Enhancing learning through adaptive gamification: A comparative study on behavioural patterns, computational thinking skills, and motivation

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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' behavioural patterns, computational thinking skills, and motivation to learn via a quasi-experiment design. Based on Bartle's taxonomy of player types, we activated Achiever and Explorer player types by assigning different game elements and challenges and students could choose their own adventures in either learning path. The results showed that AG could significantly enhance students' actual computational thinking skills compared to OG group. Regarding the behavioural pattern, the connections of "pre-task reading" to "post-task review" and "just-in-time learning" to "post-task review" are the two most common behavioural patterns in AG. The connection of "post-task review" to "pre-task reading" is the most common behavioural pattern in OG. The two groups present no significant difference in self-reported extrinsic motivation and intrinsic motivation levels. Participants in the AG setting reported six themes in terms of learning perceptions: (1) setting goals with rewards, (2) competing against self and peers, (3) access to varied challenges, (4) immediate feedback on performance, (5) collaboration and interaction, and (6) engaging narrative and fantasy. This study provides empirical evidence supporting adaptive gamified learning and demonstrates the effectiveness of adaptive gamification in addressing diverse motivational needs.

Keywords: adaptive gamification, learning types, behavioural pattern, computational thinking, learning motivation

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). 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 attribute this inconsistency to the failure to address diverse student motivations (e.g., Hallifax et al., 2021; Rodríguez et al., 2022). Similarly, research has found that students exhibit different motivations in terms of the use of leaderboards in gamified classes. In one study, some students reported being motivated by public ranking, whereas some were motivated by anonymous ranking (Bai et al., 2021a). In another study, participants reported different motivations in comparing with all peers in the class, or with a few peers who shared a similar level of learning performance (Bai et al., 2021b).

However, it is important to note that the effectiveness of gamification is not solely determined by whether game elements are adaptive or not. Other critical factors include the quality of educational content (Luo, 2022), the design of the application's user experience (Hsu et al., 2017), and the integration of supporting learning tools (Swacha & Szydłowska, 2023). These elements collectively shape learners' engagement and outcomes in gamified environments.

To overcome this limitation of OG, the emergence of adaptive gamification (AG) presents a promising alternative. AG tailors game elements to match a user's motivation in gamified systems (Hallifax et al., 2019a). The number of empirical studies on AG and OG comparison is scarce. Thus, it is necessary to examine the effects of AG further for a better understanding of this gamification approach. We proposed these four research questions:

RQ1: What are the effects of one-size-fits-all gamification and adaptive gamification on students' online learning behavioural patterns?

RQ2: What are the effects of one-size-fits-all gamification and adaptive gamification on students' computational thinking skills?

RQ3: What are the effects of one-size-fits-all gamification and adaptive gamification on students' motivation to learn?

RQ4: What are students' learning perceptions of adaptive gamification?

Literature Review

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

Gamification has become a popular instructional approach in education, with the goal of enhancing students' motivation, engagement, and academic outcomes (Attali & Arieli-Attali, 2015; Oliveira et al., 2023). OG is defined as applying the same game elements (e.g., badges) to all users in a non-game context (Oliveira et al., 2023).

Recent meta-analyses and systematic reviews reveal mixed but generally positive effects of OG on motivation, engagement, and academic outcomes. For instance, Sailer and Homner's (2020) meta-analysis found small to moderate positive effects of gamification on cognitive ($g = 0.49$), motivational ($g = 0.36$), and behavioural outcomes ($g = 0.25$), though motivational and behavioural effects were less stable across studies. Another meta-analysis by Li and colleagues (2023) reported a large overall effect size ($g = 0.822$) for gamification on learning outcomes, but emphasized that results vary depending on user type, discipline, and design principles, highlighting the limitations of OG approaches. Overall, while OG can be effective, its impact is highly context-dependent and may not equally benefit all learners, underscoring the need for more adaptive and personalized gamification strategies.

Many empirical studies reported that OG can motivate students to complete more online learning activities and increase learning performance. For instance, Tsay et al. (2018) reported that OG motivated students to complete more learning activities and improved performance by embedding game elements, such as badges, leaderboards, and rapid feedback, into a student-centred system that supported autonomy, competence, and social relatedness. Their empirical study showed that students who engaged with the gamified system completed significantly more activities and achieved higher final grades than those in the traditional course.

Nevertheless, some research indicated contradictory results. For instance, Kwon and Özpolat (2021) found that applying the same game elements to all learners such as uniform reward systems and fixed task structures, led to significantly lower motivation and final exam scores in the gamified group. The OG approach overlooks individual differences in learning preferences and motivational styles, with only 17% of students preferring competitive formats while 65% favoured cooperative learning. This lack of adaptivity undermined autonomy and engagement, causing the novelty of gamification to fade and performance to decline over time. Many researchers (e.g., Hallifax et al., 2021; Rodríguez et al., 2022) have suggested that the reason for this inconsistency lies in the inability of the one-size-fits-all approach to accommodate different student motivations.

