

## RESEARCH ARTICLE

# Gamification through leaderboards: An empirical study in engineering education

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## Abstract

Universities are looking for solutions to engage more students in STEM domains and enhance their learning performance (LP). In this context, gamification is put forward as a solution to achieve this aim. The present study examined the effect of gamification – building on leaderboards – on LP. Furthermore, mediating variables, such as intrinsic motivation, self-efficacy, engagement, and background variables, such as sex, previous gaming experience, and undergraduate major, were considered. A pretest-posttest quasi-experimental design with an experimental and a control condition was set up ( $n = 89$ ) in an Introductory Computer Programming course. We observed a significant improvement in the LP of students in the gamified condition. However, no interaction effect was detected, due to mediating and background variables. The high learning gain is a favorable indicator that gamification might be a promising approach to promote STEM programs.

## KEYWORDS

gamification, intrinsic motivation (IM), leaderboards, learning performance (LP), STEM

## 1 | INTRODUCTION

Worldwide, STEM education is expected to develop critical knowledge and skills demanded by the labor market [1]. For instance, in Europe and the USA, it has become a priority to boost student motivation to pursue STEM-related careers [2]. However, current STEM education programs meet challenges; such as low numbers of students in STEM domains [3], low performance or success rates [4,5] and underrepresentation of women [6]. In the specific case of engineering, low enrollment numbers, and a high dropout rate are also evident [7,8]. It is, therefore, not surprising that higher education institutions want to engage more students in this domain [9].

In this context, gamification is put forward as an alternative to engage and motivate students and to improve learning performance (LP) [10]. Gamification

builds on the implementation of game design elements, such as points, badges, and leaderboards. Available research reflects shortcomings. One fundamental limitation is that most studies build on a mix of game design elements, biasing the understanding of which element invokes an impact on student performance [11].

The current study, therefore, evaluated a particular gamification element – namely leaderboards – to boost LP. Moreover, recent literature reviews [12,13], emphasize that we should go beyond studies focusing on the direct relationship between gamification and Learning Performance. Thus, we also considered student variables that are mediated between the differential impact of gamification, such as intrinsic motivation (IM), self-efficacy (SE), and engagement.

This article presents the conceptual/theoretical base for a quasi-experimental pretest-posttest study. Building

on the results, we present a discussion and address limitations and directions for future research.

## 2 | CONCEPTUAL AND THEORETICAL FRAMEWORK

### 2.1 | Gamification in education and learning performance

Gamification refers to “the use of game design elements in nongame contexts [14].” Werbach and Hunter [15] distinguish three types of design elements: dynamics, mechanics, and components. Dynamics are abstract and refer to latent variables such as emotions; mechanics promote action (eg, competition), and components are concrete elements (eg, badges).

General and STEM-oriented gamification research report an increase in motivation and engagement, as well as in learning performance of students [12,13]. However, in most studies, the impact on learning performance is usually studied directly, without considering the mediating or moderating variables affecting the interaction between research conditions and the dependent variable learning performance. The latter implies that less attention is paid to how changes in, for example, motivation or engagement, affect learning performance.

To explain the potential of gamification we built on the theory of Gamified Instructional Design by Landers [16], stressing how gamification affects learning via mediation or moderation.

Through mediation, a game element (eg, leaderboards), positively affects an attitude or behavior (eg, student motivation), and this increase, in turn, has a positive effect on learning performance. Through moderation, the game element (eg, badges) alters a behavior or attitude (eg, motivation). That behavior or attitude strengthens the effectiveness of an existing instructional design, which ultimately affects learning performance.

In this study, we focused on mediation. Available research underpins Landers’ theory. For instance, using leaderboards increased time-on-task behavior which increased LP [17], or badges increased self-assessment that translated into higher scores [18]. The studies as mentioned above stress the indirect impact on LP. However, a recent review study [12] suggest also testing the direct impact of gamification on LP.

### 2.2 | Leaderboards as a gamification element

Leaderboards are defined as a “visual display that ranks players according to their accomplishment [19].” Depending on their design, they emphasize continuous performance,

status reporting, and performance comparison of users [19] as well as competition [20]. Thus, we can distinguish two design types, also explained by Marczewski [21] and Zichermann and Cunningham [22]: absolute/infinite or relative/no-disincentive.

