Kashihara, A. et al. (Eds.) (2024). Proceedings of the 32nd International Conference on Computers in Education. Asia-Pacific Society for Computers in Education

Comparing Effects of Adaptive Gamification and One-Size-Fits-All Gamification on Students' Task Completion Process and Learning Performance

Shurui BAI[a*] **& Yingxue LIU**[b]
[a]*Department of Mathematics and Information Technology, The Education University of Hong Kong, Hong Kong SAR, China*
[b]*National Institute of Education, Nanyang Technological University, Singapore*
*tstbai@eduhk.hk

Abstract: Gamification applies game elements, such as points, badges, and leaderboards, to influence people's motivation to complete certain tasks. One-size-fits-all gamification (OG) uses the same game elements for all users, while adaptive gamification (AG) customizes game elements to align with individual users' motivations in gamified systems. This study compares the effects of AG (n = 36) and OG (n = 37) on students' task completion process and learning performance via a quasi-experiment design. The results showed that AG could significantly enhance students' task engagement and learning performance by applying different game elements based on player types. The connections of "pre-task reading" to "post-task review" and "just-in-time learning" to "post-task review" are the two most common task completion processes in the adaptive gamification group. The connection of "post-task review" to "pre-task reading" is the most common task completion process in the one-size-fits-all gamification group. This study contributes empirical evidence to the adaptive gamified learning and indicates the effectiveness of the use of adaptive gamification to cater to diverse motivation needs.

Keywords: Adaptive gamification, one-size-fits-all gamification, task completion process, learning performance

1. Introduction

Gamification involves incorporating game elements into non-game contexts (Deterding et al., 2011). These elements, such as points, badges, and leaderboards, can be readily enabled or disabled to influence individuals' motivation to accomplish specific tasks (Sailer et al., 2017). For example, airlines use mile points in frequent-flyer programs to boost customer brand loyalty.

In education, the current gamification strategy typically applies the same game elements to all students, a method known as one-size-fits-all gamification (OG) (Oliveira et al., 2023). OG has produced mixed findings in enhancing student motivation compared to non-gamified settings (Koivisto & Hamari, 2019). Many researchers (e.g., Hallifax et al., 2021; Rodríguez et al., 2022) attribute this inconsistency to the failure to address diverse student motivations. To address the limitations of OG, adaptive gamification (AG) has emerged as a promising alternative. AG customizes game elements to align with individual users' motivations in gamified systems (Hallifax et al., 2019). However, Oliveira et al. (2022) found no significant difference in student motivation between AG and OG groups. The number of empirical studies on AG and OG comparison is scare. Thus, it is necessary to examine the effects of AG further for a better understanding of this gamification approach. We proposed these two research questions:

Research question 1: What are the effects of one-size-fits-all gamification and adaptive gamification on students' task completion process?

Research question 2: What are the effects of one-size-fits-all gamification and adaptive gamification on learning performance?

2. Literature Review

2.1 From one-size-fits-all gamification to adaptive gamification

Despite widespread use in education, the effectiveness of OG in boosting student motivation remains inconsistent (Koivisto & Hamari, 2019; Oliveira et al., 2023). While some studies reported increased motivation and performance (Tsay et al., 2018). On the other hand, some research indicated contradictory results. Kwon and Özpolat (2021) found that students in the gamified group were significantly less motivated to learn and achieved lower scores on the final exam. This inconsistency may be attributed to the inability of OG to accommodate diverse student motivations (Hallifax et al., 2021; Rodríguez et al., 2022). AG tailors game elements to individual motivations (Hallifax et al., 2019). For example, achievers, motivated by competence and seeking progress through task completion (Tondello et al., 2016), can be effectively motivated by achievement badges (Reyssier et al., 2022).

