A Playful Game Changer: Fostering Student Retention in Online Education with Social Gamification

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ABSTRACT
Many MOOCs report high drop off rates for their students. Among the factors reportedly contributing to this picture are lack of motivation, feelings of isolation, and lack of interactivity in MOOCs. This paper investigates the potential of gamification with social game elements for increasing retention and learning success. Students in our experiment showed a significant increase of 25% in retention period (videos watched) and 23% higher average scores when the course interface was gamified. Social game elements amplify this effect significantly – students in this condition showed an increase of 50% in retention period and 40% higher average test scores.

Author Keywords
Massive Open Online Courses; MOOC; Gamification; Social Engagement

ACM Classification Keywords
J.1 [Administrative Data Processing]: Education
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INTRODUCTION
Low retention rates are a widely discussed issue of learning at scale. Students of online courses report various inconveniences resulting in their dropout. Gamification is a promising method to strengthen student engagement and ease some of the disadvantages connected to online education [27]. High dropout rates are often attributed to feelings of isolation and lack of interactivity [15]—reasons directly relating to missing social engagement. Thus, we use social game elements to strengthen social engagement in students of online courses.

We conducted a controlled experiment with 213 students majoring in psychology or computer science. To discriminate the effects of gamification from effects induced through social elements, we compare three conditions: (1) a baseline condition without explicit gamification, (2) a version with game elements, but no social elements, and (3) a gamified version with social elements. We hypothesize that gamification has a stronger effect when it exhibits social elements. We found that students in our gamification condition had 23% higher average scores and an increase of 25% in retention. With social elements, the increase was almost 40% for final scores and 50% for retention period.

Figure 1. We investigate the impact of social gaming elements on student retention in online learning. Shown here is the interface of our system on a tablet. In particular, the lesson panel of the *social* game condition.

RELATED WORK
Retention remains a major challenge in MOOCs. Jordan reported that although completion rates occasionally exceed 40% the average rate is below 13% and sometimes even below 1% [13]. When analyzing retention it is important to note that student motivation is more diverse in online courses than traditional courses. The motivation also varies significantly between courses [17]. Willkowski et al. [32] asked students about their motivation to take part in the MOOC *Mapping with Google*. Only 10% of students reported that they wanted to earn a certificate. Kizilcec et. al [17] investigates this diversity in student motivation more closely. Their findings also suggest that getting a certificate is not the primary intention of students in MOOCs. Kizilcec et. al [17] further illustrate that the retention rate of students actually taking a course for a certificate are still low. According to Willkowski et. al [32] only 25% percent of those students aiming for a certificate actually achieved their goal. These results show that even students with the goal to complete the course struggle to achieve it.

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There has been work on using games or game-like elements for education [1,27,30] and training [31] and explorative studies on the effects of game elements in online courses [10]. Domínguez et al. [8] investigated the effects of gamification on adult learners. Their study indicates that gamification may have an effect on students. In contrast to these explorative studies, we investigate a more specific question:

RQ1: Does gamification have a positive effect on retention?

Khalil et al. [15] investigates why students drop off from online courses and proposes strategies how to increase retention. They report that feelings of isolation and a lack of interactivity are both factors for high drop of rates in MOOCs. This indicates that social engagement is an important aspect of students' success. This is also consistent with other studies [7,17,25], which hypothesize that social engagement is a relevant factor for student retention, success, and satisfaction.

Research on social factors of learning is a well-established field [3,28,34] and there are attempts to strengthen social interactions in MOOCs [29] and various endeavors to understand social elements in online and distance education [4,18,19]. Simões et al. [25] use social elements to support younger students (K-6) in an offline environment with social game elements. Thus, there is evidence that social elements may amplify the effect of gamification. Therefore, we extend our initial research question and ask:

RQ2: Is gamification with social elements more efficient?

STUDY DESIGN

Our study follows a between subjects design with three different conditions. The first condition has no game elements (*plain* condition), while the second condition has game elements (*game* condition), and the third condition has social game elements (*social* condition). Apart from the main factor (*condition*) we also collect information on two more fixed factors: *gender* and *major*. As we required verified information of these factors, we integrated our experiment with offline courses at a university. Student retention is valuable and even more when it is correlated with learning success. Therefore, we also analyze how much students can recall from a lecture. We hypothesize that:

H1: Gamification increases retention.