Some researchers even caution that using gamification does not necessarily bring about positive learning outcomes (Schöbel et al., 2023). Research investigating the effects of specific or multiple game elements in gamification has revealed that students often respond differently to game mechanics (Lavoué et al., 2019), influenced by their distinct

expectations, preferences, and needs (Bennani et al., 2022). For example, while studies by Landers et al. (2015) and Bai et al. (2022a) demonstrated that incorporating elements like points, leaderboards, and badges boosted student participation and task performance. Findings from Schöbel et al. (2023) indicated that points and badges did not directly enhance cognitive abilities. More concerning, Hanus and Fox (2015) discovered that these game elements could reduce motivation and lead to poorer exam results. These findings underscore a critical consideration: individual differences, such as player profiles   (Hallifax, et al., 2019b; Kappen & Orji, 2017; Monterrat et al., 2017), learning styles (Sanjabi & Montazer, 2020), and learners' responsiveness to various teaching methods significantly shape the effectiveness of gamification in education. As Harviainen (2014, p.6) concluded, "the very elements that motivate some learners (e.g., competition) are the ones disliked by others, and also those that when taken to excess, cause problems." Therefore, it is essential to explore how gamification can be tailored to accommodate personal learning needs, ensuring that the benefits of this instructional approach are more equitably distributed.

   To address the limitations of a one-size-fits-all approach to gamification, which applies uniform game mechanics to all learners, researchers have increasingly emphasized the importance of customizing game elements to align with students' unique characteristics, needs, and behaviours (Klock et al., 2020; Oliveira et al., 2020; Oliveira & Bittencourt, 2019; Tondello et al., 2019). This approach, known as adaptive gamification, can be implemented in either static or dynamic forms (Hallifax et al., 2019a). In a static system, adaptations are made once, typically before learners begin using the educational platform. These adaptations are based on a learner profile, with different game elements and mechanics assigned to students depending on their identified profiles. In contrast, a dynamic system involves continuous adjustments throughout the learning process, allowing for real-time modifications to better suit learners' evolving needs and behaviours (Rodríguez et al., 2022).

Empirical evidence of adaptive gamification on student learning

Research on the design, implementation, and impact of adaptive gamification on student learning remains scarce (Böckle et al., 2017; Koivisto & Hamari, 2019), with mixed findings reported in the literature (Hallifax et al., 2019a; Reyssier et al., 2023). Several studies have demonstrated positive outcomes when gamification is tailored to learners' individual profiles. For example, Hassan et al. (2021) found that students whose game elements matched their learning styles exhibited higher motivation compared to those with randomly assigned elements. Similarly, Roosta et al. (2016) customized game elements based on students' motivation types (e.g., mastery approach vs. avoidance, performance approach vs. avoidance) and observed that learners with aligned elements

displayed increased motivation after a month of using an online tool, in contrast to those with mismatched elements. Additionally, Mora et al. (2018) reported that university students, categorized according to their Hexad player profiles (Marczewski, 2015), demonstrated improved behavioural and emotional engagement after 14 weeks of using a learning tool with personalized game elements. These findings suggest that adaptive gamification, when designed to align with individual learner characteristics, has the potential to enhance engagement and motivation.

On the other hand, some studies have reported mixed or even counterintuitive results regarding the effectiveness of adaptive gamification. For example, Monterrat et al. (2017) discovered that middle-school students who were exposed to counter-adaptive game elements (those that did not match their player profiles) reported greater enjoyment and perceived usefulness compared to students who received adaptive or randomly assigned elements. Rodrigues et al. (2021) found that tailored gamification could have unintended negative consequences. Specifically, learners with less familiarity with programming experienced reduced motivation when exposed to adaptive game elements.

In summary, while adaptive gamification shows promise, its effectiveness remains inconsistent. The outcomes appear to depend on the specific game elements utilized, the adaptation strategies applied, and the context in which they are implemented (Hallifax et al., 2019b). There is limited understanding of how to effectively tailor game elements and mechanics to align with students' learning profiles (Lavoué et al., 2019). Further research is essential to determine which learner characteristics, such as player types, profiles, motivation types, or prior knowledge levels, should be prioritized to inform the design and customization of gamified learning experiences.

Adaptive gamification based on player types

Bartle's taxonomy of player types offers a basic and feasible framework for understanding user motivations and behaviours in the context of adaptive gamified learning (Lavoué et al., 2019). This taxonomy categorizes players into four groups: achievers, explorers, socializers, and killers (Bartle, 1996). The distinctive features of these player types are briefly summarized below.

Achievers are players who are primarily motivated by goals, rewards, and progress. They derive satisfaction from completing challenges, earning points, levelling up, and collecting achievements. For these individuals, the appeal of gaming lies in mastering game mechanics and gaining recognition for their accomplishments. Achievers are often found at the top of leaderboards or diligently working to complete every task or objective the game presents.

Explorers are characterized by their focus on discovery and experimentation. These players are driven by the desire to uncover hidden elements, such as secret levels, unique

game mechanics, or narrative lore. Unlike achievers, their primary goal is not to win but to satisfy their curiosity and deepen their understanding of the game world. Explorers are likely to invest significant time investigating every aspect of the game environment to uncover its intricacies.

Socializers prioritize interaction and relationships over competition or exploration. They are most engaged when collaborating, communicating, or role-playing with other players. For socializers, the game serves as a platform for building connections and fostering a sense of community. Their enjoyment stems from the social dynamics and relationships they develop within the game, rather than from achieving in-game objectives or discovering hidden content.

Killers are players who are primarily motivated by competition and the desire to demonstrate superiority in a game environment. They enjoy challenges that allow them to outperform others, often seeking opportunities for strategic gameplay and competitive interactions. While this drive can foster high engagement in competitive settings, it may not always align with collaborative or mastery-oriented learning goals. In educational contexts, careful design is needed to ensure that competitive elements support constructive learning experiences without undermining cooperation or inclusivity.