2.2 Bartle taxonomy of player types

Bartle's taxonomy of player types offers a valuable framework for understanding user motivations and behaviors in the context of adaptive gamified learning. This taxonomy categorizes players into four groups: achievers, explorers, socializers, and killers (Bartle, 1996). Achievers prioritize point accumulation and level progression; explorers seek to understand game mechanics and explore its features; socializers value player interaction above gameplay, prioritizing relationships; and killers find satisfaction in causing destruction and competition, viewing the game as a proving ground for their skills (Kim, 2015). In adaptive gamified learning, understanding these player types can help design gamified learning experiences that effectively cater to different learners' motivations. Achievers would earn these badges by correctly answering questions at different difficulty levels within the quiz. As they progressed, they would unlock higher-level badges categorized as bronze, silver, and gold (Reyssier et al., 2022). The results showed that awarding achievers with badges greatly increased their quiz completion. These badges are often awarded for achieving clear goals (Krath & von Korflesch, 2021).

3. Method

3.1 Quasi-experiment Design

We adopted a quasi-experiment approach to compare the effects of AG and OG on students' task completion process and learning performance. The experiment group was exposed to an adaptive gamified class setting that tailors game elements to match a user's motivation in gamified systems. The control group was exposed to the one-size-fits-all gamified condition, where all students received the same game elements and mechanism.

The OG was conducted during the Spring semester of 2023 (January to April 2023), while the AG was implemented in the Fall semester of 2023 (September to December 2023). Apart from introducing different gamification settings, all other aspects of the learning environment remained the same. This included the same teaching team, learning materials, and assessments. The Moodle learning management system organized all learning resources and presented the gamified learning tasks. Ethical approval for conducting this study was obtained from the university affiliated with the first author. Only participants who provided their consent were included in the final report of the findings.

3.2 Participants

We employed a historical cohort control group was a practical solution for this quasi-experiment. This control group comprised pre-intervention archival data matched to the current cohort receiving the intervention. This method, involving two intact groups from different years, mitigates concerns about denying intervention access to any students (Walser, 2014). By carefully controlling for confounding variables (e.g., instrumental variables and participants' baseline differences), this design can effectively establish causality between the interventions and the observed outcomes (Gopalan et al., 2020). Apart from the scaffolding methods, the teaching materials, instructor, and assignments were identical for both groups.

The OG group consisted of 37 postgraduate students, comprising 21 females and 16 males. The participants' ages varied from 22 to 49, with a mean age of 25.7 and a standard deviation of 4.8. Out of all the participants, 32 were from mainland China, three were from Hong Kong SAR, one was from Italy, and one was from Australia. The AG group consisted of 36 postgraduate students, including 14 females, 18 males, and four individuals who preferred not to disclose their gender. The ages of the participants varied from 21 to 45, with a mean age of 24.59 and a standard deviation of 4.51. All participants in the AG group originated from Asian countries.

3.3 Gamified Class Settings

The interventions were conducted in a postgraduate class about coding and computational thinking. This is the core course of a master's program, and no prerequisite is required. This course followed a blended learning approach and catered to individuals pursuing a master's degree in education technology and Artificial Intelligence. The duration of the course spanned 13 weeks.

We adopted the Goal-Access-Feedback-Challenge-Collaboration-Fantasy, GAFCC-F model (Bai et al., 2022) to design the AG and OG gamified classes. (1) Goal: There were six stages of learning tasks throughout the entire semester. Every stage has four tasks, and each task has five questions, so in total there were 120 questions. Students were asked to complete 75% of the learning tasks to achieve a full participation score. At the same time, students played the main fictitious character's role, who needs to get a job promotion by solving clients' requests as a goal in the storyline. (2) Access: We implemented a restricted access function in Moodle, where students can only unlock the next task once they have satisfied the performance requirements of the previous one. For example, an easy-mode task is a prerequisite for a more challenging task. If a student fails to complete a difficult task after three attempts, they will be granted access to new easy-mode tasks. This allows them to focus on more accessible content and rebuild their confidence before revisiting the harder material. (3) Feedback: By setting up the correct answer to each question ahead of time and automating the scoring process, students could receive immediate feedback on their performance in learning activities based on demonstrating skills or completing tasks. (4) Challenge: The learning activities were structured at varying difficulty levels to allow students to compete against themselves and their peers. Basic tasks focused on understanding concepts and simple applications, while advanced tasks required applying skills to solve real-world problems. Difficult tasks were locked initially and unlocked as students completed the relevant easier tasks. Both individual and group-based challenging tasks were included. (5) Collaboration: In the first session of the class, we asked students to form their study groups. Both in-class and out-of-class group activities contribute a significant portion of the overall points. Most group work involved completion-based tasks, where the system would award student points when the work is submitted on Moodle. (6) Fantasy: We incorporated storylines and narrative-based scenarios to establish a fantasy context within the gamified class. Throughout the semester, there is an overarching thematic story that connects all of the learning tasks. Students were encouraged to select a character to begin their journey as part of this story. The story in the two interventions was “Tom’s IT Startup Company.” Students took on the role of the entrepreneur, Tom, as they worked to solve complex problems in building a food delivery mobile application startup company. This required them to apply their coding and computational thinking skills.

