Computers & Education 212 (2024) 105000

Contents lists available at ScienceDirect

Computers & Education

journal homepage: www.elsevier.com/locate/compedu

Approaches and game elements used to tailor digital gamification for learning: A systematic literature review

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ARTICLE INFO

Keywords:
Tailored digital gamification
Teaching and learning
Tailored approach
Game elements and clusters
Systematic literature review

ABSTRACT

The systematic review examined research on tailored digital gamification for learning based on 43 peer-reviewed articles published between 2013 and 2022. The study aimed to investigate tailored approaches and game elements, contributing to the use of tailored digital gamification in educational settings. The tailored approaches were categorized as personalization, adaptation, and recommendation, with user modeling as their basis. Five clusters of game elements were employed when using these tailored approaches in digital gamified classes. The findings imply that most of the articles in this review were still in the stage of class preparation and focused on what information can be used to tailor. More empirical studies need to be conducted to examine the motivating effects of tailored digital gamifying classes, using the approaches of personalization, adaptation, and recommendation. Additionally, twenty-three game elements were found in this review study, among which reward was the most often used. Then these game elements were grouped into five clusters based on their functions, that is, performance, personal, social, ecological, and fictional cluster. A variety of game element clusters reflect multiple aspects of gamification. The use of them in each tailored approach might contribute to a better understanding and selection of game elements when tailoring digital gamification. These findings provide a holistic picture of common approaches and related game elements in tailored digital gamifying classes. Teachers and curriculum designers can benefit from this study by considering appropriate approaches and game elements.

1. Introduction

Gamification is the use of game elements in non-game contexts (Deterding et al., 2011) and it is typically employed by relying on digital platforms or applications (Qiao et al., 2023). The role of gamification in students' learning, motivation and outcomes is controversial and the subject of heated discussion (cf. Almeida et al., 2023; Hanus & Fox, 2015; Toda et al., 2017; Van Roy & Zaman, 2018; Yildirim, 2017). One key reason for this is that game elements may generate different gamified effects on individual students' learning. According to Oliveira and Bittencourt (2019), students may be motivated or not by certain game elements since their characteristics and learning needs vary. Many studies have found that one-size-fits-all gamified classes can cause or aggravate demotivation if they do not consider students' individual differences (e.g., Koivisto & Hamari, 2019; Toda et al., 2017). A tailored

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https://doi.org/10.1016/j.compedu.2024.105000
Received 27 May 2023; Received in revised form 17 January 2024; Accepted 20 January 2024
Available online 21 January 2024
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approach is regarded as a way to improve student gamification experiences, which corresponds to any changes in learning contents or strategies to reach individual learning needs and preferences (Kreuter et al., 2013).

Tailored gamification is the integration of a tailored approach and gamification, which tailors different game elements according to personal user profiles to maximize the expected goals of individuals (Altaie & Jawawi, 2021). Although it is expected to motivate students by taking their individual differences into account, it is a challenge for teachers and curriculum designers to implement it in class and only a few studies have discussed the use of tailored gamification in educational settings. To understand it in depth, it is not only necessary to know different tailored approaches in educational gamified contexts, but also which game elements are used for tailoring. As two common approaches, personalization could involve tailoring activities to students' interests based on questionnaire answers, while adaptation tailors learning contents based on students' performances in class. Besides, it is essential to clearly distinguish between different game elements before tailoring gamification. For instance, challenge is regarded as a conflict between the gamified system and users, while competition is a conflict between users.

Previous review studies lacked a clear classification of either the tailored approaches or game elements applied in gamification, and this may have hindered teachers from understanding and tailoring gamified classes. Additionally, they did not distinguish between digital and non-digital gamification when searching for related works. Although computer-based mechanisms are used in most gamified classes, they are not a prerequisite. The current review study aimed to explore what approaches and game elements have been used in the selected studies to provide practical recommendations for implementing tailored digital gamification in educational settings.

