Mastery Learning as Gamification: Level-Up Through High-Transparency Assessments

Guttorm Sindre[1] and Line Kolås[2]
[1]Norwegian University of Science and Technology (NTNU), Trondheim, Norway
[2]Nord University, Levanger, Norway

guttorm.sindre@ntnu.no
line.kolas@nord.no

Abstract: Self-paced mastery learning aims to give the students more autonomy over their own learning process. Typically, such course designs have many lesser tests during the semester rather than one big exam. This pattern of repeated passing of obstacles and gradual level-up resembles a gamified approach to learning. An interesting question is to what extent a self-paced mastery learning course can be considered gamified even in cases where it does not aim to be entertaining. This paper makes a case study of an introductory programming course for first-year STEM teacher students at NTNU, Norway. The course is analyzed through the lens of gamification, using the Learning Mechanics – Game Mechanics (LM-GM) model. Relating this to student satisfaction and performance data indicates that there are many gamification-related aspects of such a course, contributing positively to student engagement. This paper provides a better understanding of how self-paced mastery learning can be considered a gamified course design and a promising approach for those looking to incorporate more explicit game elements into a course. Additionally, it shows how self-paced mastery learning could be an interesting pedagogical strategy for gamifying traditional higher education settings, especially focusing on affordances related to achievement / progression as well as social affordances.

Keywords: Mastery learning, Gamification, Learning mechanics, Game mechanics, LM-GM framework

1. Introduction

Mastery learning was proposed in the 1960s by Bloom (1971) and Keller and Sherman (1974), the latter approach called *Personalized System of Instruction* (PSI) with a focus on student self-pacing. Despite positive empirical evaluations of student outcomes (Kulik, Kulik et al. 1990), interest gradually declined (Buskist, Cush et al. 1991) but developments in e-learning technology inspire a revival (Eyre 2007), and interest in self-paced mastery learning is on the rise again (Mannion, Coyne et al. 2023, Pérez and Verdín 2023). Especially for introductory programming courses, there are several recent reports on course designs (Purao, Sein et al. 2017, Garner, Denny et al. 2019). The key idea of self-paced mastery learning is to divide a course into modules, each small enough not to become overwhelming. Students must master the first module before moving on to the second, and so forth, each going at their own pace. Mastery of a module is typically documented by tests with a high pass threshold like 90% (Keller and Sherman 1974). The students' progress through the course could resemble gameplay with levels. This comparison will be especially appropriate if the grade is determined by the number of modules passed.

At NTNU, an introductory Python programming course (CS1) using self-paced mastery learning was introduced for a class of approximately 50 first-semester STEM teacher students in the autumn of 2023, and then run again for a similar class in the autumn of 2024. The course design has several elements that align with game mechanics, such as levels and automated tests yielding quick feedback. Gamification – the addition of game elements into a non-gaming context (Deterding, Dixon et al. 2011) – has seen many uses in education. The course did not use visual gamification elements and was not "sold" as being gamified. Hence, we are not studying a course with mastery-learning plus gamification, rather investigating *mastery-learning as gamification,* and how this may have contributed to course outcomes. On an overarching level, gamification involves three primary elements situated within a certain context (Hamari, Koivisto et al. 2014): the *affordances* applied to a system or service leads to *psychological outcomes*, which subsequently lead to *behavioral outcomes – a sought effect in educational gamification might* for instance be that challenges, quests and team collaboration (affordances) might lead to increased engagement (psychological outcomes), which in turn leads to increased study effort (behavior). Our research questions are:

- RQ1: What gamification-related affordances can be found in the self-paced mastery learning course design?
- RQ2: How did the course affordances yield psychological and behavioral outcomes?
- RQ3: How can self-paced mastery learning contribute to gamified learning in higher education?

The rest of the paper is structured as follows: Section 2 presents related research and Section 3 our research method. Section 4 provides the design of the course through a lens of gamification. Section 5 analyzes the gamification-related affordances and outcomes, as evidenced through student opinion and performance. Finally, section 6 discusses the implications of the findings, providing advice on how self-paced mastery learning can be a basis for gamified course designs.

2. Related Work

There are few publications dealing with courses combining all three topics CS1, self-paced mastery learning, and gamification. One exception is (de Pontes, Guerrero et al. 2019), reporting experiences from a gamification experiment in CS1. The gamification was only used for the last four weeks, and students were randomly divided into two groups: treatment (gamified e-learning tool with badges, personal record-tracking, and leaderboards) and control (non-gamified tool). The treatment group solved more assignments than the control group, but it is unclear whether they achieved better learning. Their paper describes an experimental addition of gamification features on top of a course, while our paper analyzes a course through a lens of gamification, but without any experimental addition of gamification features.