3.3.1 Adaptive Gamified Class Settings (Experiment Group)

In this group, we implemented two gamification player types: achiever and explorer (Bartle, 1996). There were six stages of learning tasks throughout the entire semester. Students could freely choose either the “achiever” or “explorer” path by interacting with a fictitious character named Peter at the beginning of each stage (see one example in Figure 1). After satisfied the passing grade of one learning task, students could unlock and move forward to the next task in the same path.

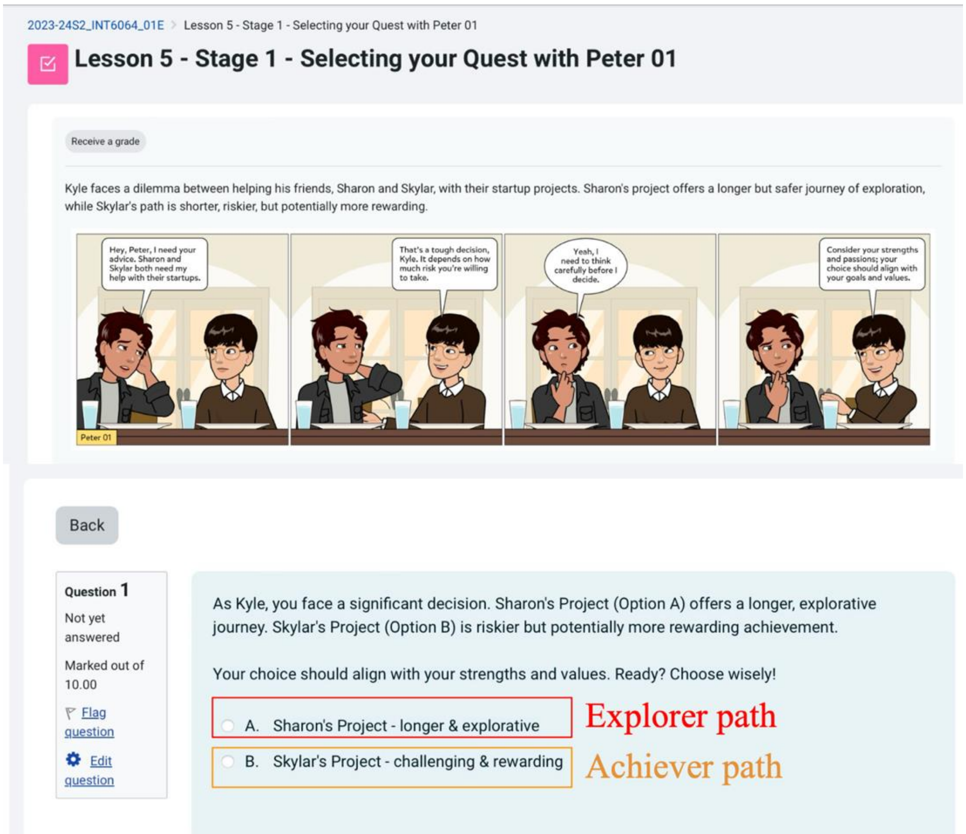

Figure 1. Select Your Quest with Peter for the “Explorer” or “Achiever” Path.