We decided to use Bartle's taxonomy of player types as the foundation for designing adaptive gamification for two primary reasons. First, this typology is a well-established and widely recognized framework for explaining gamers' behaviours and the motivations behind their in-game decisions (Lavoué et al., 2019). Numerous studies have explored the development of adaptive gamification systems based on Bartle's taxonomy, making it a relatively robust and validated approach (e.g., Ferro et al., 2013; Marczewski, 2013; Oliveira et al., 2022).

In this study, we chose to focus on Achievers and Explorers based on Bartle's taxonomy of player types. Achievers are motivated by goals, rewards, and measurable progress, making them highly responsive to gamified elements such as badges, experience points, and structured challenges. These elements align well with instructional goals that emphasize mastery, performance, and self-regulated learning (Tondello et al., 2016; Reyssier et al., 2022). Explorers, on the other hand, are driven by curiosity, autonomy, and the desire to uncover new information or experiences. Their motivations resonate with discovery-based learning and open-ended tasks, which are particularly effective in fostering deep engagement and cognitive exploration (Bartle, 1996; Lavoué et al., 2019).

We selected these two player types because their motivational profiles align closely with the pedagogical goals of our study, namely, enhancing computational thinking skills and promoting reflective learning behaviours. The adaptive gamification design allowed

us to tailor learning paths and challenges that matched these motivations, thereby supporting both goal-oriented and curiosity-driven learners.

Socializers prioritize interaction and relationship-building, which can contribute to learning outcomes through collaborative engagement and peer support. This aligns with theories such as connectivism and collaborative learning, which emphasize the importance of social interaction in knowledge construction and skill development (Cleary, 2021). However, in certain instructional contexts, particularly those focused on individual mastery or discovery, these motivations may be less directly aligned with task performance goals, requiring careful instructional design to ensure that social engagement complements core learning objectives.

Killers are primarily motivated by competition and the desire to outperform others. While competitive elements can enhance engagement and drive performance in some learners, they may also introduce challenges in collaborative or mastery-oriented learning environments. Excessive competition has been associated with reduced cooperation, increased anxiety, and potential disruption of group dynamics if not carefully balanced (Houshmand, 2015). Given the focus of this study on fostering deep engagement through self-directed exploration and achievement, we opted not to include Killer-type elements in the initial design. This decision was made to maintain a supportive and inclusive learning environment and to avoid introducing dynamics that might conflict with the pedagogical goals of autonomy, mastery, and reflective learning.

The GAFCC-F model: Theory and application in practice

The Goal-Access-Feedback-Challenge-Collaboration-Fantasy (GAFCC-F) model was proposed by Bai et al. (2022b) and has been approved as effective in online gamified learning design. This model is intricately woven from the threads of six motivational theories: goal-setting theory (Locke & Latham, 2002), flow theory (Csikszentmihalyi, 1990), self-determination theory (Deci & Ryan, 2000), social comparison theory (Festinger, 1954), behavioural reinforcement theory (Skinner, 1965), and theory of intrinsically motivating instruction (Malone, 1981).

Bai et al. (2022b) used the GAFCC-F model revealed that students in a gamified e-learning design course performed better than those in a non-gamified course, as measured by online discussion engagement and learning performance. This study also examined how the GAFCC-F model affected students' peer-feedback quality and interactions in online discussion forums. The results suggested that the gamified group had a denser social network and higher critical thinking skill levels than the control group. Additionally, the study found that the fantasy elements helped create a more engaging and motivating learning environment, leading to a denser social network among students.

Another study explores the application of the GAFCC-F design model in online gamified classes, focusing on the impact of exogenous and endogenous fantasies on student motivation and engagement (Bai et al., 2022a). Study 1 involved an exogenous fantasy where the storyline was unrelated to learning tasks, while Study 2 used an endogenous fantasy where the plot aligned with the tasks. Results indicated that endogenous fantasy significantly enhanced student motivation and engagement compared to exogenous fantasy. Students found learning tasks more enjoyable in the endogenous fantasy context.

Bai and Hew (2024) examined the use of GAFCC-F model by activating two types of fantasy: exogenous fantasy ($n = 23$) and endogenous fantasy ($n = 23$). Intrinsic motivation was measured through surveys, and behavioural engagement was tracked over 10 weeks using online trace data. Semi-structured interviews provided insights into student perceptions. The endogenous fantasy group showed significantly higher intrinsic motivation and engagement in pre-task analysis and post-task reflection, while the exogenous group focused more on quiz work and post-task reflection. Participants in the endogenous fantasy setting reported increased cognitive engagement and strong identification with their fictional characters. Integrating endogenous fantasy into the curriculum can enhance students' intrinsic motivation, engagement, and self-identification.

Here we discuss each motivational element, goal, access, feedback, challenge, and collaboration. Firstly, the goal component involves helping students set both long-term and short-term targets through rewarding game elements like badges and experience points for participation. Secondly, access provides students with the liberty to choose challenges of various difficulty levels, thereby nurturing a sense of autonomy. Thirdly, feedback focuses on offering immediate responses to students' performance in learning tasks, thus engaging them in self-assessment. The challenge element, fourth, encourages students to compete against themselves and their peers, adding an element of excitement and competition. Fifth, collaboration fosters interaction among learners, allowing them to share common objectives and enhance their collective learning experience. Finally, fantasy allows players to fulfill their desires by creating a virtual world separate from reality (Malone, 1981). The embedded narrative within the environment plays a crucial role in generating a sense of fantasy (Shi & Shih, 2015).

Method

Quasi-experiment design

We adopted a quasi-experiment approach to compare the effects of AG and OG on students' behavioural patterns, computational thinking skills, and motivation to learn.