H1a: Gamification increases learning success.

H2: Social game elements amplify retention gain.

H2a: Social game elements amplify learning success.

The course used for the experiment introduces *Python* as a programming language for statistical analysis and has an expected duration of four-weeks with an average workload of 4 hours per week. We organized the *course* into four *lectures,* each lecture containing 15 video *lessons* on average. No video lesson was longer than 4 minutes and videos showed either tablet drawings or code examples. Each video also features a short quiz. Quizzes are either multiple-choice questionnaires or free text input.

The online course was not required for any course of the university but lecturers of graduate and undergraduate courses in computer science (human-computer interaction) and psychology promoted the course in their lectures as a valuable addition.

PARTICIPANTS

We collected data from 71 students in the *plain* condition, 67 students in the *game* condition, and 68 students in the *social* condition. Students were studying either computer science (113) or psychology (93) for their undergraduate (87), master (116), or Ph.D. (3). Only 12 participants reported prior knowledge in python. Many students, however, had basic knowledge of statistics (85) and sometimes experience with R (56), Java (95), or C/C++ (56).

PROCEDURE

Students had to sign up for the course via an online system. As we had verified information about gender and major of students, we were able to balance condition assignment of students based on gender and major. Table 1 shows the final distribution of students in each condition:

	Gender		*Major*	
Condition	***Female***	***Male***	***Psych.***	***CS***
Plain	30	41	32	39
Game	28	39	30	37
Social	28	40	31	37

Table 1. Demographics of students in each condition.

Plain Condition

The *plain* condition does not have explicit game elements. After logging in with their university credentials students can choose one of the four lectures from a dashboard. The dashboard also provides an overview of the progress in each course and lesson. Figure 2 shows a screenshot of the dashboard. Selecting a lecture in the dashboard opens the respective lesson panel.

The lesson panel has four central elements: a video in the center, an element to navigate over the video, and a quiz panel on the left. Quizzes could take one of two forms either a multiple-choice quiz or a free text question. Students only need to type one or two words to answer free text questions.

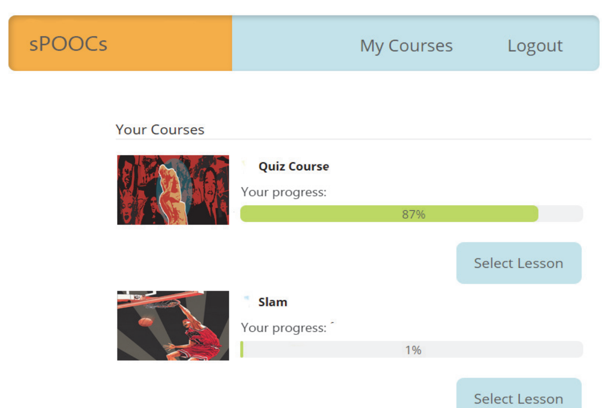

Figure 2. The dashboard of the *plain* condition. Students get an overview of their progress in courses and lessons.

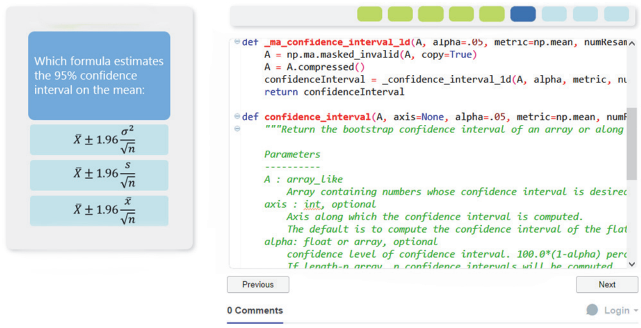

Figure 3. Main components of the lesson panel of the baseline condition (*plain*). We omitted the discussion board under the video, as it we did not change it.

The system is able to deal with common spelling errors. The lesson panel shows a discussion board below the video as seen in Figure 2.