Gamification in CS1 courses has been addressed by several researchers, showing mixed results. One review (Shahid, Wajid et al. 2019) looked at programming concepts covered by gamification approaches, another (Maryono, Budiyono et al. 2022) at what gamification elements have been used. Costa (2023) investigated the learning effect of gamification approaches in programming, finding a moderately positive learning effect from *levels*, while badges, points, avatars, and leaderboards showed no significant effect. This is particularly relevant to us since levelling is intrinsic in self-paced mastery learning. Rogers et al. (2021) discuss that some students may be motivated by gamification, others not. They found that most students either selected all game elements or none and refer to studies reporting that gamification works only in specific environments and only with certain users. Sprint and Fox (2020) found that gamification contributed to better study behavior, without significantly affecting grades. In another study, García-Iruela et al. (2022) found no significant effect on motivation from gamification.

In other disciplines than computing, several mastery learning courses have used gamification, such as (Mawson, Bodnar et al. 2020) presenting an online gamified homework portal in a first-year engineering design course, (Hou, Nagashima et al. 2022) presenting a gamified course design for high school science, and (Yang 2018) using mastery-learning with gamification in a course module about domestic and foreign food culture. A key difference with our paper is that the other papers discuss mastery learning *with gamification* as a potential add-on, while we discuss mastery learning *as gamification*. Considering the analysis of gamification approaches, there are several possible frameworks. The LM-GM (Learning Mechanics, Game Mechanics) framework (2013) is an analytical model that maps learning mechanics to game mechanics with the aim of defining serious game mechanics, and Arnab et al. (2015) argue that the LM-GM model can support serious game analysis, exemplified by an analysis of the game Re-Mission.

3. Research Method

Overall, the research method is that of a qualitative, exploratory case study (Merriam 1998) investigating to what extent the course design corresponds to gamification principles. The case study rests on two main pillars: an analytical evaluation of the course design through the lens of gamification, and investigation of empirical student data from the course.

There are many gamification frameworks that could be used for the analytical part. Mora et al. (2017) performed a systematic review of 40 design frameworks for gamification, though only a few were related to education. This paper uses the LM-GM (Learning Mechanics, Game Mechanics) framework introduced by Lim et al. (2013), which is especially suitable for educational contexts. The framework was used in an analytical way, the two authors considering which LM-GM-elements could fit which aspects of the course.

The students were all Norwegians aged 19-25, and the gender mix was about 50/50. Student satisfaction was evaluated by anonymous questionnaires (44/47 responses in 2023, 38/40 in 2024). Consent was obtained from students (27/47 in 2023, 39/40 in 2024) to use their performance data for research. All students in the course were invited to participate, only data from non-consenting students were excluded. The project was approved by SIKT, handling such applications in Norway. In this paper, only descriptive statistics are used for analyzing the results.

4. Course Design and Gamification Analysis

The course IT1001 is Python programming for beginners, given to first-year students in a degree program to become STEM teachers in secondary school. The course has 9 modules named I, H, …, A. For each module, students must pass a mastery test *and* deliver an increment of their individual programming project, as shown in Figure 1.

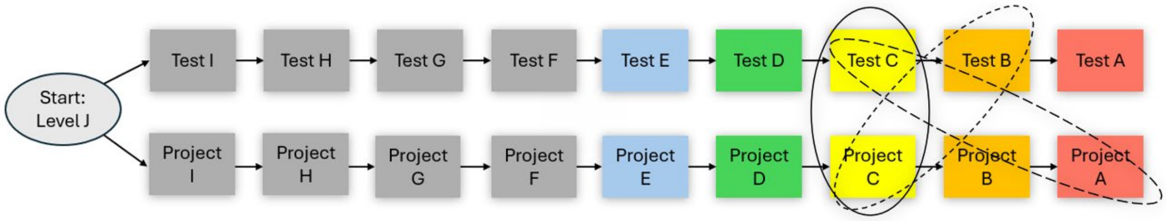


Figure 1: The mastery-path of the course, with tests and project increments per module. If ending on different levels for tests and project, the weakest grade would decide, i.e., all the three ovals on the right would give C

Graded tests were done under supervision each Friday, but each student could decide which Fridays to show. In preparation for graded tests, students watched videos explaining the relevant programming concepts and did formative practice tests. These pulled questions randomly from the same large question banks as the graded tests, thus giving students a clear idea whether their knowledge would be sufficient for passing the test. E.g., seeing a 72% score on a practice test while 90% would be needed to pass, the student could check the auto-feedback to find out where points were lost and revisit learning resources for concepts not sufficiently mastered before trying a new practice test. Random drawing would ensure they did not get the same questions repeatedly, both for practice tests and summative tests.