Absolute/infinite leaderboards display all users and their scores, making players at the top experience a broader sense of accomplishment, as compared with the players that are at the lower-bottom. With relative/no-disincentive leaderboards, users only see their rank as compared with the users ranked below and above them. Students will consequently feel less discouraged when ranked lower. The downside is that no ranking information about the other users is available, making this potentially less meaningful.

Available studies have implemented absolute [23] and relative leaderboards [24] with positive results. In the former, there was an increase in task execution punctuality, while in the latter, there was an increase in task performance. Other researchers have created alternative ways to display scores by showing rankings without presenting actual scores [25], only showing the top three players [26] or even displaying a group leaderboard only with qualitative information [27].

### 2.3 | The role of individual student variables in gamification

Apart from LP, three key mediating variables are being considered in this study: IM, SE, and engagement.

IM is considered a core variable in gamified environments [21,28]. “When people are intrinsically motivated, they play, explore, and engage in activities for the inherent fun, challenge, and excitement of doing so [29].” To boost IM, we built on the Self-Determination Theory of Ryan and Deci [30] that stresses the importance of fulfilling three core psychological needs: the need for autonomy, competence, and relatedness.

Autonomy is related to the experience of controlling one’s behavior [29]. In a gamified setting, this happens when players can choose what activities they want to carry out [15] giving them the feeling of controlling their own intentions [31]. Competence is defined as the need to feel mastery [32]. It is therefore essential to provide feedback, something that leaderboards, for instance, do when they show a student’s position based on activity results [33,34]. Finally, relatedness refers to the sense of connection with others [30]. It is achieved through leaderboards when students see the performance of one another, compare and share progress, and discuss positions [31,35].

In a gamified setting, motivational needs are not only satisfied by choosing a specific gamification element, but also by the way they are implemented; this is called

situated motivational affordance [36]. For instance, leaderboards are usually designed and implemented to show progress cumulatively, promoting competition and peer pressure, thus diminishing IM [37]. Nevertheless, the same leaderboards could be implemented differently. For instance, using them to show personal progress every week, instead of showing them at the end of the month or academic semester. This implementation could boost IM since students could analyze their performance independent of their peers' progress, provoking competition with oneself. Thus, it could have a substantial impact on autonomy and competence, but to a lesser extent on relatedness since the social comparison is less emphasized. The above example shows how the situated motivational affordances of gamification elements might differ.

Moreover, motivational affordances do not result from the choice/implementation of a single game design element, but rather depend on the entire game system design [38]. For instance, the incorporation of game rules allowing students to choose what activities to carry out could foster autonomy, next to the actual use of leaderboards.

SE is defined as a person's belief to carry out tasks successfully [39]. Judgments of SE, according to Bandura [40], are based on four principal sources of information: performance attainment, vicarious experiences, verbal persuasion with social influence, and physiological states. Performance attainment is related to getting information about mastery experience. Vicarious experiences are related to observing the impact of the performance of others. Verbal persuasion leads people to believe they can do things. Finally, physiological states refer to judging the capabilities based on how people feel. If activities cause a person to become stressed and get fatigued, they become indicators of physical inefficacy. In a gamified environment, the aspects above are evident in leaderboards since they can provide opportunities to trace a students' mastery level (performance attainment), see other students' performance (vicarious experience), and, be socially influenced (social influence) [19]. In the case of physiological states, it is essential to create activities that help students feeling active and involved without feeling stressed or exhausted, thus requiring a right balance between not too demanding and not too easy activities [41].

Finally, Gunuc & Kuzu [42] define engagement as "the quality and quantity of students' psychological, cognitive, emotional and behavioral reactions to the learning process as well as to in-class/out-of-class academic and social activities to achieve successful learning outcomes." In a gamified environment, research shows that engagement is usually measured only at a behavioral or cognitive level through log tracking of time spent, amount of contributions, and the amount of attempts to do learning activities [43,44].

## 2.4 | The role of background variables in gamification

Background variables might play a role when implementing gamification. There is evidence that, for example, sex and previous gaming experience (PGE) should be considered in gamified environments. For instance, male participants significantly outperformed female participants when using game mechanics [45]. Moreover, when it comes to PGE, Landers and Armstrong [46] concluded that people with less gaming experience might benefit less from gamified instructions than others. Literature also shows how other variables, such as university major, not directly connected to gamification but essential in the computer programming context, might impact learning [47]. For instance, in Pioro [48], women with majors in Computer Science scored higher than women with majors in Electrical Engineering.