Game Condition

We designed the *game* condition with all features of the social condition omitting only those that incorporate social elements. We only use gamification instead of more sophisticated game concepts allowing an easier interpretation of effects. We deliberately chose to leave out complex game mechanics. Complex game mechanics themselves have a learning curve and thereby introduce noise.

We restructured the dashboard. A panel on the left side shows players an overview of their achievements. This panel also contains a customizable avatar in the social condition. We show the details in Figure 5. In the *game* condition, the panel does not show this avatar but is otherwise identical. The full lesson panel is depicted in Figure 5. As the *game* condition is already very close to the *social* condition the figure shows only the final version of the panel. The lessons panels of the *game* and the *social* condition differ only in the design of their quiz elements. We show these differences in more detail in Figure 7.

For the *game* condition, we use basic gamification mechanics [33]. ***Achievements*** or ***badges*** are widespread elements in gamification. They are a representation of an accomplishment. In the *game* condition, students can acquire achievements for answering a number of quizzes correctly, taking a number of lessons, or being ranked among the top ten students of a lesson or the entire course. We award five achievements with three levels for each achievement.

Players also earn ***score points*** for each correct answer to a quiz question. We use these score points to place players in a leaderboard for each course and each lesson in a course. We are aware of the fact that ***leaderboards*** already constitute a social element and that this decision might tone down the effects between the *game* and the *social* condition.

We deliberately chose to integrate leaderboards in the game condition as they are an essential element in almost every gamification approach and do not connect players directly

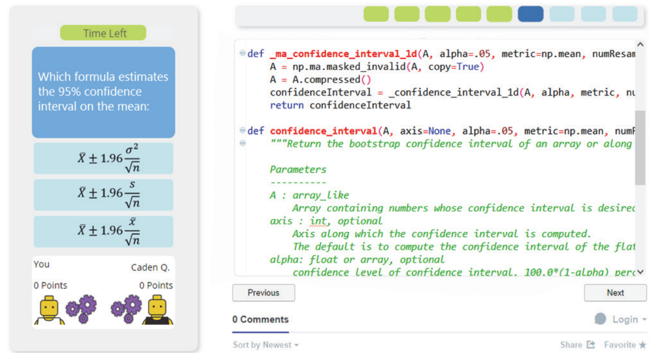

Figure 5. Main elements of the lesson panel of the *social* and *game* condition. The only differences between social and game condition is the presence of the quiz (Figure 7 shows this differences in more detail).

with one another. Aesthetics do play a relevant role in gamification using visually appealing graphics and representations one can create a sense of pleasurable satisfaction [9,14,23,24]. For the experiment, we chose a neutral comic like design. Players can design their own ***avatar***. Later during the course, students can turn in their achievements and score points to acquire different visual add-ons to place on their avatar such as hats and other items. Figure 4 shows a screenshot of the dashboard of the game condition showing an avatar and a list of achievements.

The dashboard also provides an overview of the progress in each course and lesson. Beside the integration of a customizable avatar, we overhauled the general appearance of the interface to fit the theme laid out with the avatar. Figure 6 shows the customization interface for the avatar and some of the avatars created by students during the course.

Finally, we added a countdown to each quiz in a lesson. This restricts student to a certain amount of time when solving a quiz, effectively inducing tension with this ***time limit***. To allow students to watch the video without time pressure, quizzes have to be explicitly activated via clicking. Figure 7 shows two screenshots of the quiz.

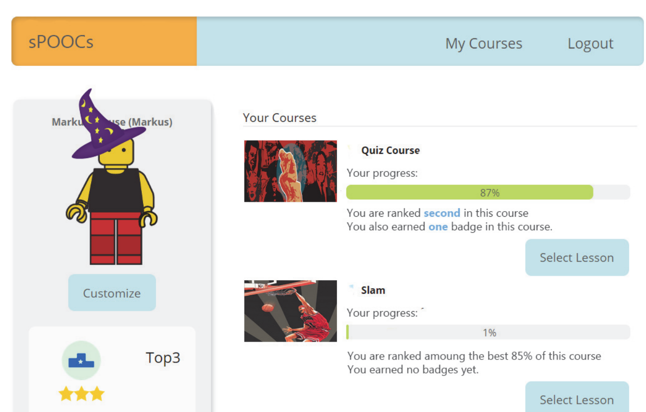

Figure 4. Dashboard of the *social* condition. Players can customize their avatar and get an overview of their progress in courses and lessons.

