scores in the course.

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