## 3 | RESEARCH DESIGN

### 3.1 | General research aim and related research hypotheses

The conceptual and theoretical base explained above helped to develop the theoretical model depicted in Figure 1.

Furthermore, on the base of this model and the available empirical evidence, we put forward the following research hypotheses:

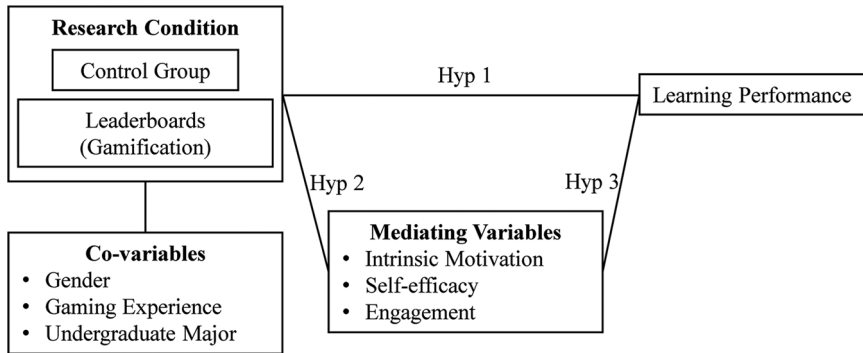
**H0a** *Students involved in a gamified course using leaderboards do not attain higher learning performance compared with students in a control condition*

**H1** *Students involved in a gamified course using leaderboards attain higher learning performance compared with students in a control condition.*

**H0b** *Students involved in a gamified course using leaderboards do not attain higher IM, SE, and engagement compared with students in a control condition.*

**H2** *Students involved in a gamified course using leaderboards attain higher IM, SE, and engagement compared with students in a control condition.*

**H0c** *Students involved in a gamified course using leaderboards do not attain higher learning gain (LG), considering the mediating effect of the changes in IM, SE, and engagement or the interaction with covariables (sex, gaming experience, and undergraduate major), compared with students in a control condition.*



**FIGURE 1** Graphical representation of the theoretical model for the present study

**H3** *Students involved in a gamified course using leaderboards attain higher LG, considering the mediating effect of the changes in IM, SE, and engagement and the interaction with co-variables (sex, gaming experience, and undergraduate major), compared with students in a control condition.*

We tested the correspondent null hypotheses for each of the hypothesis stated above.

### 3.2 | Sample

The sample consisted of 102 first-year students, enrolled in one of the three parallel classes of an introductory course in computer programming, each taught by a different teacher. These classes/teachers were selected, based on similar characteristics, such as teaching experience in the subject (from 3 to 5 years) and teacher evaluation results (9 points or more over 10). This information was obtained from the faculty evaluation system that is performed every semester. Students belonged to different undergraduate engineering programs (eg, Logistics and Transportation, Civil Engineering) at a public university in Ecuador. Due to reasons unrelated to this study (eg, illness), some students did not participate in the pre- or posttest session, resulting in a final data set from  $N = 89$  students. Randomly, one parallel class group was assigned to the control condition ( $n = 34$ , 13 females, 21 males, mean age = 19.50), while the other two class groups were assigned to the gamified condition, (class 1  $n = 24$ , 7 females, 17 males, mean age = 20.79; class 2  $n = 31$ , 15 females, 16 males, mean age = 20.52). The uneven number of students in the experimental and control condition resulted from the quasi-experimental design of the study and ethical considerations about giving students equal opportunities [49]. Informed consent was obtained from all students after ethical clearance from central university authorities.

### 3.3 | Research instruments

Before the intervention, we conducted a study to pilot-testing the research instruments with  $N = 50$  students, not involved in the current study. These students reflected the same characteristics as those involved in the main study: 19 to 20 years old, from different undergraduate programs and who had not taken programming classes before. This procedure helped to check language and translation issues, as well as to calculate preliminary reliability scores, which directed the development of a final version of the instruments.

Learning performance was measured through a knowledge test. The test consisted of 18 items (4 multiple choice and 14 free recall questions), aligned with the objectives of the course units that this study would cover, for example, “Given the following list - pairs = (2, 4, 6, 8, 10) – what would return if I write a: `len(pairs)?`”. Two parallel tests were designed (pretest and posttest). Item Response Theory through the 2-PL IRT model [50] was used to adjust the difficulty level and assure that there would be a distributed difficulty level among items. Three content experts checked all test items whether they were sufficiently clear, not ambiguous, aligned with the course, and reflected various difficulty levels.