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 mechanisms.

The OG was conducted during the Spring semester of 2023 (January to April 2023), while the AG was implemented in the Fall semester of 2024 (September to December 2024). 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.

Participants

We employed a historical cohort control group as 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.

Overall 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., 2022b) to design the AG and OG gamified classes.

(1) Goal: Students need to watch the rules to play video before the gamification journey, see Figure 1, and read the opening of the story, see Figure 2. 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 was submitted on Moodle.
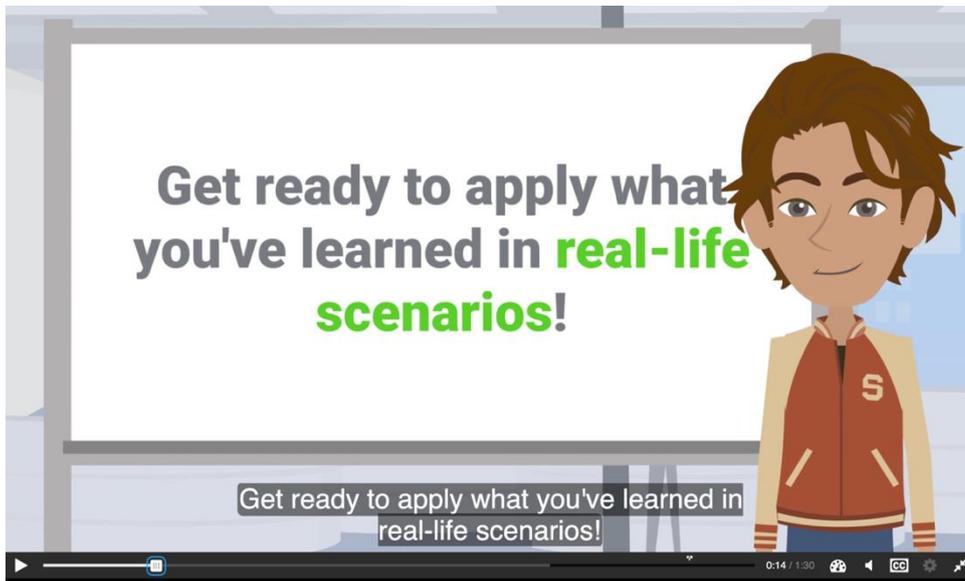
(6) Fantasy: We incorporated storylines and narrative-based scenarios to establish a fantasy context within the gamified class. Throughout the semester, there is an overarching thematic story that connects all of the learning tasks. Students were encouraged to select a character to begin their journey 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.

AG 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 3). After satisfying the passing grade of one learning task, students could unlock and move forward to the next task in the same path.

Fig. 1

"Kyle's Adventure" rules to play introduction video

Fig. 2

Moodle interface with an opening story

"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 4) than explorers to strike a balance in the game.

Fig. 3

Select Your Quest with Peter for the "Explorer" or "Achiever" Path

Fig. 4

Rules to Play for the "Explorer" or "Achiever" branching 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)

"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 4). Figure 5 showed students in the adaptive gamification group were doing gamified tasks in class.

Fig. 5

Students in the adaptive gamification group are doing gamified tasks in class

OG class setting (control group)

Students in the control group were assigned the uniform badges (only badge Y) when passing the learning tasks in one stage. Students experienced the same linear quest path and unlocked the same set of learning tasks throughout the semester. The rest settings were identical as the experiment group.

Data collection and analysis

We measured students' online learning behavioural patterns, learning performance, intrinsic motivation to learn and learning perceptions between the two groups.

Behavioural patterns

Students' trace data of completing the learning tasks on Moodle measured the behavioural patterns. We used Ordered Network Analysis (ONA) to identify the behavioural patterns 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 behavioural 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 behaviours. 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 analyse 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 behavioural patterns between the two groups.

Actual computational thinking skills

A pre- and post-test design was administered to evaluate students' changes in their actual computational thinking skills by the coursework in the gamification interventions. 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. An independent-samples t-test or a non-parametric test will be conducted based on the normal distribution of data between the two groups.

Self-reported computational thinking skills

We utilized the Computational Thinking Scales (CTS) developed by Korkmaz et al. (2017) to evaluate students' computational thinking skills. CTS is a five-point Likert type scale from "strongly disagree" to " strongly agree" and consists of 29 items that could be collected under five factors, such as algorithm thinking and critical thinking. We applied the algorithm thinking subscale. An example item is, "I can identify the steps needed to solve a problem systematically." The CTS demonstrates high internal consistency, with a Cronbach's alpha of 0.89 (Korkmaz et al., 2017). We administered this scale both before and after the intervention.

Intrinsic motivation

This refers to engaging in an activity for its inherent satisfaction (Ryan & Deci, 2000) rather than for some separable consequence. In an educational context, a student is intrinsically motivated when they learn because they find the subject matter interesting or

enjoyable. For example, a student might read a book because they are curious about the topic and enjoy the process of learning itself.

We employed the Intrinsic Motivation Inventory (IMI) (Ryan, 1982), a self-reported questionnaire, to measure students' intrinsic motivation. The IMI assesses participants' experiences related to specific activities and covers various dimensions of intrinsic motivation. For this study, we particularly focused on the interest/enjoyment subscale, which comprises seven items rated on a 7-point scale from "not at all true" to "very true." One example item was "I would describe this gamified learning experience as very interesting." The internal consistency of the interest/enjoyment subscale is acceptable, with Cronbach's alpha = 0.78 (Tsigilis & Theodosiou, 2003). We administered the interest/enjoyment subscale at both the pre-intervention and post-intervention phases.