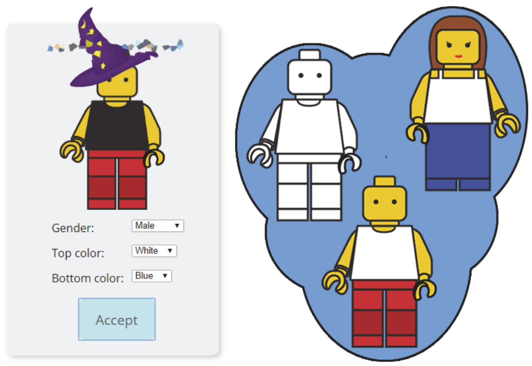

Figure 6. Students can customize their avatar. Later during the course, students can collect visual gadgets, e.g., hats or other props. Some possible avatars are shown on the right.

Social Game Condition

The *social* condition is identical to the *game* condition except for an additional set of social game elements. Prior to starting a new lecture, participants were able to choose an opponent. Students could choose a person they know from the list of participants, or play against a randomly chosen opponent. Although typical for games that highlight social aspects, we do not allow participants to invite friends via social networks or e-mail at this point. When a player starts a lesson with a random opponent, a screen illustrates the search for another player (see Figure 8).

The system does not require two players to be online at the same time. A student can play against pre-recorded actions of another student. To ensure that the system always has enough recordings we pre-recorded some sessions.

The system pairs a student with a recorded session if it cannot find another player within 30 seconds of the student choosing a random opponent. Students can also choose a specific player from a list of students currently online or with recorded play sessions. If the second student is online, the system waits until both students start the lesson. If the second

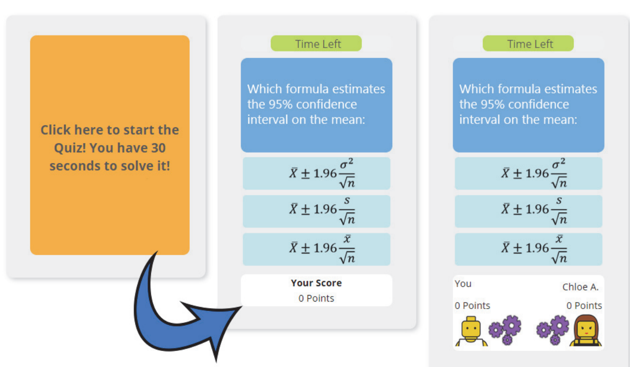

Figure 7. We changed the appearance and the behavior of the quiz from the *plain* condition. The quiz in the *game* condition (center) features a countdown (green bar) and students activate the quiz manually (left). In the *social* condition, students see the status of their opponent (right).

Figure 8. To highlight the social aspect we visualize the search process for a competitor (top). Students can skip this process (button in the center). The system then pairs students with a recorded session of another student. Otherwise, a notification window shows that the system found another student (lower part of the figure).

student is not online but has a recorded session for this lesson the first student plays against this recording.

To highlight the social interaction we add a status bar to the quiz panel. This bar illustrates the progress of ones opponent on the quiz as seen in Figure 7. Students get a notification if their opponent solves a quiz if they as well have an active quiz. Finally, we added a summary screen that compares the results of both students (see Figure 9).

MEASUREMENTS

To estimate student retention we measure the number of video lessons a student watches. We will refer to this measure as ***retention period***. For this experiment we consider video as watched if it played completely and the continue button was clicked afterwards. As basic knowledge of statistics and programming languages was present in our user group, we assumed that some participants skip lectures due to prior knowledge. For the experiment, we define skipping a lecture as starting the video but moving on to the next one before the video has finished. We asked participants to indicate if they skip a lecture because of prior knowledge. If a student skips a video because of prior knowledge, we still consider the video lesson as completed.