"Achievers" are driven by a strong desire to demonstrate competence and mastery. They are motivated to progress and advance within a structured system by completing assigned tasks and meeting defined objectives (Tondello et al., 2016). Based on existing research, we can reasonably assume that achievers respond particularly well to achievement-based badges (Reyssier et al., 2022). Achievement badges are often automatically awarded when learners demonstrate the achievement of clear, unambiguous goals, serving as tangible acknowledgments of their progress in completing course assessments like quizzes and lessons (Bai et al., 2020). Hence, we applied *achievement badges* (badge X in our design) and *challenging quests* for this path. The achiever path has more difficult tasks with multiple correct answers to one question than the “explorer” path. In this way, achievers could have a strong sense of achievement when they complete the task. However, achievers have more attempts for each task and fewer tasks (see rules in Figure 2) than explorers to strike a balance in the game.

"Explorers" are driven by autonomy. They enjoy exploring the game and figuring out how things work (Bartle, 1996). While earning points may be necessary for progressing, it is considered tedious and undemanding. Explorers' true enjoyment comes solely from exploring and creating the most comprehensive set of maps (Bartle, 1996). Research suggested unexpected elements (Kocadere & Çağlar, 2018) and stories (Ferro et al., 2013). Hence, we administered *explorer badges* (badge Y in our design) and *unexpected stories* for the explorer path. The explorer path has less difficult tasks with one correct answer to one question. However, explorers have fewer attempts for each task and more tasks (two tasks for achievers and four tasks for explorers in one stage) than the achievers. The tasks for explorers come from different clients with different story plots, while achievers deal with one client's task in which the plots are more expected. We set a lower bar for explorers than achievers so that explorers could quickly move forward to explore different clients' tasks. Yet, students had the full autonomy to complete tasks in two quests if they were intrinsically motivated to do so (see a student profile in Figure 2).

Figure 2. Rules to Play for the "Explorer" or "Achiever" Path (on the left side) and a student's profile showing the earned badges X and Y (partial of the earner badges, on the right side)

3.3.2 One-size-fits-all Gamified Class Setting (Control Group)

Students in the control group were assigned the same badges when passing the learning tasks in one stage. Students experienced the same quest path and unlocked the same set of learning tasks throughout the semester.

3.4 Data Collection and Analysis

We measured students' task completion process and learning performance between the two groups. Students' trace data of completing the learning tasks on Moodle measured the task completion process. We used Ordered Network Analysis (ONA) to identify the task completion process with directions in two gamified classes over time (Tan et al., 2023). Unlike social network analysis, which examines relationships between people, ONA focuses on extracting behavioral patterns from trace data. ONA is useful when large datasets are unavailable, as it does not require the same scale of data as techniques like sequential analysis.

We used "pre-task," "during task," and "post-task" from task-based learning (Willis, 1996) to code the competition behaviors. All the learning tasks are scenario-based. Students need to read the comic strip to understand the scenario first, then they will click the next page to read the question. After inputting the answers to five questions, they will submit answers and view the accuracy rate and explanation of each answer. Given the process of completing these scenario-based learning tasks, we coded the trace data into four categories: pre-task reading, being on-task, just-in-time learning, and post-task review. ONA models the connections between these learning activities, allowing us to visualize and analyze the dominant relationships. A research assistant and the author independently coded the data with 89% reliability, reaching 100% agreement after discussion. The coded data was then imported into ONA analysis software to compare the task completion process between the two groups.

A pre-and post-test design was administered to evaluate students' changes in their learning performance before and after the gamification intervention. The pre-test was implemented at the start of the course, assessing prior knowledge of coding and computational thinking through short-answer and multiple-choice questions. The post-test consisted of two parts: an individual project where students designed and implemented a coding program and a group project in which students collaboratively created a video game. Both the pre-test and post-test had a maximum score of 100 points. We computed a variable to denote the difference in learning performance before and after the gamification intervention, called *learning gain*. An independent-samples t-test or a non-parametric test will be conducted based on the normal distribution of data between the two groups.

4. Results

4.1 Effects on the Task Completion Process

The key findings highlight the advantages of the adaptive gamification approach over the one-size-fits-all gamification approach. In the AG group, the connection coefficient for the relationship between "pre-task reading" and "post-task review" is higher (0.32) compared to the OG group (0.25; see Table 1 for details), indicating a stronger influence of pre-task reading on post-task review in the adaptive gamification setting. See Figure 3 for a visualized comparative ONA plot and plots of AG and OG, respectively. This suggests that the adaptive gamification approach better supports the integration of pre-task reading and post-task review, which are important components of the learning process. This action directionality between pre-task preparation and post-task reflection is crucial for enabling deeper learning and skill development, as it allows learners to connect new information with their existing knowledge and experiences actively.