Extrinsic motivation

This involves performing an activity because it leads to a separable outcome, such as earn a reward or avoid a punishment (Deci & Ryan, 2002). In education, extrinsic motivation occurs when a student studies to achieve good grades or to avoid negative consequences like failing a class. For instance, a student might complete their homework to receive praise from their teacher or to avoid detention.

We utilized the external regulation subscale of the Academic Motivation Scale (AMS) by Vallerand et al. (1992) to evaluate students' extrinsic motivation. This subscale helps to understand how external influences affect students' drive to complete academic tasks. An example item is, "The knowledge gained from course assignments is more valuable to me than just receiving a good grade." The external regulation subscale demonstrates high internal consistency, with a Cronbach's alpha of 0.83 (Vallerand et al., 1992). We administered this subscale both before and after the intervention.

Learning perception of the adaptive gamification

At the conclusion of our intervention, we posted several open-ended questions to 77% of the students (n = 24) in the experimental group. One such question was, "How would you describe your learning experience in Kyle's adventure (e.g., selecting explorer or achiever quests, unlocking new clients, earning badges, cartoon format, scenario design, task content)?"

For the data analysis, we employed the directed content analysis method (Hickey & Kipping, 1996), which provides a systematic coding process that utilizes pre-established codes from prior research (Hsieh & Shannon, 2005). New codes were created when the text did not fit within the existing coding scheme (Hsieh & Shannon, 2005). We also conducted a frequency analysis of the emerging themes. The GAFCC-F model served as our preliminary coding framework, as it reflected the gamified class design.

To improve coding consistency, we selected several examples that effectively demonstrated each theme. We performed several reviews of the data to gain a comprehensive understanding of each theme (Creswell, 2012). Two authors cross-coded all data to ensure reliability. We also compared the coding results to evaluate inter-rater reliability, achieving a Cohen's κ of 0.88, indicating substantial agreement, as a value of 0.75 is regarded as significant (Viera & Garrett, 2005). Any differences were carefully addressed through collaborative discussions between the two authors until a consensus was reached.

Result

Behavioural pattern difference between AG and OG

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 6 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 upon completed the task 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

Fig. 6

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)
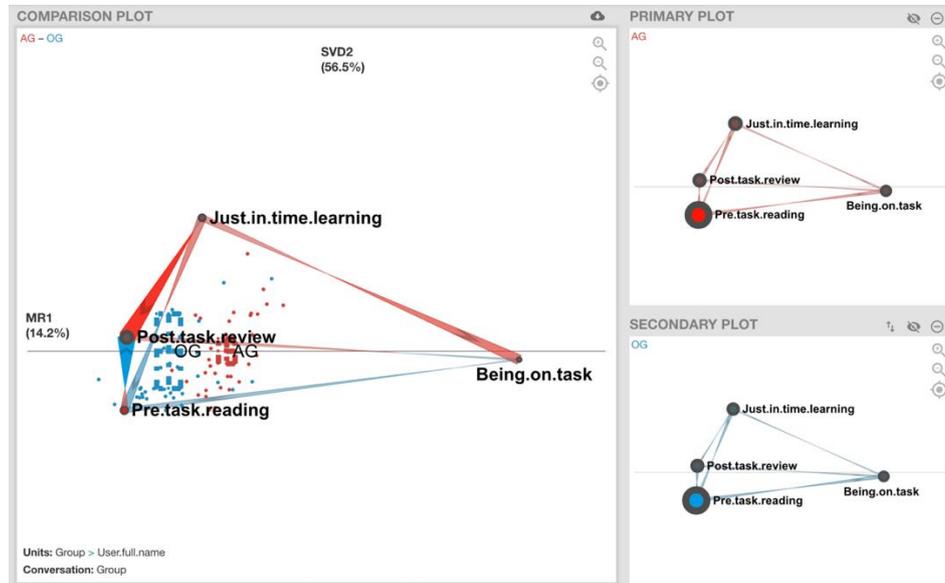
Note. Red dot ● = a student in the adaptive gamification group; blue dot ● = a student in the one-size-fits-all gamification group; red square ■ = the centroid (mean position of the projected points) of the students in the adaptive gamification group; blue square ■ = the centroid (mean position of the projected points) of the students in the one-size-fits-all gamification group; MR = mean rotation; SVD = singular value decomposition.