To measure learning success we conducted an exam with some of our students. We invited students that took part in our experiment to an offline test. We scheduled this test 3 month after the start of the course. 101 Students took part in

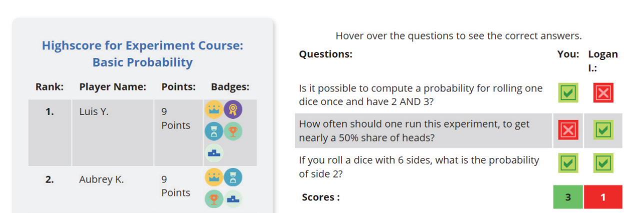

Figure 9. The resume screen of the social condition. Illustrates the player performance compared to her opponent. On the left is a leaderboard showing ranking and badges.

this test. On average, students took the test one week after the course (self-assessed). We asked students to write a python script that calculates the 95% confidence interval of the distribution of means using only standard functions.

We reviewed and graded all submissions in a blind review process. At least three different reviewers graded each submission on a range from 5 (excellent) to 1 (a lot of room for improvement). We averaged the ***test performance*** of all reviewers to measure learning success for each participant.

Besides test scores, we also use a second measure to estimate learning success. Students solve quizzes throughout the course; the average ratio of correctly solved quizzes is our last measurement: ***quiz accuracy***.

RESULTS

In accordance with Cramer and Bock [5], we performed a MANOVA on the means to help protect against inflating our Type-I error rate in the follow-up ANOVAs and post-hoc comparisons. Prior to conducting the MANOVA, we calculated a series of Pearson correlations between all dependent variables in order to test the MANOVA assumption that the dependent variables correlate. We found correlations ranging between 0.2 and 0.4 all correlations are significant at an α-level of 0.01 or lower. These values are within acceptable ranges according to Meyers et al. [26].

Additionally, the Box's M value of 16.25 was associated with a p value of 0.012, which was interpreted as non-significant in accordance with Huberty and Petoskey's (i.e., $p < .005$) [12]. Thus, the covariance matrices between the groups were assumed equal for the purpose of the MANOVA. We conducted a three-way multivariate analysis of variance (MANOVA) to test the hypothesis that there would be one or more mean differences between our conditions (*plain*, *game*, and *social*) and our measurements (*retention period*, *quiz accuracy*, and *test score*). A significant MANOVA effect was obtained, Pillais' Trace = 0.22, $F(6, 176) = 3.38$, $p = 0.003$ with an estimated multivariate effect size of 0.112.

Retention Period

We calculate the average retention period for each condition and the 95% confidence interval of the distribution of means as shown in Table 2. To estimate confidence intervals we draw 10,000 bootstrap samples from each condition using sampling with replacement.

All three conditions differ by their mean but show a slight overlap of their confidence intervals. As hypothesized the *game* and *social* conditions have a higher average retention period than the version without game elements. The *game* condition shows a 25% increase in retention period compared to the *plain* condition. The *social* condition more than doubles this effect showing an increase of the average retention period of more than 55% compared to *plain*.

Before testing our results for significance, we ensured that our data is suitable for parametric tests as hypothesized. We used an omnibus test for normality [6] for each condition and did not find significant differences from a normal distribution. As we have different numbers of participants in our conditions, we also verified that our conditions have equal variance for the dependent variable prior to executing an analysis of variance (ANOVA).

Cond.	n	$\bar{x}$	95% CI
plain	71	11.9	[10.2, 13.6]
game	67	14.9	[12.9, 16.9]
social	68	18.5	[16.5, 20.7]

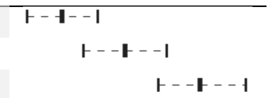

Table 2. Number of participants (n), mean retention period ($\bar{x}$), and the 95% confidence interval of the distribution of retention period means. The CI and the boxplot of means are calculated from 10,000 bootstrap samples.

As the distributions do not differ significantly from normal distributions, we use Bartlett's test for homoscedasticity (equal variance) [2]. We found, as assumed, that the variance does not differ significantly between our conditions $t(2) = 2.649$, $p = 0.265$. As our data does not hold evidence that it violates the assumptions of the ANOVA we analyze main and interaction effects with a three-way independent analysis of variance. Table 3 shows the results of this test.