2. Tailored gamification in education

Tailored gamification is expected to enhance student motivation and performance by considering their individual characteristics and needs such as learning styles (Azzi et al., 2020). It has been examined in previous review studies.

Aljabali and Ahmad (2018) reviewed 13 papers from 2010 to 2017, mainly exploring three parameters to differentiate individuals: learning styles, player types, and personality traits. They stated that most studies identified the positive influence of tailored gamification on student motivation and learning performance. This review revealed a change of direction in research on gamification from studying one-size-fits-all gamification (2010–2013) to tailored gamification (2014–2017). However, the approaches to tailor were not explained in this study.

Another systematic review study (Hallifax et al., 2019) analyzed 20 papers published from 2014 to 2019 and identified another parameter 'expertise', as well as 'player types' and 'personalities'. In addition, the authors divided tailored approaches into two systems: dynamic and static adaptations. **Dynamic** adaptations use learner activities and behaviors during gamified learning to modify the functioning of the game elements. In contrast, **static** adaptation relies on students' static information such as player-type questionnaire answers. The findings showed that most of the tailored gamification studies had a positive effect on student motivation. Only a few studies differentiated between tailored approaches according to students' static or dynamic information. In the same year, Lopes et al. (2019) conducted a review of 16 papers published between 2012 and 2018. The authors listed examples of how different researchers tailored their classes, but did not analyze them systematically.

Yet another review (Klock et al., 2020) revealed that three approaches personalization, adaptation, and recommendation were often used for tailoring gamification. **Personalization** modifies gamified systems to fulfill students' needs based on their static data in the user profiles, whereas **adaptation** relies heavily on student dynamic data in the user profiles to identify their needs and thus adapt the gamified systems. **Recommendation** provides students with game elements that people with similar tastes liked in the past. Additionally, according to this study, **user modeling** is a basis for these approaches, which models and creates student user profiles by storing personal data associated with individuals. The authors then distinguished more than 30 game elements without considering their clusters. Different clusters reflect different functions of game elements. Understanding them facilitates the easy selection of game elements. Moreover, since Klock et al. (2020) explored tailored gamification regardless of its application context, there is still a need to explore how these approaches can be used effectively in the educational domain. More recently, Oliveira et al. (2022) reviewed 19 studies published from 2014 to 2020 and listed the approaches used in tailored gamification. Their conclusions revealed that there was a lack of studies on game elements in the tailored gamification literature.

The above reviews synthesized tailored gamification studies in education mainly before 2020. Yet the findings did not include sufficient information about game elements and their categories and the use of them in a tailored gamified approach to learning. Besides, these studies explored tailored gamification regardless of digital or non-digital contexts. Our contribution will focus on tailored digital gamifying classes.

This review paper elaborates on the tailored approaches and game elements for learning and two main research questions direct the review study.

RQ1. Which approaches are employed to tailor digital gamification in education?

RQ2. Which game elements are used when using these tailored approaches?

3. Methodology

This study adopted the systematic literature review. The principles of the PRISMA statement (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) (Moher et al., 2009) were used as a guideline to conduct and report this review work. The eligibility criteria, information sources, search strategy, selection process, data collection, data items, and synthesis process were described in the following subsections.

3.1. Eligibility criteria

This study focused on tailored gamification for education and thus the keywords for searching consisted of synonyms of tailor (e.g., personalize) and variants of gamification (e.g., gamified) and education (e.g., school, learning, and teaching). The selected papers had to be: (a) focused on tailored digital gamification (i.e., excluding general gamified techniques or non-digital gamification or irrelevant to gamification); (b) written in English; (c) records with full access; (d) available in full text; (e) primary studies providing first-hand data (i.e., not surveys or systematic mappings or reviews); (f) peer-reviewed articles; (g) in educational settings; and (h) published from 2013 to date. The period chosen, from 2013 to 2022, started when tailored gamification began to be studied (Klock et al., 2018) and was extended through to the year 2022 in order to collect state-of-the-art research data on this topic.