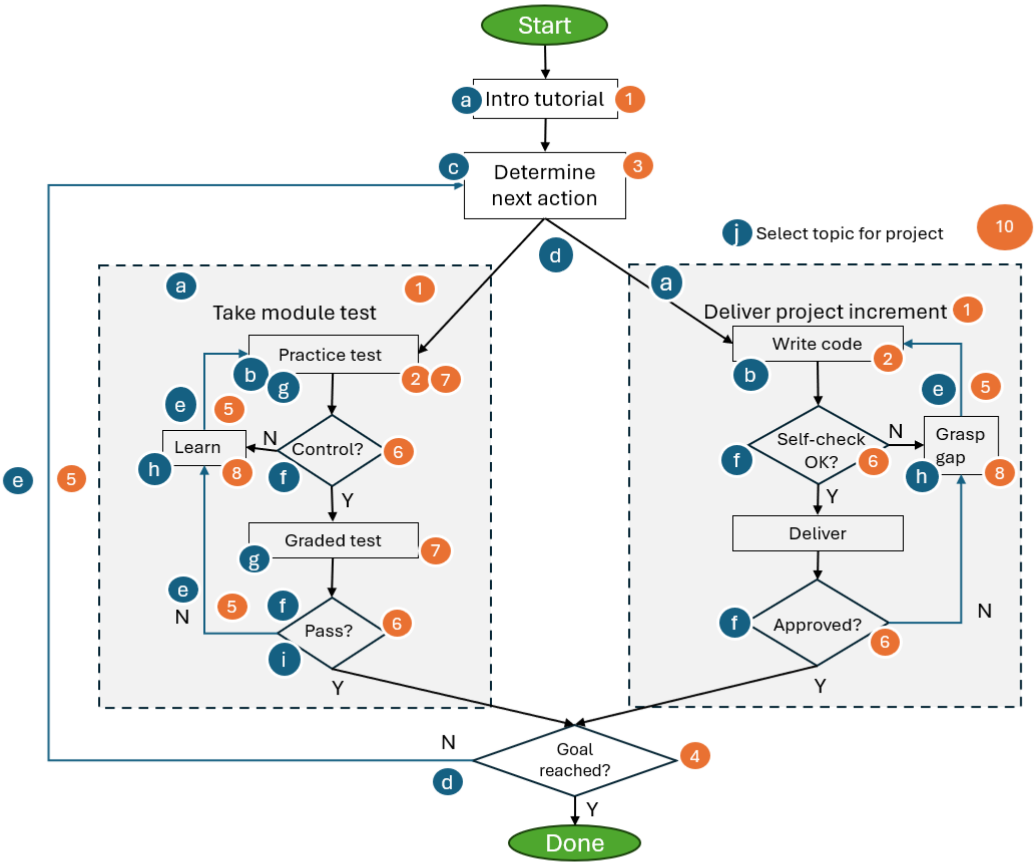
The result of the analysis using the LM-GM framework is shown in Table 1. The two leftmost columns indicate the link between game mechanics and learning mechanics, while the third explains how the mechanics were implemented in the course, and the fourth briefly indicates the purpose that the mechanic had in the course.

Table 1: Analysis of game and learning mechanics in the course, based on the LM-GM framework

Game mechanics	Learning mechanics	Implementation	Usage
Tutorial	Tutorial	1st seminar course intro, videos per module	Inform students about possible actions
Cooperation	Reflect / Discuss	Group work in seminars	Learn together, facilitate social belonging in class
Time pressure / Resource management	Plan, Responsibility	Self-pacing	Promote student agency
Levels	Guidance, Motivation	Sequence of modules	Guide students how to progress
Behavioral momentum	Repetition	Levels, auto-scored tests, unpenalized retakes	Motivation: visible progress
Assessment	Assessment	Grades derived directly from N modules taken	Give students a better sense of control
Questions and Answers	Questions and Answers	Test tasks	Divide curriculum in manageable parts
Feedback	Feedback	Auto-corrected tests, teacher review of project	Indicate mastery gaps, path for improvement
Tokens	Plan	3x “80% passes”	Smoother progress without grade inflation
Ownership	Ownership	Self-chosen project	Motivation: relate to student’s future job

Figure 2 shows how the various mechanics described in Table 1 are involved in the flow of the course, with letters a-j linking to learning mechanics and numbers 1-10 to game mechanics in the LM-GM framework.