Source	df	*SS*	MS	F	p
(C)ondition	2	1559.1	779.5	11.53	<0.001
(G)ender	1	194.3	194.3	3.07	0.081
(M)ajor	1	52.6	52.6	0.83	0.362
C×G	2	187.5	187.5	1.48	0.229
C×M	2	14.1	14.1	0.11	0.894
C×G×M	2	133.9	133.9	1.05	0.348
Residual	194	12270.0	63.24		

Table 3. Interaction and main effects on retention period. Abbreviations: df (degrees of freedom), SS (sum of squares), MS (mean squares).

We found that our conditions are the only significant factor in our experiment. We use post-hoc one-tailed t-tests to test for significance between individual levels of this factor and use the Holm–Bonferroni [11] method to control for family wise error rates. Figure 10 shows a violin plot of the retention periods found in our experiment. From the results we can support hypothesis *H1* as the game condition has a significantly higher average retention period (M = 14.9, SD = 8.2) than the *plain* condition (M = 11.9, SD = 6.6), with $t(137) = 2.22$, $p = 0.02$, $d = 0.38$. We can also support *H2* as the social condition has a significantly higher average retention period (M = 18.5, SD = 8.7) than the *game* condition (M = 14.9, SD = 8.2), with $t(134) = 2.48$, $p = 0.01$, $d = 0.42$. Accordingly the social condition also has a significantly higher average retention period (μ=18.5, σ=8.7) than the *plain* condition (M = 11.9, SD = 6.6), with $t(138) = 4.82$, $p<0.001$, $d = 0.79$.

Quiz Accuracy

In order to assess the influence of our conditions on students success we calculate average quiz accuracy for each condition and the 95% confidence interval of the distribution of means as shown in Table 4.

Cond.	n	$\overline{x}$	95% CI
plain	71	0.46	[0.40, 0.52]
game	67	0.52	[0.46, 0.58]
social	68	0.62	[0.55, 0.66]

Table 4. Number of participants (n), average *quiz accuracy* ($\overline{x}$), and the 95% confidence interval of the distribution of means. The CI and the boxplot are calculated from 10,000 bootstrap samples.

To estimate confidence intervals we draw 10,000 bootstrap samples from each condition using sampling with replacement. All three conditions differ by their mean and overlap in their confidence intervals. The *game* and *social* conditions have a higher average quiz accuracy than the *plain* condition. The *game* condition shows a 12.5% increase in quiz accuracy compared to the plain condition. The *social* condition again doubles this effect showing an increase of quiz accuracy of more than 31%. As for the previous measures, we conducted an omnibus test for normality and Bartlett's test for homoscedasticity. We did not find our distributions to differ significantly from the ANOVA assumptions. We therefore analyze main and interaction effects again with a three-way independent ANOVA. Table 5 shows the results of this test.

Condition is the only significant factor for quiz accuracy. Figure 11 shows a violin plot of the quiz accuracy found in our experiment. From the results we cannot entirely support hypothesis *H1a* as the difference between the *plain* (M = 0.46, SD = 0.25) and the *game* condition (M = 0.52, SD = 0.25) is not significant t(137) = 1.34, p=0.09, d = 0.23. We can however support our hypothesis *H2a* as the *social* condition has a significantly higher average quiz accuracy (M = 0.61, SD = 0.21) than the *game* condition, with t(134) = 2.19, p = 0.031, d = 0.37 and the *plain* condition, with t(138) = 3.63, p<0.001, d = 0.59.