3.2. Search

This study was conducted using electronic searches and the snowballing technique to retrieve relevant studies. Nine databases were used for the electronic searches, including SpringerLink, Taylor & Francies Online, Wiley Online Library, SAGE Journals, Web of Science, JSTOR (Journal STORage), ScienceDirect (Elsevier), ProQuest, and Scopus. A snowballing technique was utilized to identify extra studies by searching the reference lists of eligible publications in the databases mentioned above.

In total, this search yielded 1772 articles (1768 from electronic search and 4 from snowballing). However, only 1025 articles (1021 from electronic search and 4 from snowballing) from the year 2013 to date were available in full texts. Table 1 shows the information sources and search strategies, which explains 1) the number of articles found by the electronic searches in each of the 9 databases; 2) the number of articles found by the snowballing technique.

3.3. Selection

The remaining 1025 papers were reviewed and selected by a single author, since this was an effective use of time and resources. After screening the search results, 43 papers were identified for further study (Fig. 1). The screening resulted in 46 papers being excluded due to duplication, 50 for being written in languages other than English and 835 articles were removed because they were not related to tailored digital gamification. Then after reading the last 94 articles, 18 articles were deleted because they did not provide first-hand data (such as a review study), 1 paper because it had not been peer-reviewed, and 32 because they were not in educational settings.

Table 1
Databases collection.

Search strategy	Number of articles found in the databases
Electronic searches	1021
SpringerLink[1]	26
Taylor & Francies Online[2]	18
Wiley Online Library[3]	15
SAGE Journals[4]	11
Web of Science[5]	5
JSTOR (Journal STORage)[6]	3
ScienceDirect (Elsevier)[7]	3
ProQuest[8]	2
Scopus[9]	938
Snowballing Reference lists	**4**
Total	1025

In March 2022, the author conducted the search and the search criteria for the nine databases were as follows: Searching in the title: (tailored OR tailoring OR tailor OR adaptation OR adaptive OR adapt OR adapting OR personalization OR personalize OR personalized OR personalizing OR recommend OR recommendation OR recommending OR recommended OR model OR modeling) AND (gamification OR gamified OR gamify OR gamifying). Searching in any field: AND (education OR school OR teaching OR learning).

[1] https://link.springer.com/.
[2] https://www.tandfonline.com/.
[3] https://onlinelibrary.wiley.com/.
[4] https://journals.sagepub.com/.
[5] https://clarivate.com/products/scientific-and-academic-research/research-discovery-and-workflow-solutions/webofscience-platform/.
[6] https://www.jstor.org/.
[7] https://www.sciencedirect.com/.
[8] https://www.proquest.com/.
[9] https://www.scopus.com/home.uri.