- (1,a) The teacher explained the design of the course during the first half hour of the first seminar. Otherwise, nothing was lectured, concepts instead explained through videos and e-notebooks.
- (2,b) Cooperation was facilitated during the seminars, students grouped by level, either practicing for tests or working on their project.
- (3,c) The course lasted 14 weeks, during which 9 modules had to be passed for A, 5 for E. Students had 4 courses in parallel, so they needed to allocate their time across courses over the semester. Through self-pacing, students were encouraged to plan and take responsibility for their own learning.
- (4,d) By means of the sequence of modules I, H, ..., A resembling levels in a game, students got implicit guidance on what to do next. Succeeding with one module gave motivation for the next level.
- (5,e) Repetition existed in several cycles: Nodes “Practice test” – “Control?” – “Learn” in Figure 3 show that students may take formative practice tests to improve. Outside of that, doing “Summative test” – “Pass?” – which will also give a repetition loop if failing. If passing, a new round of the outermost loop is enabled (“Goal reached?” – “Determine next action”) allowing to proceed to the next level.
- (6,f) Assessment was present in each of these loops, for the inner loop self-assessment, for the graded loop teacher-assessment, and for the outer loop again self-assessment on a higher level (do I have capacity to aim for a higher grade?).
- (7,g) Q&A was present both in the test tasks, and in the self-assessment checklists that students filled in per delivery of project increments.
- (8,h) Tests provided automated feedback, while project deliveries got teacher email feedback.
- (9,i) Students had 3x “80% passes” which could be used to pass tests (threshold otherwise 90%). In 2023 this was introduced ad hoc, late in the semester, as many had gotten stuck with repeated failures of the F and E tests. In 2024, they were announced from the start, though only usable from the F-test onwards. These 80% passes are a way to achieve some smoothness in test passing, where the original PSI instead gave students opportunities to explain their knowledge orally in cases where they were just a few points short of the threshold (Keller and Sherman 1974).
- (10,j) The open project assignment let each student choose a topic related to their major subject. This created a sense of personal ownership for the project.



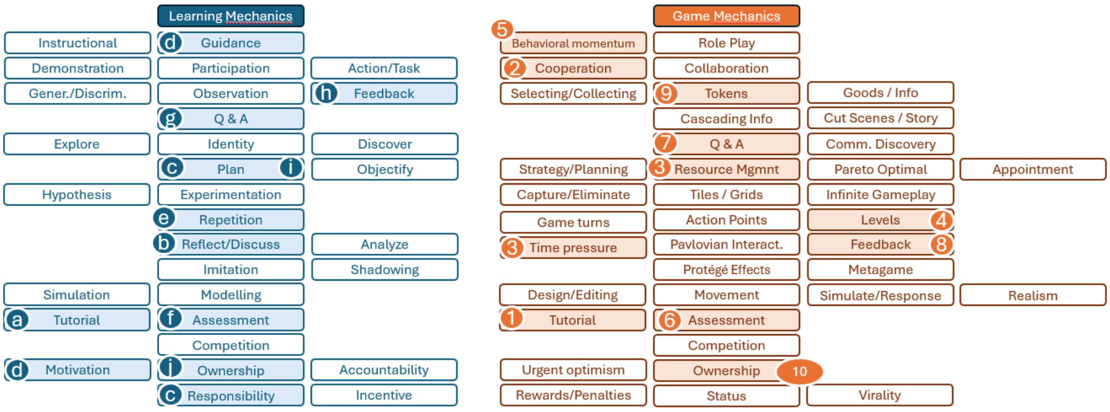


Figure 2: Illustrating how game and learning mechanics are realized in the course design. The upper part of the figure shows the flow of student activities throughout the course, where tests and projects are done in parallel, and each of these pursued module by module, with repetition loops within a module in case of failure

5. Affordances and Outcomes

The above identification of mechanics in the course design leads to an identification of affordances and outcomes as discussed by (Koivisto and Hamari 2019). They identify affordances in several groups, where the following appear most relevant in our case:

- Affordances related to achievement / progression:
- *Challenges, quests, missions, tasks, clear goals* – the modularized design made it clear for the students at any point what must be learnt next.
- *Levels, increasing difficulty* – module I was easy, thereafter gradually more challenging.
- *Performance feedback* – autoscored practice tests providing a possibility for 24/7 frequent feedback where the student could immediately compare score with threshold (e.g., got 72%, needing 90%) and be made aware which concepts needed to be learnt better.
- *Progress* – passing modules gives a clear sense of progress and the students know any time what grade they were currently at.
- Social affordances:
- *Cooperation, teams.* There were no fixed teams since the project was individual. However, in weekly seminar there were small groups of students (3-7) seated together because they were at the same level, thus with the same mission.
- *Customization, personalization*. Each student could pursue the course at their own pace and choose their favorite STEM topic for their project.