To determine IM, we adopted the Intrinsic Motivation Inventory of Ryan et al [51]. Only the interest/enjoyment subscale was adopted for this study since the latter helped to map IM. Building on the guidelines of Ryan & Deci [52], the scale was adapted to the programming context and translated into Spanish. The final version of this scale consisted of seven items. Students were asked to indicate on a 7-point Likert scale their agreement with a statement; such as “programming is fun.” We found strong support for its validity in McAuley et al [53]. Cronbach's alpha was 0.903 at pretest and 0.917 at Posttest.

To assess SE, we developed a 20-item SE scale based on Bandura's guidelines [54]. The statements asked students to indicate their degree of confidence, on a scale from 0 to 100, to carry out programming activities



that reflect the course aims. For example, “identify the data needed to solve a programming problem.” Items focused on four programming domains, building on the model of Pólya [55] and Pennington & Grabowski [56]: understand the problem, design a strategy to solve the problem, write the program, and verify the program. To test structural validity, we designed the instrument with a single factor solution in mind. The results of the exploratory factor analysis (EFA) point at a two-factor solution, explaining 74% of the variance. Five scale items, loading on the second factor were excluded from the instrument since they seemed less central to capture the SE concept. Thus, the final version consisted of 15 items. A subsequent EFA confirmed the adequacy of the one-factor solution, explaining 71.3% of the variance. Applying confirmatory factor analysis with Amos (version 23), and checking the single factor solution, results in indexes reflecting a good fit ( $X^2[df\ 64] = 81.50$ ,  $P = 0.069$ ,  $CMIN/df = 1.27$ ; root mean square error of approximation [RMSEA] = 0.056; standardized root mean square residual [SRMR] = 0.029; comparative fit index [CFI] = 0.98). Cronbach's alpha was 0.97 at pretest and 0.982 at posttest.

Finally, we measured engagement by counting the number of optional activities (two in total) carried out in the university's learning management system (LMS).

### 3.4 | Design of the gamified intervention

The gamified intervention lasted 4 weeks and was implemented in the context of a regular course. All messages related to the study were delivered through the university's LMS. Each week, the class's teacher would randomly choose one in or out-of-class activity to be shown on a leaderboard. This activity could have been a compulsory or an optional one. The compulsory activities were presented as quizzes about unit chapters (weeks 1 and 3); the optional activities included the completion of one unit in Code Academy (week 2) and solving one programming exercise in the students' LMS (week 4).

We built on Werbach and Hunter [15] to take into account their concepts of dynamics, mechanics, and components to design the game environment, as well as the recommendations by Shi and Cristea [31] to boost IM. Furthermore, we also took into account measures to foster SE and engagement.

At the dynamics level, we invoked emotions (curiosity) by not telling them in advance, which activity would be presented each week and by waiting until every Friday to present the leaderboard.

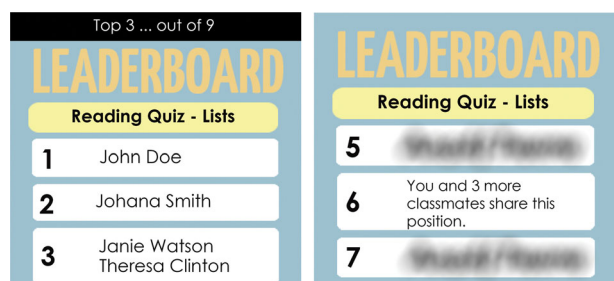
At the mechanics level, we applied competition, not only against others, due to the competitive nature that leaderboards have, but also against oneself. We stressed

through the LMS, the new chances they would get each week to prove they could succeed, and not that they were better than others. Furthermore, since there were no accumulative points, each student could see his/her succeed every week but also compare with the other students. Feedback was also evident through the weekly visualization of the leaderboard, fostering competence and SE. We also introduced chance (element of randomness) for two reasons. First, to avoid students guessing which activity would be presented each week, and second, to avoid students limited their effort to a specific activity. Within chance, the fact that they were free to choose to do the activity or not, fostered autonomy and engagement in students.