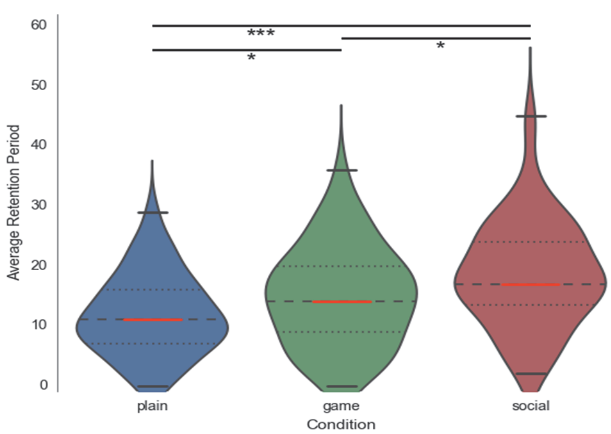

Figure 10. The *social* condition shows a significantly higher *retention period* than the *game* and *plain* conditions. The *game* condition also shows significantly higher retention rates than the plain condition. The grey lines in the violin plot indicate min and max values the grey lines on top significant differences: ∗∗∗: p < 0.001, ∗: p < 0.05.

Source	df	*SS*	MS	F	p
(C)ondition	2	76.75	76.75	6.54	0.002
(G)ender	1	5.36	5.36	0.91	0.340
(M)ajor	1	15.92	15.92	2.71	0.101
C×G	2	4.87	2.43	0.41	0.661
C×M	2	27.74	13.87	2.36	0.097
C×G×M	2	28.06	14.03	2.39	0.094
Residual	194	113.81	5.86		

Table 5. Interaction and main effects of *quiz accuracy*. Abbreviations: df (degrees of freedom), SS (sum of squares), MS (mean squares).

Final Test Performance

Our finale measurement for student success is test performance in our offline exam. We again calculate the mean and the 95% confidence interval as shown in Table 5. Again, all three conditions differ by their mean and overlap in their confidence intervals. Students in the *game* and *social* conditions have higher test scores than students in the *plain* condition. Students in the *game* condition have a 22.5% higher test performance than those in the *plain* condition. Students in the *social* condition show 40% higher scores on average.

We conducted an omnibus test for normality and Bartlett's test for homoscedasticity and analyzed main and interaction effects with a three-way ANOVA. Table 6 shows the results of this test. Condition is, as expected, the only significant factor for quiz accuracy. Figure 12 shows a violin plot of the quiz accuracies found in our experiment.

From the results we can support hypothesis *H1a* as the difference between the *plain* (M = 2.5, SD = 1.12) and the *game* condition (M = 3.06, SD = 1.10) is significant t(64) = 2.01, p = 0.049, d = 0.49. We cannot directly support our hypothesis *H2a* as the *social* condition does not show significantly higher average test scores (M = 3.50, SD = 1.12) than the *game* condition, with t(68) = 2.19, p = 0.055, d = 0.39 and the *plain* condition, with t(67) = 3.63, p < 0.01, d = 0.81.

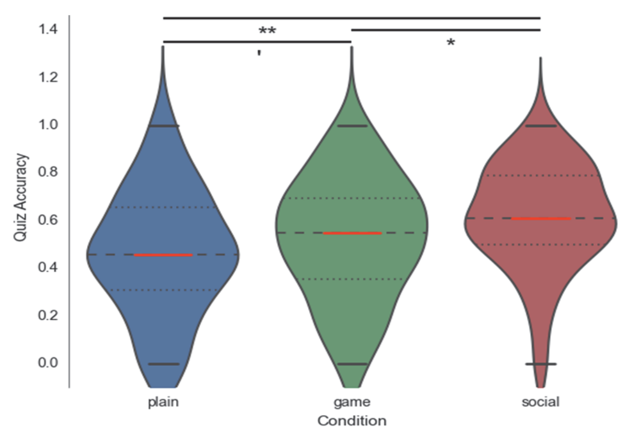

Figure 11. Student success measured with *quiz accuracy*. The grey lines in the plot indicate min and max values the grey lines on top significant differences: ∗∗: p < 0.01, ∗:p < 0.05, ':p < 0.1.

Cond.	n	$\overline{x}$	95% CI
plain	32	2.50	[2.12, 2.87]
game	33	3.06	[2.69, 3.45]
social	36	3.50	[3.13, 3.86]

Table 6. Number of participants (n), average *test score* ($\overline{x}$), and 95% confidence interval of the distribution of means (CI is estimated from 10,000 bootstrap samples).

CONCLUSION

This work presented a systematic analysis of the impact of social gamification on student retention and learning success in online courses. We posed two research questions: ***RQ1:*** does gamification support students of our online course and ***RQ2:*** do social elements amplify possible positive effects. We hypothesized that social gamification increases retention as well as strengthening learning success.