Annotation: The subtracted epistemic network shows the differences between the students in the AG and OG groups. The numerical values on the lines indicate the differences in connection coefficients between two codes. A thicker line indicates a greater difference. For example, a connection coefficient of 0.08 between the codes *Post-task review* and *Just-in-time learning* indicates the largest difference. The color of the line denotes the dominant group. The red line with a connection coefficient of 0.08 indicates that the AG group dominates the relationship between the codes *Post-task review* and *Just-in-time learning*. The arrows indicate the direction between the two codes. For instance, students in the AG group tended to perform *Just-in-time learning* and then *Post-task review*.
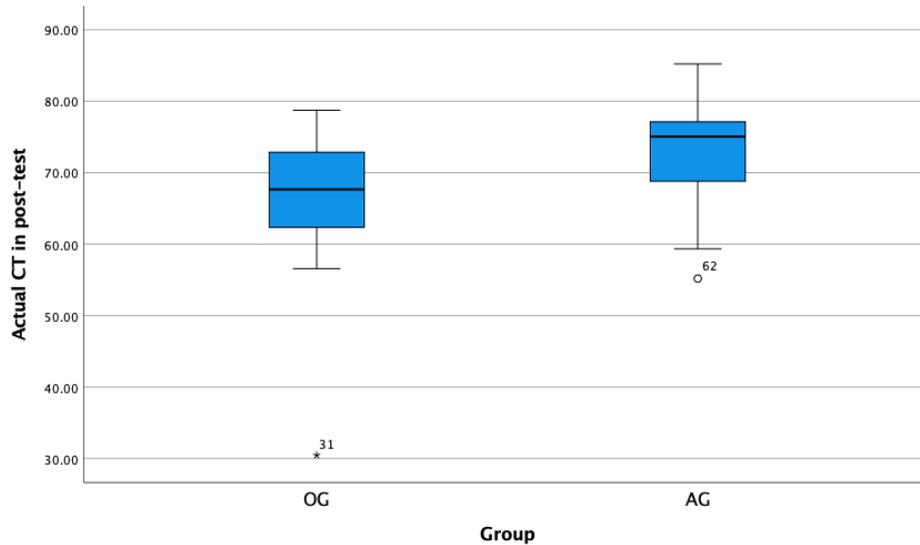
Effects on actual computational thinking skills

Participants completed a series of pre-tests at the beginning of the course to determine group equivalence. There were no significant differences between the AG and OG at the start of the course on the actual and self-reported computational thinking skills, self-reported intrinsic motivation level and self-reported extrinsic motivation level.

We conducted a Shapiro-Wilk test to assess the normality of the post-test of actual computational thinking skills. The results indicated that the data were not normally distributed, $W(60) = 0.90$, $p < .001$. Hence, a Mann-Whitney U test was conducted to determine whether there were differences in test scores between AG and OG. The results indicated that there was a significant difference in test scores between the two groups, $U = 303$, $z = -0.35$, $p = .006$. Specifically, students in AG (Mdn = 75.06) had significantly

higher test scores of actual computational thinking skills than those in OG (Mdn = 67.67), see as illustrated in Figure 7.

Fig. 7

A boxplot comparing the learning gain between the OG and AG groups

Note. We kept data point of 31 and 62 as they were actual students' performance.

Effects on self-reported computational thinking skills

We performed a Shapiro-Wilk test to check if the post-test scores for self-reported computational thinking skills followed a normal distribution. The findings showed that the data were normally distributed, $W(60) = 0.96$, $p = .078$. Subsequently, we conducted an independent-samples T-test to examine the differences in self-reported computational thinking skills between the AG and OG groups. The analysis indicated that there was no significant difference in self-reported computational thinking skills between the two groups, $t(58) = 1.50$, $p = .139$. Notably, students in the AG group (M = 3.77, SD = 0.66) reported lower computational thinking skills compared to those in the OG group (M = 4.01, SD = 0.57).

Effects on intrinsic motivation

We evaluated the post-test scores for intrinsic motivation using a Shapiro-Wilk test, which confirmed normal distribution, $W(60) = 0.96$, $p = 0.065$. Subsequently, an independent-samples T-test revealed no significant difference between the AG and OG groups, $t(58) = 0.18$, $p = 0.855$. Participants in the AG group (M = 3.99, SD = 1.08) reported marginally lower levels of intrinsic motivation compared to those in the OG group (M = 4.03, SD = 0.58).

Effects on extrinsic motivation

We conducted a Shapiro-Wilk test to determine the normality of the post-test scores for extrinsic motivation levels. The results indicated that the data were not normally distributed, $W(60) = 0.96$, $p = .045$. As a result, a Mann-Whitney U test was carried out to compare the levels between AG and OG groups. The findings revealed no significant difference between the two groups, $U = 334$, $z = -1.72$, $p = .085$. Specifically, students in the AG group (Mdn = 4) exhibited the same level of extrinsic motivation as those in the OG group (Mdn = 4).

Learning perceptions of AG

The GAFCC-F model provides a comprehensive framework for understanding students' learning experiences in an adaptive gamified environment. Based on the responses from the students, several key themes emerged regarding their perceptions of adaptive gamification in Kyle's adventure, as shown in Table 2. The themes are (1) setting goals with rewards ($n = 9$), (2) competing against self and peers ($n = 9$), (3) access to varied challenges ($n = 6$), (4) immediate feedback on performance ($n = 6$), (5) collaboration and interaction ($n = 3$), (6) engaging narrative and fantasy ($n = 3$).

Firstly, the goal component was highlighted by students who appreciated the rewarding elements such as badges and experience points. They found these elements engaging and motivating, aligning with the goal-setting theory by Locke and Latham (2002). The access component was reflected in the students' ability to choose challenges of varying difficulty levels. This sense of autonomy allowed them to customize their learning journey based on their preferences and goals, which is a core aspect of self-determination theory (Deci & Ryan, 2000).

Feedback was another crucial element, with students expressing the need for immediate responses to their performance. They indicated that effective feedback mechanisms are essential for engaging in self-assessment and improving their learning experience. The challenge component was evident in the students' experiences of competing against themselves and their peers. While some found the competition exciting and motivating, others felt it was exhausting. This mixed feedback suggests that challenges can add excitement but must be balanced to avoid overwhelming students.

Collaboration was appreciated by students who enjoyed interacting with their peers. They valued the opportunity to work together, share ideas, and learn from each other, which aligns with social comparison theory (Festinger, 1954) and the theory of intrinsically motivating instruction (Malone, 1981). Lastly, the fantasy component was mentioned by students who enjoyed the embedded narrative and virtual world. They found the storyline and characters engaging, which made the learning process more

immersive and enjoyable. This reflects the importance of a well-designed narrative in creating a sense of fantasy (Shi & Shih, 2015).