Additionally, the connection coefficient for the relationship between "just-in-time learning" and "post-task review" is higher in the AG group (0.25) compared to the OG group (0.21), suggesting a stronger relationship between these activities in the adaptive gamification setting. This finding implies that the adaptive gamification approach may better facilitate integrating just-in-time learning and post-task review. In other words, they valued the opportunity to close knowledge gaps through the real-time application of their learning in appropriate scenarios. This seamless integration of just-in-time learning and post-task review is a key advantage of the adaptive gamification approach. By fostering this feedback loop, students are better able to consolidate their understanding, identify areas for improvement, and continuously refine their skills. This dynamic learning process is essential to effective skill development and knowledge retention.

In contrast, the OG group exhibits a stronger relationship between "post-task review" and "pre-task reading," with a connection coefficient of 0.25 compared to 0.17 in the AG group. This suggests that in the one-size-fits-all gamification approach, post-task review has a stronger influence on pre-task reading, potentially indicating a more linear or sequential learning process. It is to say that students tended to read the feedback on task completion performance and then use the new attempt to re-read and understand the scenario better.

Overall, the results highlight the advantages of the adaptive gamification approach, which appears to foster stronger relationships between key learning activities, such as the influence of pre-task reading on post-task review and the integration of just-in-time learning and post-task review. These findings have important implications for designing and implementing effective instructional strategies and learning environments.

Table 1. *Connection Coefficients of the Overall ONA Networks in AG and OG*

Connection	AG	OG	Difference
"Pre-task reading" to "Being on-task"	0.19	**0.21**	-0.02
"Being on-task" to "Pre-task reading"	0.21	0.21	0
"Being on-task" to "Just-in-time learning"	**0.1**	0.06	0.04
"Just-in-time learning" to "Being on-task"	**0.1**	0.07	0.03
"Pre-task reading" to "Just-in-time learning"	0.15	**0.18**	-0.03
"Just-in-time learning" to "Pre-task reading"	**0.25**	0.21	0.04
"Being on-task" to "Post-task review"	0.08	**0.1**	-0.02
"Post-task review" to "Being on-task"	**0.11**	0.09	0.02
"Pre-task reading" to "Post-task review"	**0.32**	0.25	0.07
"Post-task review" to "Pre-task reading"	0.17	**0.25**	-0.08
"Just-in-time learning" to "Post-task review"	**0.25**	0.21	0.04
"Post-task review" to "Just-in-time learning"	**0.17**	0.09	0.08