In order to assess the impact of social gamification, we analyzed three dependent variables (DVs) (*retention period*, *quiz accuracy*, and *test scores*) on three independent variables (IVs) (*condition*, *gender*, and *major*). All DVs showed a significant increase for the factor *condition* between the *plain* and *social* level. For *retention period* and *quiz accuracy*, we found two differences that were not significant on a α level of 0.05 but on a level of 0.1. However, given the p-values from both ANOVA and MANOVA a Type-I error seems unlikely in both cases. In response to our hypothesis *H1* we analyzed retention period and observed a significant increase of 25% between our *plain* and our *game* condition and a significant increase of 55% from *plain* to *social*. This lends strong support to our initial hypothesis that gamification can increase retention and that social gamification amplifies this effect.

For quiz accuracy, we found an increase of 12.5% between our *plain* and *game* conditions and an increase of 31% between *plain* and *social*, in the final test students in the *game* condition had a 22.5% higher test score compared to students in the *plain* condition. Students in the *social* condition showed an even stronger increase of almost 40% compared to students in the *plain* condition. This again lends support for our hypothesis *H2* that we can amplify beneficial effects with social gamification.

FUTURE WORK

In our experiment, social elements showed a significant impact. To control our population variables and to reduce noise

Source	df	*SS*	MS	F	p
(C)ondition	2	76.75	76.75	6.54	0.002
(G)ender	1	5.36	5.36	0.91	0.340
(M)ajor	1	15.92	15.92	2.71	0.101
C×G	2	4.87	2.43	0.41	0.661
C×M	2	27.74	13.87	2.36	0.097
C×G×M	2	28.06	14.03	2.39	0.094
Residual	194	113.81	5.86		

Table 7. Interaction and main effects of quiz accuracy. Abbreviations: df (degrees of freedom), SS (sum of squares), MS (mean squares).

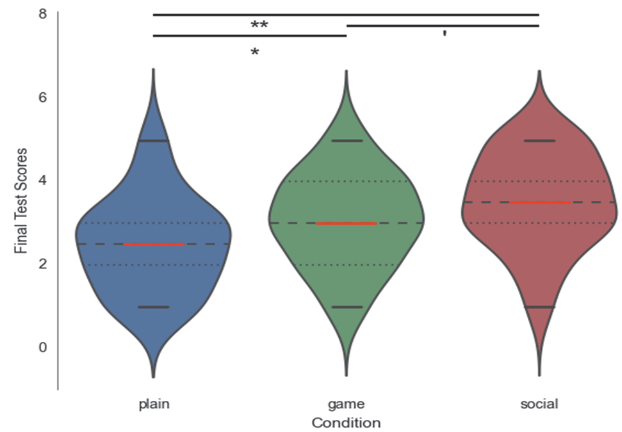

Figure 12. We measured learning success with a final offline test. In this test, students wrote a short Python script to estimate confidence intervals of means. Three independent reviewers graded each submission on a scale from 5 (excellent) to 1 (underperformed). The grey lines indicate min and max values, the grey lines on top significant differences: $**$: $p < 0.01$, $*$:$p < 0.05$, ‘:$p < 0.1$.

we restricted our experiment in terms of the user pool and the used game mechanics. Based on our findings and previous experiments we expect positive effects to be much stronger when we apply more sophisticated design concepts. Badges, achievements, and leaderboards are visually pleasing and provide a certain engagement. However, we do not expect these basic mechanics to uphold student motivation for a complete online curriculum.

In the future, we plan to investigate different social game mechanics and their impact on student success. In this paper we explored the effects of a competitive setting were students challenge each other. In the future, we also want to investigate the differences between playful elements that foster collaboration instead of competition and both methods combined. We also aim at providing sophisticated feedback to support students. However, complex game mechanics may require more advanced interaction techniques. For instance, the game could allow students who earned a certain status to add questions to the system. Thereby expanding the learning materials and allowing advanced students to compete on another level. Tools [20] and methods [16,21] that support such games already exist [22].

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