Overall, the students' responses indicate that while the GAFCC-F model provides a robust framework for gamified learning, there are areas for improvement. Balancing the difficulty of challenges, enhancing feedback mechanisms, and enriching the narrative elements can further enhance the learning experience.

Table 2

Students' learning perceptions of adaptive gamified learning with summarized the themes, frequency, and sample quotations

Theme	Frequency	Sample Quotations
Setting Goals with Rewards	9	"Kyle's adventure offers a unique and engaging learning experience through its combination of explorer and achiever quests, unlocking new clients, earning badges, cartoon format, scenario design, and task content." - Respondent 21
Competing Against Self and Peers	9	"Competing against my classmates in Kyle's adventure added a fun and challenging element to the learning process. It motivated me to put in more effort and stay engaged." - Respondent 3 "Kyle's adventure really pushed me to compete with myself. I found myself trying to beat my previous scores and improve my performance each time." - Respondent 1
Access to Varied Challenges	6	"We have the option to choose between explorer quests and achiever quests. Explorer quests encourage learners to explore new concepts, topics, or areas of knowledge. Achiever quests, on the other hand, focus on demonstrating mastery and achieving specific learning outcomes. This choice allows us to customize the learning journey based on our preferences and goals." - Respondent 16
Immediate Feedback on Performance	6	"Playing Kyle's adventure is good, however, it seems very difficult to answer them correctly the first time. However, it can let us practice the way of thinking in real case." - Respondent 22
Collaboration and Interaction	3	"I appreciated the opportunity to interact with my peers during Kyle's adventure. It helped me understand different perspectives and learn from others." - Respondent 12

| Engaging Narrative and Fantasy | 3 | "The narrative aspect of Kyle's adventure kept me hooked. The characters and plot twists made me look forward to each new task." - Respondent 9 |
| | | "The storyline in Kyle's adventure made the learning process feel like an exciting journey. It was much more engaging than traditional methods." - Respondent 7 |

Discussion

Understanding the conditional effectiveness of adaptive gamification

While our findings suggest that AG can enhance actual computational thinking skills and behavioural engagement, it is important to acknowledge that prior research has reported inconsistent results regarding the effectiveness of AG. For example, Monterrat et al. (2017) found that students exposed to counter-adaptive game elements, those not aligned with their player profiles, reported greater enjoyment and perceived usefulness than those with matched elements. Similarly, Rodrigues et al. (2021) observed that AG could have unintended negative consequences, such as reduced motivation among learners with less programming experience. These findings suggest that the success of AG may depend heavily on contextual factors, including learners' prior knowledge, the nature of the game elements, and the adaptation strategy employed. Therefore, while our study supports the potential of AG, further research is needed to explore its limitations and boundary conditions.

Close feedback loop in AG

The ONA findings reveal a significant advantage of AG approach in creating a close feedback loop that enhances the learning process. The higher connection coefficients between "pre-task reading" and "post-task review" (0.32 in AG vs. 0.25 in OG) and between "just-in-time learning" and "post-task review" (0.25 in AG vs. 0.21 in OG) indicate that the AG approach better integrates these key learning activities. 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 and 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 help increase their time engaging with the gamified environment (Lavoué et al., 2019). Furthermore, a study by Zourmpakis et al. (2023) analysed the

impact of adaptive gamification in science education, finding that adaptive criteria and personalized learning strategies significantly improved students' engagement and learning outcomes. This study underscores the effectiveness of AG in creating a close feedback loop that enhances the overall learning experience. Students' need of autonomy has been enhanced in the AG setting, where they can choose either explorer or achiever quests that interest them the most. This, in turn, increases behavioural engagement.

Improved actual computational thinking skills in AG

The results indicated a significantly higher actual computational thinking skills of AG than OG. Our 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.

Recent literature further supports these findings. For instance, 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). Altaie and Jawawi (2021) proposed an AG framework that supports adaptive features based on students' dimensions (verbal, visual). Their study demonstrated that the use of AG significantly enhanced students' computational thinking skills compared to traditional methods. Hallifax et al. (2019a) conducted a comprehensive literature review on AG in education, concluding that tailored game elements are more effective in increasing learner engagement and performance compared to non-adaptive approaches. Their findings emphasize the role of AG in fostering a dynamic and integrated learning process.

Same motivation levels between AG and OG

The results of this study indicate that there is no significant difference in motivation levels between students in the AG group and those in the OG group. An empirical study by Oliveira et al. (2022) suggest that AG does not necessarily lead to higher motivation levels. A review of 19 primary studies by Oliveira et al. (2023) even found that non-tailored system was more effective than the tailored system in enhancing students' motivation. Therefore, both AG and OG approaches can be effective in maintaining students' motivation, depending on the context and implementation.

For instance, challenge difficulty level is one important context in gamified learning. Some studies offer various challenges at different difficulty levels, allowing students to choose those they feel comfortable with to achieve autonomy (Pedro Lopes, 2014). This approach enhances autonomy by offering assignment options, enabling students to choose their paths to achieve desired grades (Jones et al., 2023). However, too many choices can lead to choice overload, causing feelings of incompetence and anxiety,

leading to low motivation (Beymer & Thomson, 2015). For autonomy to be beneficial, individuals need relevant prior experience or skills, fostering a sense of competence. Those who feel less competent may avoid decision-making and experience greater motivation with fewer choices (Patall et al., 2014). Hence, providing structured guidance with limited choices, two to four, is preferable for students with lower competence (Patall, 2012).