Psychological outcomes mentioned by (Koivisto and Hamari 2019) that are relevant for our analysis are:

- *Overall assessment / attitude:* Perceptions of, preferences for, and satisfaction with the course;
- *Affective outcomes*: Engagement;
- *Cognitive outcomes:*
- Perceived usefulness / effectiveness;
- Perception of learning;
- *Effort in use / Experienced challenge:*
- Effort, perceived difficulty, challenge;
- Perceived stress, cognitive load;

Evidence that the students were satisfied with the course and had positive perceptions of it can be found in the data from the questionnaire survey. Figure 3 shows results from two questions, about the overall satisfaction with the course (left), and satisfaction relative to other courses the students took in the same semester – the course coming out positively both years, and especially in 2024.

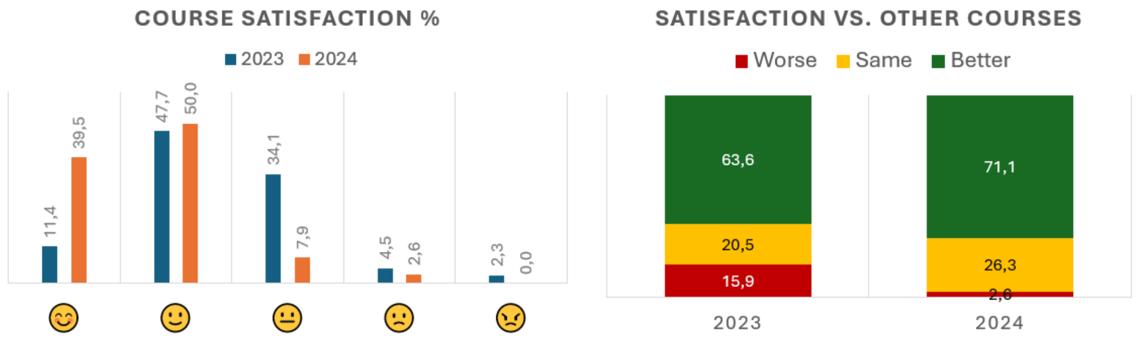


Figure 3: Course satisfaction from student survey. The left diagram summarizes responses to "Overall, how satisfied are you with this course?" with a 5-point Likert scale from "Very satisfied" (happiest emoji) to "Very dissatisfied" (angry emoji). The right diagram shows answers to "How satisfied are you with this course compared to other courses you took in the same semester?", on a 3-point scale Worse, Same, Better

The overall satisfaction as shown in Figure 3 does not, as such, imply that it was the mechanics and affordances identified above that caused this result. However, a more detailed look into other survey questions gives some indication. Figure 4 shows the answers for questions concerning experienced mastery, stress, and control. Survey questions were in full sentences in the students' native language, while shortened English labels have been used here. As can be seen, responses are dominantly positive for 2024 (with none "very dissatisfied"). Responses for 2023 lean positive for clear goals and mastery, though students felt more stressed and with less control of their grade. The ability to control one's own pace and grade (cf. Fig. 4) can be related to the personalization and customization as mentioned as social affordances above, and many students mentioned as positive in free-text responses in the questionnaire related to the seminar that they found it rewarding to collaborate with peers who were at a similar pace and level.