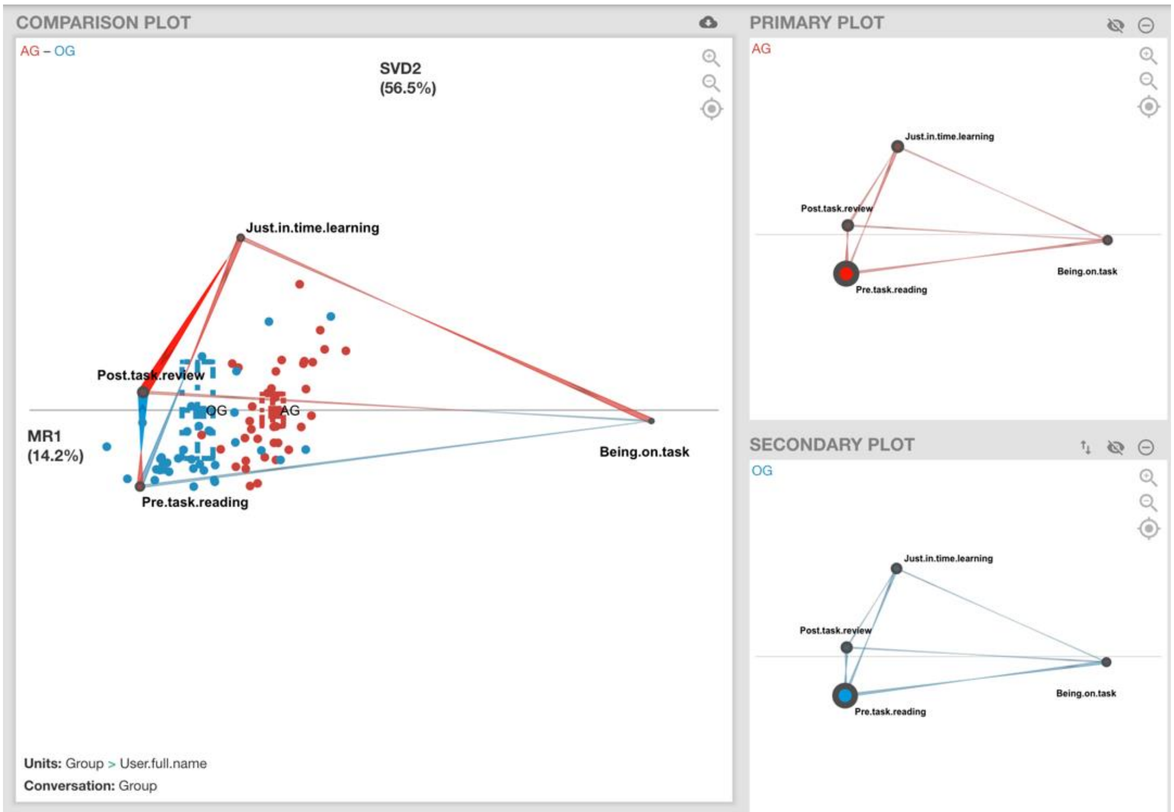

Figure 3. A subtraction plot of ordered network constructed using trace data of students' completion of tasks in the adaptive gamification (AG) and one-size-fits-all gamification (OG).

4.2 Effects on Learning Gain

The data of computed learning gain were found to be normally distributed in the two groups, Skewness and Kurtosis, within -1 and 1. Hence, we conducted an independent-samples t-test to compare the learning gain between AG and OG. The results found that the AG (difference mean = 75.64, SD = 9.86) achieved a significantly higher learning gain than the OG (difference mean = 60.83, SD = 12.18), t (66) = -5.52, $p < .001$, see Figure 4 below.