Implications of teaching practices

We summarized four implications of teaching practices based on the results of this study. Implement player-type-based learning paths: Design gamified learning experiences with options for students to choose between different paths (e.g., Achiever or Explorer) based on their individual motivations and preferences. This aligns with Bartle's taxonomy of player types, allowing students to engage with content in ways that resonate with their personal learning styles. Teachers can survey students at the start of the course to understand their learning preferences (e.g., goal-driven vs. curiosity-driven) and create pathways that students can select for their learning tasks.

Incorporate adaptive challenges: Provide learning challenges at varying difficulty levels and allow students to unlock more complex tasks as they demonstrate mastery of simpler tasks (e.g., Maiga, 2019; Yunyongying, 2014). This could cater to both high-achieving students and those who need more scaffolding. Teachers can use learning management systems like Moodle to set up task prerequisites where students must complete easier tasks to access harder.

Automate feedback provision, foster post-task review and just-in-time learning in completing gamified learning challenges: Automating feedback provision is essential for effective gamified learning (Dæhli et al., 2021). Immediate, personalized feedback helps students understand their performance and areas for improvement (Vasilyeva et al., 2008). This continuous feedback loop fosters post-task review, allowing students to reflect on their learning and consolidate their understanding. Additionally, integrating just-in-time learning ensures that students receive the necessary information and resources precisely when needed, bridging knowledge gaps and enhancing real-time problem-solving skills, also viewed as a troubleshooting skill (Kester et al., 2006). Together, these elements create a dynamic learning environment that supports ongoing improvement and deeper engagement with the material.

Narrative and Fantasy Integration: Integrating narrative and fantasy into the learning experience can significantly increase student engagement. By embedding learning tasks within an engaging story or theme, educators create a more immersive environment that enhances motivation and makes learning enjoyable (Malone, 1981). As demonstrated in

this study, students respond positively to learning settings that combine meaningful narratives with game mechanics, leading to higher levels of engagement and better learning outcomes (Bai et al., 2022a). Teachers should integrate endogenous fantasy elements into course designs, ensuring that the fantasy context is closely aligned with the instructional content (e.g., skills and knowledge to be acquired, Bai & Hew, 2024).

Limitations and future work

The results showed that AG could significantly enhance students' actual computational thinking skills compared to OG group. Regarding the behavioural pattern, the connections of "pre-task reading" to "post-task review" and "just-in-time learning" to "post-task review" are the two most common behavioural patterns in AG. The connection of "post-task review" to "pre-task reading" is the most common behavioural pattern in OG. The two groups present no significant difference in self-reported extrinsic motivation and intrinsic motivation levels. Participants in the AG setting reported six themes in terms of learning perceptions: (1) setting goals with rewards, (2) competing against self and peers, (3) access to varied challenges, (4) immediate feedback on performance, (5) collaboration and interaction, and (6) engaging narrative and fantasy.

The primary limitation of this study is the focus on only two player types, i.e., Achievers and Explorers. This limited scope may not fully capture the diverse range of student motivations and behaviours, as other player types such as Socializers and Killers were not considered. Future research should explore the inclusion of all four player types from Bartle's taxonomy to provide a more comprehensive understanding of how different game elements can be tailored to various learner profiles.

Another limitation is the reliance on students' self-reported data for assessing learning preferences and motivation. Self-reported data can be subjective and may not accurately reflect actual behaviours and preferences. To address this, future studies should incorporate more objective measures, such as tracking students' log data and behaviour data (Rodríguez et al., 2022). By analysing these data points, researchers can gain deeper insights into students' interactions with the gamified learning environment and develop more precise adaptive learning algorithms (Hallifax et al., 2021).

Additionally, the study's sample size was relatively small, which may limit the generalizability of the findings. Future research should aim to include larger and more diverse samples to enhance the robustness and applicability of the results. Expanding the study to different educational contexts and age groups can also provide valuable insights into the effectiveness of adaptive gamification across various learning environments. Moreover, the study did not explore the long-term effects of adaptive gamification on learning outcomes and motivation. Longitudinal studies are needed to examine how sustained exposure to adaptive gamification influences students' academic performance,

engagement, and motivation over time. This can help identify any potential long-term benefits or drawbacks of using adaptive gamification in educational settings.

Conclusion

This study compared the effects of AG and OG on students' behavioural patterns, computational thinking skills, and motivation. The findings highlight the significant advantages of AG in enhancing students' computational thinking skills and fostering a more integrated learning process. AG demonstrated higher connection coefficients between key learning activities, such as "pre-task reading" and "post-task review," and "just-in-time learning" and "post-task review," indicating a more effective integration of these activities.

   Despite these advantages, the study found no significant difference in motivation levels between the AG and OG groups. This suggests that while AG can enhance engagement and performance, it does not necessarily lead to higher motivation compared to OG. The context and implementation of gamification play a crucial role in its effectiveness. In conclusion, AG offers a promising approach to enhancing learning outcomes and engagement by tailoring game elements to individual learner profiles. Future research should explore the potential of AG in different educational contexts and with diverse learner populations to further refine and optimize its implementation. By leveraging these strategies, educators can create more effective and personalized learning experiences that support ongoing improvement and deeper engagement with the material.

Author's contributions
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Availability of data and materials

The data that support the findings of this study are available on request. The data are not publicly available due to privacy or ethical restrictions.

Declarations

Competing interests
The authors declare that they have no conflict of interest.

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