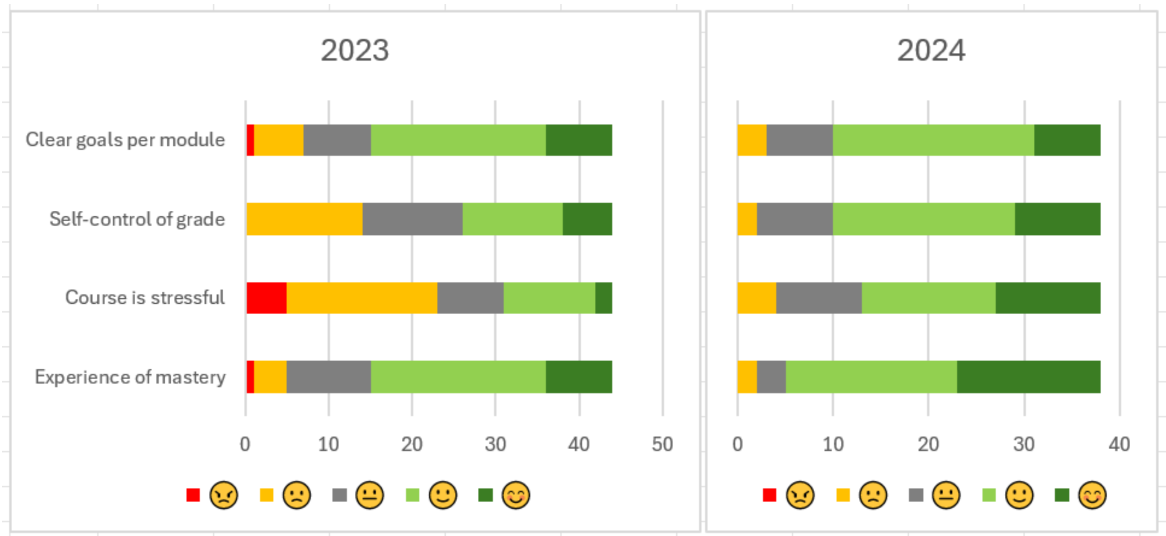


Figure 4: Students' experience of goal clarity, grade control, stress, and mastery, 2023 and 2024 on a 5-point Likert scale from Very Dissatisfied (angry emoji, red) to Very Satisfied (happiest emoji, dark green)

Some quotes from free-text responses in the questionnaire can also shed light on this:

> *I like that it has become gradually more difficult, yet clear what grade you are at. (2023)*

> *To avoid the end-of-course exam, rather working continually and always knowing your current grade – I love that! [...] feel more in control. The mastery ladder «forces» me to work every week [...] I learnt more from that than cramming for a final exam. (2023)*

> *I enjoy that we can progress our grade during the term, instead of having the entire curriculum in one big exam. (2024)*

> *I like the course because I can regulate my own progress, not moving on to new things before I master what I'm doing. Thus, the curriculum does not become overwhelming. (2024)*

Of course, there were also negative opinions expressed, particularly in 2023. However, the above quotes are representative in reflecting common themes among many respondents, especially that they liked the absence of an end-of-course exam to determine the grade, instead having the self-paced mastery learning with frequent testing and a laddered grading approach, which made them feel more in control of their progress.

Behavioral outcomes identified in (Koivisto and Hamari 2019) that also may be relevant to us, is behavior related to engagement: Participation in system; Participation in discussions; and Course material views / downloads. In addition, behavior related to performance is relevant to our study: Academic performance; Learning, progression; and Number of attempts.

Evidence of student behavior can be found in log data from tests of consenting students. Figure 5 shows that student participation in the summative Friday tests was highest in the early part of the semester, then gradually decreasing towards the end. Dark green shows number of 90% passes, light green is 80% passes and black are fails. The higher test participation early in the semester indicates that self-pacing did not lead to procrastination, rather many tried to achieve some progress up the mastery ladder early.

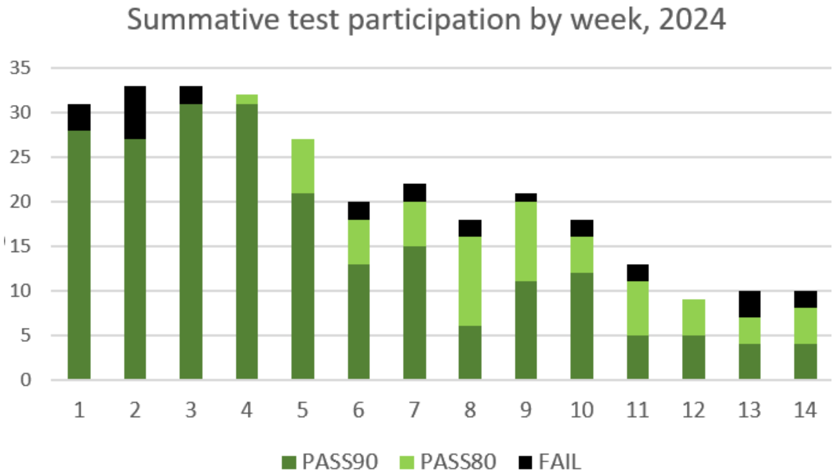


Figure 5: Students' participation in the summative Friday tests by week, 2024. Passes at the 90% threshold are dark green, 80% light green, and fails are shown as black

Another clear indication of student effort during the course is activity with the formative practice tests. Table 2 shows the number of attempts added up for students consenting to research usage of their performance data in 2024 (39/40). The bottom rows give the average number of training tests per student for that module, based on the number of students making it to or beyond that grade. The average number of training attempts is low for the I-test (below 5) but then increasing per level up to the E-test, which was the last test that was needed for the lowest passing grade. The standard deviation is quite high, as some students had previous programming knowledge and needed few practice tests, while others needed many more.

Table 2: Attempts on practice tests for consenting students, 2024

Module	I	H	G	F	E	D	C	B	A
Attempts	173	302	344	401	462	343	313	91	113
Students	39	39	39	39	39	30	23	10	7
Avg per stud.	4.4	7.7	8.8	10.3	11.8	11.1	11.6	7.0	14.1
Std. Dev.	4.3	3.9	5.0	6.5	9.5	5.5	7.6	5.8	18.2

6. Discussion

Below we reiterate our research questions, and their answers. For RQ1, we analyzed which gamification-related affordances could be found in the course design. Of performance-related affordances, the most notable seem to be levels with increasing difficulty and missions with clear goals – with quick feedback from automated tests.