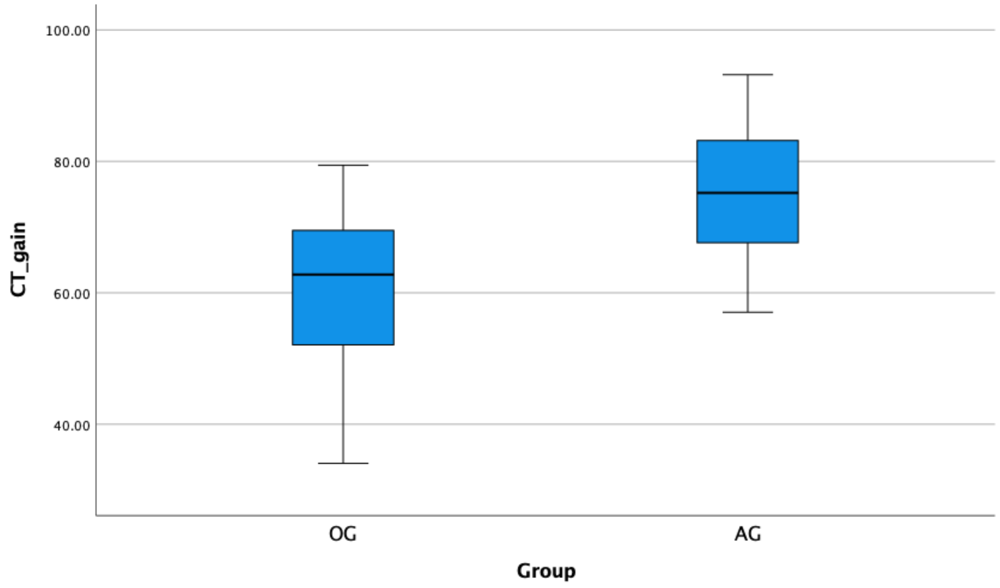

Figure 4. A boxplot comparing the learning gain between the OG and AG groups

5. Discussion

The results suggested that students tend to engage in different task completion processes in the AG and OG for scenario-based tasks. Among the 12 connections (see Table 1 numbers in bold), AG students demonstrated higher engagement, with eight connection coefficients exceeding those of their OG counterparts. AG tailors game elements to match a student's motivation in the gamified learning system. Adaptive gamification considers learners' personal and contextual differences (Raleiras et al., 2020). This finding corroborates the previous literature that adapting game elements to the player type could increase their time engaging with the gamified environment (Lavoue et al., 2019). Autonomy has been enhanced in the adaptive gamification setting, where students can choose either explorer or achiever quests that interest them the most. This, in turn, increases their intrinsic motivation and engagement. The results indicated a significantly higher learning performance of the adaptive gamification group than the one-size-fits-all gamification group. Lopez and Tucker (2021) found that the performance of individuals who interacted with an adapted gamified application was greater than that of any other group (i.e., non-adapted and non-gamified groups). In contrast, the performance of individuals who interacted with a counter-adapted gamified application was worse than any other group. The current study contributes to the finding that individuals with different player types can be motivated by game elements differently, and this adaptability helps improve learning performance.

6. Conclusion and Limitations

This study compared adaptive and one-size-fits-all gamification on students' task completion process and learning performance. The results showed that AG could significantly enhance students' task engagement and learning performance by applying different game elements based on player types. The connections of "pre-task reading" to "post-task review" and "just-in-time learning" to "post-task review" are the two most common task completion processes in the adaptive gamification group. The connection of "post-task review" to "pre-task reading" is the most common task completion process in the one-size-fits-all gamification group. This study only applied achiever and explorer player types to design the AG. Future studies could consider implementing all four player types. The small sample sizes of both groups restricted the generalizability of the findings. To enhance the robustness of future studies, using larger samples would be beneficial.

Acknowledgements

The research is supported by a grant from the Research Grants Council of Hong Kong (Project reference no: 28600024).

References

Bai, S., Hew, K. F., Gonda, D. E., Huang, B., & Liang, X. (2022). Incorporating fantasy into gamification promotes student learning and quality of online interaction. *International Journal of Educational Technology in Higher Education*, *19*(1), 29. https://doi.org/10.1186/s41239-022-00335-9

Bai, S., Hew, K. F., & Huang, B. (2020). Does gamification improve student learning outcome? Evidence from a meta-analysis and synthesis of qualitative data in educational contexts. *Educational Research Review*, *30*, 100322. https://doi.org/https://doi.org/10.1016/j.edurev.2020.100322

Bartle, R. (1996). *Hearts, clubs, diamonds, spades: Players who suit MUDs*.

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011). From game design elements to gamefulness. *Proceedings of the 15th International Academic MindTrek Conference on Envisioning Future Media Environments - MindTrek '11*. https://doi.org/10.1145/2181037.2181040

Ferro, L. S., Walz, S. P., & Greuter, S. (2013). Towards personalised, gamified systems. *Proceedings of The 9th Australasian Conference on Interactive Entertainment: Matters of Life and Death*, 1–6. https://doi.org/10.1145/2513002.2513024

Gopalan, M., Rosinger, K., & Ahn, J. Bin. (2020). Use of Quasi-Experimental Research Designs in Education Research: Growth, Promise, and Challenges. *Review of Research in Education*, *44*(1), 218–243. https://doi.org/10.3102/0091732X20903302

Hallifax, S., Serna, A., Marty, J. C., & Lavoué, E. (2021). Dynamic gamification adaptation framework based on engagement detection through learning analytics. *GamLA@LAK21*.

Hallifax, S., Serna, A., Marty, J.-C., & Lavoué, É. (2019). Adaptive Gamification in Education: A Literature Review of Current Trends and Developments. In *Transforming Learning with Meaningful Technologies* (Vol. 11722, pp. 294–307). Springer. https://doi.org/10.1007/978-3-030-29736-7_22

Kim, B. (2015). Gamification in education and libraries. *Library Technology Reports*, *51*(2), 20–28.

Kocadere, S. A., & Çağlar, Ş. (2018). Gamification from Player Type Perspective: A Case Study. *Educational Technology & Society*, *21*, 1436–4522.