Finally, regarding components, we designed and adapted two leaderboard types in our experimental condition. An absolute leaderboard only ranking the first quartile of students with the highest scores and a relative leaderboard showing the position relative to the student who is viewing it (one below and one above him/her). Leaderboard design can also be linked to IM. When students share the same score in both leaderboards, all students appear at the same position, fostering relatedness. They feel they are part of a group and can discuss results with their peers. The leaderboards do not show any score either. Furthermore, we designed the gamified experience in such a way that scores were not the result of accumulated points. Each week, a new opportunity was presented, increasing students' sense of capability, competence. By doing this, we expected to motivate students to keep trying. There is a difference though in the type of leaderboard: in the absolute one, student names are displayed, while in the relative one, names are not presented and names of students in the position below and above were presented in a blurred way. By doing this, we expected to diminish the sense of competitiveness that leaderboards usually transmit. The first leaderboard type was shown via an external site through a link inserted in the weekly LMS announcements. The relative leaderboard results were sent to individual students via the LMS. Figure 2 depicts a sample of the absolute and relative leaderboard type.

### 3.5 | Procedure

The study took place during the first half of the first semester of the academic year 2016-2017. Before the intervention, to guarantee treatment confidence, the teachers participated in a meeting to agree on the activities, in class and out of class, for the duration of the study. Teachers were not acquainted with the actual activities to be tackled each week. The researcher developed the activities and grading system for the



**FIGURE 2** Sample of an absolute (left-hand side) and relative (right-hand side) leaderboard

optional activities; and, published the leaderboards each week. To inform students about the optional activities, the researcher asked each teacher to send an announcement via the LMS; this reinforced the idea the teacher was in the lead of the task. To establish student “trust,” the researcher took the role of a researcher’ assistant, collaborating with the teacher.

The intervention started with the pretest. During a face-to-face class, students filled out the knowledge test while the other questionnaires about SE, IM, and background information (sex, undergraduate major, and PGE), were filled out online via Google forms. Next, students in the experimental condition followed the gamified course while the students in the control condition followed regular classroom sessions, carrying out the same amount of activities as in the experimental condition. The optional activities did not help to get extra points, nor penalize students. At the end of the 4 weeks implementation, students filled out the posttest version of the instruments: the knowledge test during class time, while the SE and IM instruments online.

### 3.6 | Analysis approach

We used SPSS (V20) and AMOS (V18) to conduct the analyses. We tested assumptions (eg, normal distribution), set a significance level of  $P < 0.05$ , and used Bonferroni correction to adjust the impact of multiple comparisons. For hypothesis testing, we carried out repeated measures analysis of variance (ANOVA), ANOVA, and structural equation modeling (SEM). Given the small samples sizes, we calculated effect sizes (Cohen’s  $d$ ) and interpreted them based on the following criteria: small effect size (from  $d = 0.2$ ), medium effect size (from  $d = 0.5$ ), large effect size (from  $d = 0.8$ ) [57]. As for the SEM results, we considered the following fit indexes and benchmarks, not sensitive to small sample sizes: CFI  $> 0.93$  and goodness-of-fit index (GFI)  $> 0.90$  [58]; RMSEA between 0.05 and 0.08 [59] and SRMR  $< 0.08$  [60].

## 4 | RESULTS

### 4.1 | Descriptive information

Table 1 summarizes the mean and standard deviations for all research variables.

### 4.2 | Hypothesis 1: impact on LP

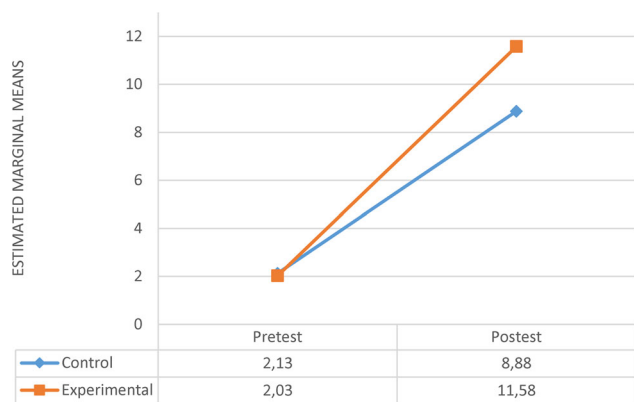
First, we conducted an ANOVA to identify whether there were significant differences between conditions at the pretest level, resulting in no differences  $F(1, 87) = 0.071$ ,  $P = 0.790$ . Second, we used repeated measures ANOVA between conditions to test LP. This test reflected a significant interaction effect between time and condition,  $F(1, 87) = 19.22$ ,  $P < 0.001$ . Pairwise comparison using the Bonferroni correction, revealed that LP is significantly higher in the experimental condition compared with the control group ( $P < 0.001$ ). Cohen’s  $d = 0.96$ , 95% CI = 0.51, 1.41, reflected a large effect size. Since students from two different classes were involved in the experimental conditions, readers might be concerned as to potential differences within the condition. Statistical analysis revealed that LP was not significantly different between both experimental classes  $F(1, 53) = 0.998$ ,  $P = 0.322$ .