Of social affordances, the most notable seem to have been the collaboration between students working on the same levels in seminars, and the personalization of being allowed to choose one's own pace and ambition level.

Related to RQ2, we studied how the course affordances yield psychological and behavioral outcomes. One evident psychological outcome was high student satisfaction with the course, related to usefulness of the module-based levels, with practice tests for gradual improvement. Students appreciated the increased sense of control and mastery, although the 2023 cohort also found the course stressful. An important behavioral outcome was high engagement with the course from the outset (cf. Figure 5 with more tests taken early in the semester). This is different from experiences in many other self-paced mastery learning courses, where procrastination among students has been a notable challenge (Ott et al., 2019).

For RQ3 we studied how self-paced mastery learning can contribute to gamified learning in higher education. This course was not "sold" as gamification, and did not use badges, trophies or similar – yet still achieved engagement and behavioural outcomes resembling those that gamification typically aims for. To some extent, the level structure of self-paced mastery learning can be considered gamification in itself – hence self-paced mastery learning and gamification could go very well together.

It is hard to know whether the course would have benefited from more explicit gamification such as badges and trophies. When the number of modules directly determines the grade, that might feel enough of a prize. Getting a badge in addition might feel as a superfluous add-on. Costa (2023) investigated the learning effects of various gamification approaches in programming and also found levels to have most effect. Our study focused on mastery learning as gamification and the students' responses from our courses were positive already in 2023 and more positive in 2024. The students particularly appreciated the absence of an end-of-course exam and favored the self-paced mastery learning with frequent testing and a laddered grading approach, which made them feel more in control of their progress.

7. Conclusion

We present a case study of CS1 for first-year STEM teacher students at NTNU, analyzed through the gamification lens using the Learning Mechanics – Game Mechanics (LM-GM) model and by examining student satisfaction and performance data. The paper gives an improved understanding of how self-paced mastery learning can be seen as a gamified course design, thus a possible basis for those who might want to add more explicit game features to a course, without necessarily using the traditional visual gamification elements like badges and trophies. Also, it indicates how self-paced mastery learning might be an interesting underlying pedagogical approach for gamification of traditional learning environments within higher education, especially regarding a ladder approach to grading.

8. Limitations

While some students are motivated by gamification, others are not (Rogers et al., 2021). García-Iruela et al. (2022) did not find that gamified elements had a significant effect on motivation. Further research should investigate effects on students' motivation in self-paced mastery learning courses to see if there are similar results as in more specifically gamified learning environments.

A limitation of this study is that neither the course nor the student satisfaction questionnaire was designed with gamification in mind, nor with the dedicated purpose to measure outcomes and affordances related to gamification so the analysis of the course and its affordances and outcomes is purely post hoc, and its interpretations must thus be taken with some caution. Interesting opportunities for further work would thus be to make more dedicated investigations with subsequent runs of the course, for instance investigating to what extent students experience the level-up feature and other aspects of the course as resembling gamification.

Another limitation is that the course had only 50 students each year, so scalability to bigger classes might be an issue. In 2023, the course had 7 teaching assistants à 100 hours, but in 2024 it had to do with just 2 TA's à 50 hours - yet student satisfaction increased. Also, it can be noted that a somewhat similar course design by (Toti, Chen et al. 2023) had about 300 students, so there is nothing inherent in mastery-learning that prevents scale.

Ethics declaration: Research was applied to SIKT, ref.no. 342944 Date of approval: 26 Jun 2024

AI declaration: No AI was used.

References

Arnab, S., T. Lim, M. B. Carvalho, F. Bellotti, S. De Freitas, S. Louchart, N. Suttie, R. Berta and A. De Gloria (2015). "Mapping learning and game mechanics for serious games analysis." British Journal of Educational Technology 46(2): 391–411.

Bloom, B. S. (1971). Mastery learning. Mastery learning: Theory and practice. J. H. Block. New York, Holt, Rinehart & Winston: 47–63.

Buskist, W., D. Cush and R. J. DeGrandpre (1991). "The life and times of PSI." Journal of Behavioral Education 1(2): 215–234.

Costa, J. M. (2023). "Using game concepts to improve Programming Learning: A multi-level meta-analysis." Computer Applications in Engineering Education 31(4): 1098–1110.

de Pontes, R. G., D. D. Guerrero and J. C. de Figueiredo (2019). Analyzing gamification impact on a mastery learning introductory programming course. Proceedings of the 50th ACM technical symposium on computer science education: 400–406.