Koivisto, J., & Hamari, J. (2019). The rise of motivational information systems: A review of gamification research. *International Journal of Information Management*, *45*, 191–210. https://doi.org/10.1016/j.ijinfomgt.2018.10.013

Krath, J., & von Korflesch, H. F. O. (2021). Player Types and Game Element Preferences: Investigating the Relationship with the Gamification User Types HEXAD Scale. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *12789 LNCS*, 219–238. https://doi.org/10.1007/978-3-030-77277-2_18/TABLES/8

Kwon, H. Y., & Özpolat, K. (2021). The dark side of narrow gamification: Negative impact of assessment gamification on student perceptions and content knowledge. *INFORMS Transactions on Education*, *21*(2), 67–81. https://doi.org/10.1287/ITED.2019.0227

Lavoue, E., Monterrat, B., Desmarais, M., & George, S. (2019). Adaptive Gamification for Learning Environments. *IEEE Transactions on Learning Technologies*, *12*(1), 16–28. https://doi.org/10.1109/TLT.2018.2823710

Lopez, C. E., & Tucker, C. S. (2021). *Adaptive Gamification and Its Impact on Performance* (pp. 327–341). https://doi.org/10.1007/978-3-030-77277-2_25

Oliveira, W., Hamari, J., Joaquim, S., Toda, A. M., Palomino, P. T., Vassileva, J., & Isotani, S. (2022). The effects of personalized gamification on students' flow experience, motivation, and enjoyment. *Smart Learning Environments*, *9*(1), 16. https://doi.org/10.1186/s40561-022-00194-x

Oliveira, W., Hamari, J., Shi, L., Toda, A. M., Rodrigues, L., Palomino, P. T., & Isotani, S. (2023). Tailored gamification in education: A literature review and future agenda. *Education and Information Technologies*, *28*(1), 373–406. https://doi.org/10.1007/s10639-022-11122-4

Raleiras, M., Viana, J., & Costa, F. (2020). *Adaptive gamification models in higher education: Is there a place for self-regulated learning?* 5949–5955. https://doi.org/10.21125/edulearn.2020.1555

Reyssier, S., Hallifax, S., Serna, A., Marty, J. C., Simonian, S., & Lavoue, E. (2022). The Impact of Game Elements on Learner Motivation: Influence of Initial Motivation and Player Profile. *IEEE Transactions on Learning Technologies*, *15*(1), 42–54. https://doi.org/10.1109/TLT.2022.3153239

Rodríguez, I., Puig, A., & Rodríguez, À. (2022). Towards Adaptive Gamification: A Method Using Dynamic Player Profile and a Case Study. *Applied Sciences*, *12*(1), 486. https://doi.org/10.3390/app12010486

Sailer, M., Hense, J. U., Mayr, S. K., & Mandl, H. (2017). How Gamification Motivates: An Experimental Study of the Effects of Specific Game Design Elements on Psychological Need Satisfaction. *Computers in Human Behavior*, *69*, 371–380. https://doi.org/https://doi.org/10.1016/j.chb.2016.12.033

Tan, Y., Ruis, A. R., Marquart, C., Cai, Z., Knowles, M. A., & Shaffer, D. W. (2023). Ordered Network Analysis. *Communications in Computer and Information Science*, *1785 CCIS*, 101–116. https://doi.org/10.1007/978-3-031-31726-2_8

Tondello, G. F., Wehbe, R. R., Diamond, L., Busch, M., Marczewski, A., & Nacke, L. E. (2016). The gamification user types Hexad scale. *CHI PLAY 2016 - Proceedings of the 2016 Annual Symposium on Computer-Human Interaction in Play*, 229–243. https://doi.org/10.1145/2967934.2968082

Tsay, C. H.-H., Kofinas, A., & Luo, J. (2018). Enhancing student learning experience with technology-mediated gamification: An empirical study. *Computers & Education*, *121*, 1–17. https://doi.org/10.1016/j.compedu.2018.01.009

Walser, T. M. (2014). Quasi-experiments in schools: The case for historical cohort control groups. *Practical Assessment, Research and Evaluation*, *19*.

Willis, J. (1996). *A flexible framework for task-based learning* (62nd ed., Vol. 52). Harlow: Longman.