Figure 3 shows how the experimental group outperformed the control group. Hence, we reject the null hypothesis and accept  $H_1$ : studying in a gamified condition leads to a significantly higher LP.

**TABLE 1** Mean and standard deviation of research variables

Variables	Control (n = 34) M (SD)	Experimental (n = 55) M (SD)
Learning Performance		
Pretest	2.03 (1.80)	2.13 (1.60)
Posttest	8.88 (2.95)	11.58 (2.44)
Learning Gain	6.85 (2.66)	9.45 (2.75)
Intrinsic Motivation		
Pretest	5.34 (1.14)	4.98 (1.23)
Posttest	4.78(1.47)	5.13(1.15)
Difference in IM	−0.56 (0.97)	0.15 (0.99)
Self-Efficacy		
Pretest	64.08 (20.51)	62.28 (20.99)
Posttest	62.96 (22.26)	60.79 (21.72)
Difference in SE	−1.12 (23.86)	−1.50 (19.93)
Engagement	1.59 (0.56)	1.40 (0.66)

Abbreviation: SE, self-efficacy.



**FIGURE 3** Differences in pretest and posttest learning performance scores among conditions

### 4.3 | Hypothesis 2: impact on IM, SE, and engagement

We ran an ANOVA to identify whether there were significant differences between conditions at the pretest level, resulting in no differences neither in IM  $F(1, 87) = 1.89$ ,  $P = 0.173$ , nor in SE  $F(1, 87) = 0.16$ ,  $P = 0.693$ . We also used a repeated measures ANOVA between conditions to test IM and SE. In addition, we used ANOVA to test engagement differences between conditions. In terms of IM, results showed a significant interaction between time and condition,  $F(1, 87) = 11.06$ ,  $P = 0.001$ . However, pairwise comparisons using the Bonferroni correction revealed no significant differences between conditions ( $P = 1.00$ ). Regarding SE, results showed no significant differences between time and condition  $F(1, 87) = 0.006$ ,  $P = 0.937$ . As to engagement, ANOVA results showed no significant differences between conditions  $F(1, 87) = 1.730$ ,  $P = 0.192$ . Based on these analysis results, we could not reject the null hypothesis and  $H_2$  is not accepted: studying in a gamified condition does not affect either students' IM, SE, or Engagement.

### 4.4 | Hypothesis 3: impact on LG mediated by IM, SE, and engagement with covariables

We ran a preliminary ANOVA analysis between the covariables (sex, PGE, and undergraduate major) with the mean difference between pre and posttest scores for learning performance (LG). Only PGE turned out to be significant  $F(1, 87) = 5.42$ ,  $P = 0.022$ . Thus, only the latter was included in the subsequent analysis model. We also checked for differences between the two classes that were involved in the experimental condition. Statistical analysis reveals that LG was not significantly different between both experimental classes  $F(1, 53) = 0.461$ ,  $P = 0.500$ . Furthermore, we checked correlations between all research variables. Table 2 reflects a significant correlation between the difference in SE and the difference in IM, as well as PGE with LG. The latter confirmed the previous ANOVA analysis result about a positive association between PGE and LG.