Deterding, S., D. Dixon, R. Khaled and L. Nacke (2011). From game design elements to gamefulness: defining" gamification". Proceedings of the 15th international academic MindTrek conference: Envisioning future media environments.

Eyre, H. L. (2007). "Keller's Personalized System of Instruction: Was it a Fleeting Fancy or is there a Revival on the Horizon?" The Behavior Analyst Today 8(3): 317.

García-Iruela, M., R. Hijón-Neira and C. Connolly (2022). "Can Gamification Help in Increasing Motivation, Engagement, and Satisfaction? A gamified experience in teaching CS to students from other disciplines." Education in the Knowledge Society (EKS) 23: e26932–e26932.

Garner, J., P. Denny and A. Luxton-Reilly (2019). Mastery learning in computer science education. Proceedings of the Twenty-First Australasian Computing Education Conference: 37–46.

Hamari, J., J. Koivisto and H. Sarsa (2014). Does gamification work?--a literature review of empirical studies on gamification. 2014 47th Hawaii international conference on system sciences, Ieee.

Hou, X., T. Nagashima and V. Aleven (2022). Design a Dashboard for Secondary School Learners to Support Mastery Learning in a Gamified Learning Environment. European Conference on Technology Enhanced Learning, Springer.

Keller, F. S. and J. G. Sherman (1974). PSI, the Keller Plan Handbook: Essays on a personalized system of instruction, WA Benjamin Advanced Book Program.

Koivisto, J. and J. Hamari (2019). "The rise of motivational information systems: A review of gamification research." International Journal of Information Management 45: 191–210.

Kulik, C.-L. C., J. A. Kulik and R. L. Bangert-Drowns (1990). "Effectiveness of mastery learning programs: A meta-analysis." Review of educational research 60(2): 265–299.

Lim, T., S. Louchart, N. Suttie, J. M. Ritchie, R. Aylett, I. A. Stanescu, I. Roceanu, I. Martinez-Ortiz and P. Moreno-Ger (2013). Strategies for effective digital games development and implementation. Cases on digital game-based learning: Methods, models, and strategies, IGI Global Scientific Publishing: 168–198.

Mannion, A., R. Coyne, C. Ferrari, M. Neşeli, C. McGee, S. Mollaoglu and G. Leader (2023). "Personalized System of Instruction in Higher Education: A Systematic Review." Journal of Behavioral Education: 1–41.

Maryono, D., S. Budiyono and M. Akhyar (2022). "Implementation of gamification in programming learning: literature review." Int. J. Inf. Educ. Technol 12(12): 1448–1457.

Mawson, C., C. A. Bodnar and S. D. Streiner (2020). Examining the connection between student mastery learning experiences and academic motivation. 2020 ASEE Virtual Annual Conference Content Access.

Merriam, S. B. (1998). Qualitative Research and Case Study Applications in Education. Revised and Expanded from" Case Study Research in Education.", ERIC.

Mora, A., D. Riera, C. González and J. Arnedo-Moreno (2017). "Gamification: a systematic review of design frameworks." Journal of Computing in Higher Education 29(3): 516–548.

Pérez, C. L. and D. Verdín (2023). "A Systematic Literature Review for Mastery Learning in Undergraduate Engineering Courses." International Journal of Engineering Education 39(6): 1358–1385.

Purao, S., M. Sein, H. Nilsen and E. Å. Larsen (2017). "Setting the Pace: Experiments With Keller's PSI." IEEE Transactions on Education 60(2): 97–104.

Rogers, M., W. Yao, A. Luxton-Reilly, J. Leinonen, D. Lottridge and P. Denny (2021). Exploring personalization of gamification in an introductory programming course. Proceedings of the 52nd ACM Technical Symposium on Computer Science Education.

Shahid, M., A. Wajid, K. U. Haq, I. Saleem and A. H. Shujja (2019). A review of gamification for learning programming fundamental. 2019 International Conference on Innovative Computing (ICIC), IEEE.

Sprint, G. and E. Fox (2020). Improving student study choices in CS1 with gamification and flipped classrooms. Proceedings of the 51st ACM Technical Symposium on Computer Science Education: 773–779.

Toti, G., G. Chen and S. Gonzalez (2023). Teaching CS1 with a Mastery Learning Framework: Impact on Students' Learning and Engagement. Proceedings of the 2023 Conference on Innovation and Technology in Computer Science Education V. 1: 540–546.

Yang, K.-H. (2018). Learning behavior and achievement analysis of a digital game-based learning approach integrating mastery learning theory and different feedback models. Learning Analytics, Routledge: 93–106.