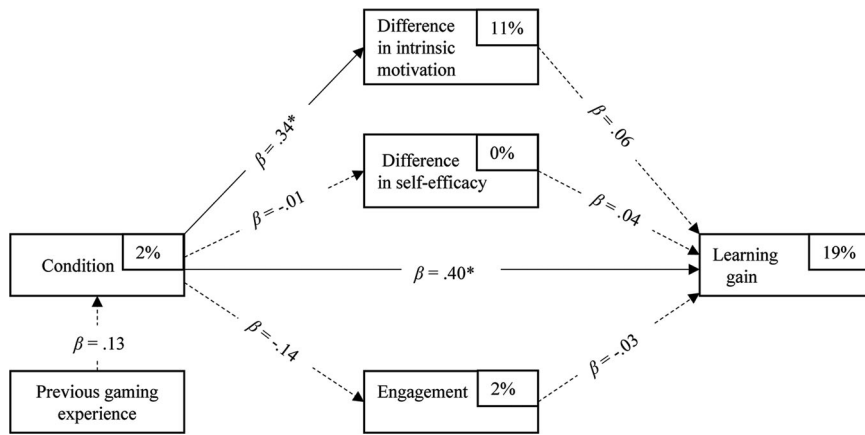
Though these results helped develop first insight into the relationship between variables, they did not clarify their complex interplay. Thus, SEM was applied to test the model, building on variables based on the mean difference between pre- and posttest scores for IM (Diff\_IM), SE (Diff\_SE) and learning performance (LG). SEM results reflected adequate goodness-of-fit indices ( $\chi^2(df = 6) = 8.563$ ; CMIN/df = 1.43; RMSEA = 0.070; SRMR = 0.063; CFI = 0.94; GFI = 0.971). The data seemed to fit the theoretical model reasonably well. Overall, the model explained 19% of the overall variance in LG. The largest contribution from the model came from the intervention (experimental or controlled condition) on LG ( $\beta = 0.40$ ;  $P < .01$ ), and on IM ( $\beta = 0.34$ ;  $p < .01$ ). However, the direct effect of the intervention on SE and engagement, as well as the mediating effect of IM, SE, and engagement did not appear to be significant; confirming the earlier analysis results. The same applies to the effect of PGE. In Figure 4, the model including all path coefficients is depicted. The dashed lines represent an insignificant effect, while solid ones, point at a significant effect. Overall, the model only

**TABLE 2** Pearson correlation coefficients among the research variables ( $n = 89$ )

	E	Diff_SE	Diff_IM	LG	PGE
Engagement (E)	1				
Difference self-efficacy (Diff_SE)	0.165	1			
Difference intrinsic motivation (Diff_IM)	-0.048	0.355**	1		
Learning gain (LG)	-0.083	0.053	0.208	1	
Previous game experience (PGE)	-0.104	0.110	0.086	0.242*	1

\* $P < 0.05$ .

\*\* $P < 0.01$ .



**FIGURE 4** Full model of the impact of gamification on LG considering mediating and covariables

explained 19% of the variance in learning gain. Thus, we could not reject the null hypothesis and  $H_3$  is not accepted. Studying in a gamified condition directly increases LP, but apparently without the mediating effect of IM, SE, or engagement or the interaction effect of PGE as covariables.

## 5 | DISCUSSION

Following hypothesis 1, the results show how gamifying a course using leaderboards, lead to significantly higher LP, reflecting a high effect size. Unfortunately, our findings cannot be contrasted with other studies, mainly due to the lack of studies focusing on the unique impact of leaderboards in an ecological setting with engineering students. Nevertheless, compared with studies building on multiple game elements, the available literature confirmed that gamification improves LP [32,35,51,52]. Building on the theory of Landers [16], about a mediating or moderating effect of gamification on LP, this study goes beyond the available studies by explaining a direct effect.

Regarding hypothesis 2, only a significant interaction of time and condition was found with IM. Nevertheless, the further analysis did not show significant differences between conditions. Once again, these results could not be compared with other studies because of the nature of our study. However, in studies focusing on multiple gamification elements, our results seem to be aligned. For instance, Hanus and Fox [61], reported a lower IM over time. However, at the same time, our study contradicts what was found in Jurgelaitis et al [62]. They found a significant increase in IM over time. Our finding of the increase in IM - although not significant - is in line with the theoretical expectations as reflected in Landers [16], explaining how game characteristics influence changes in behaviors or attitudes.

As for hypothesis 3, even though there was a positive but not significant impact of gamification on the difference in IM, it did not mediate the impact on changes in LP, as

suggested by our theoretical base. Though we reiterate the positive impact of gamification on LP through leaderboards, we could not confirm the impact and interaction of/with mediating or co-variables. A similar result was found in Hanus and Fox [61] reporting no direct effect of condition on the final examination score as mediated by IM.

Concerning the lack of significant results in SE and IM, an explanation could be found in the self-report measurements, as well as their online administration. Both explanations stress risk to measurement reliability [63]. Another reason could be the course subject. Research shows that introductory computer programming courses are considered difficult by students with and without Computer Science majors [64,65]. When measuring SE and motivation at the start of a course, student scores are usually high, but after students encounter challenging programming tasks, SE and motivation tend to go down; whatever the nature of the instructional strategy [66]. In our case, the data collection was set up within the first 2 weeks of the class course when students' perspective towards programming might still seem "optimistic." Posttest administration was set up a week before the midterm examination when students had experienced the demanding nature of the course topics. Another explanation for the less clear impact on motivation is related to our too strong focus on IM. This is the ultimate motivational level in the SDT framework. Maybe, widening our motivation spectrum to autonomous motivation, including next to intrinsic, also identified and integrated regulation, could have helped to identify basic levels of changes in motivation. Research shows that the types of motivation mentioned above also positively affect LP [67]. An additional reason could be related to the way autonomy, satisfaction and relatedness were satisfied. Niemec and Ryan [29] affirm that to maintain IM, both autonomy and competence needs are essential. If a student feels competent but lacks autonomy, IM will not be sustained. In our study, though competence was designed to be achieved by the constant feedback received through the leaderboard, autonomy might have been perceived as limited (students could only choose



to do or not the optional activity). Thus, causing an effect in IM. One final explanation could be related to the way the gamified learning environment was set up. As much as we tried to create an environment invoking IM, some students might still see the leaderboard gamification elements as extrinsic motivators, as is stressed by some specific authors [68]. This suggests that leaderboards might be detrimental to students' motivation due to feelings of competition.

Regarding engagement, research shows that optional activities do increase student engagement and LP [69,70]. However, our findings are not in line with previous research [71]. Maybe due to our specific gamified design, only one activity a week, and optional activities only once every other week, it might have been too early to expect an impact on mediating variables. Another reason could be the way engagement was operationalized. The concept of user engagement is complex, and assessment should be considered at a behavioral, affective, and cognitive level [75]. Thus, it is crucial to find an assessment method aligned with these three dimensions.

## 6 | LIMITATIONS AND FUTURE RESEARCH

Despite of the promising results, the current study reflected some limitations. First, though we tried monitoring teachers' profiles, we did not focus on this critical actor during the actual implementation of our gamification study. This could have introduced bias. Second, we did not control how students tackled the online pre/post questionnaires. Third, we acknowledge the need for involving a larger sample to obtain results with sufficient power for generalization. Finally, we recognize this intervention was short, compared with other studies (a full semester). Nevertheless, this short study helped to uncover a positive impact.

The former inspires future research directions. First, we need to extend the duration of the gamified experience. Second, more control is needed of variables in students (eg, online administration of instruments). Third, we should collect data from teachers (eg, beliefs or engagement) to find out their view on gamification and whether gamification is perceived as an effective instructional approach to enhance learning. Fourth, we could set up studies in other STEM domains, such as math and science. Fifth, from a technical point of view, automating the leaderboards could boost the related feedback mechanism to students. Sixth, an additional study could include an analysis of student's reactions when facing the different leaderboard types in terms of the variables studied. Lastly, next to self-report questionnaires, interviews, observation, and video-analysis could provide us with reliable data to develop a picture of the gamified

learning experience and underpin in a more profound way the mechanisms described to explain the gamification effect.

## 7 | CONCLUSION

This study presented evidence about the impact of leaderboards on LP in an engineering course. Next to direct effects, the study also considered the impact of changes in IM, SE, and engagement. The results reflected a significant increase in LP. However, no impact on/of mediating or background variables could be observed. The positive results support the idea of developing additional gamified engineering courses. However, building on the results, we should move to adopt a more programmatic approach, resulting in systemic changes in the engineering curriculum that also includes teachers as key actors. The latter introduces the importance of studies that focus on in-depth mechanisms underlying gamified course design. This can only be attained by involving, next to students, teachers, and by including a qualitative approach to evaluate the impact of gamified learning experiences.

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## CONFLICT OF INTERESTS

The authors declared no potential conflict of interests concerning the research, authorship, and publication of this article.

## DATA AVAILABILITY

Data of this study can be accessed upon request.

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