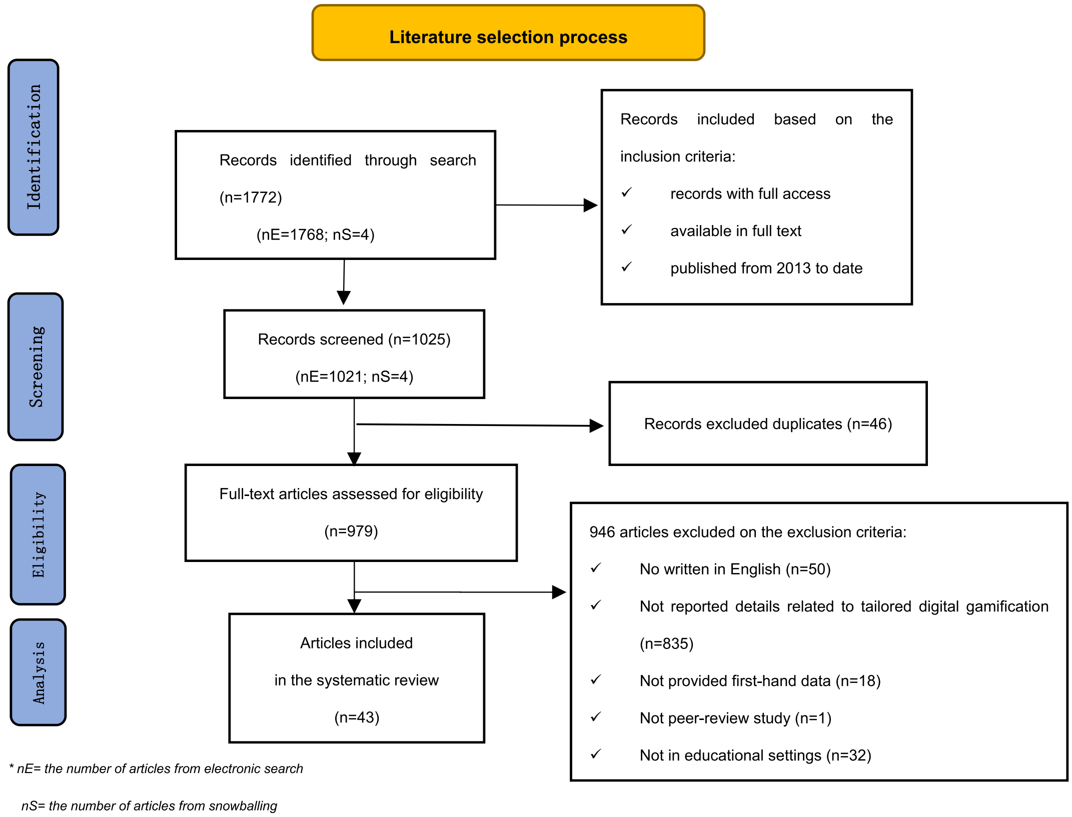


Fig. 1. Literature selection process.

Two co-authors were invited to evaluate the relevance and quality of the 43 identified articles according to the eligibility criteria. There was a 100% match in the inclusion and exclusion of articles by both raters. Ultimately, the manual selection resulted in 43 eligible papers for this systematic review study.

3.4. Data analysis

The data analysis included the categorization of both approaches and game elements. As shown in Table 4 of the Appendix, we adopted the taxonomy of Klock et al. (2020) and categorized the tailored approaches as personalization, adaptation, and recommendation. User modeling was also included since it is the basis of all three approaches. Personalization, adaptation and recommendation are all the implementation of tailored gamification using different kinds of user data. Personalization is a one-time adjustment of the system to satisfy people's needs and preferences based on user static data. Once the data is gathered, the user model is not changed. For example, users are provided with game elements based on their preferences collected in a questionnaire. Adaptation is a continuous adjustment of the system to satisfy people's needs and preferences, based on user dynamic data. It allows an up-to-date representation of users. For example, users are provided with various learning tasks based on their real-time performances. Recommendation uses information about user characteristics (e.g., age, gender) to suggest the elements and activities that are preferred and needed by people who had similar user characteristics (e.g., age, gender) in the past. It is similar to personalization in terms of data collection since they both rely on user static data. However, the difference is that recommendation also builds on existing data from other learners. It allows predictions about a user's needs and preferences even if there is not sufficient user data, since the user profiles have shown that other users with similar characteristics have certain needs and preferences. For example, YouTube recommends different videos to users of different ages. The implementation of all these three approaches depends heavily on the information contained in user profiles. User modeling is the process of creating user profiles by storing data about individuals, which is the preparation for tailored gamification. In this review study, articles on user modeling only described what information they can rely on to tailor their gamified class. However, since they did not conduct the class in practice, it is not yet clear what tailored approaches they would use.

In Table 5 of the Appendix, we applied the method of Toda et al. (2019) to group game elements for tailored gamification in education into five clusters: performance, personal, social, ecological, and fictional cluster. The authors of Toda et al. (2019) firstly standardized the concepts of 19 game elements and verified their relevance for educational settings through employing online surveys with gamification experts. The semantic analysis was used to evaluate the results of the surveys, which suggested that there was a high internal consistence among the experts regarding the description of the 19 game elements (Cronbach's Alpha> 0.8). Then 5 experts, classified the 19 game elements into 5 clusters. The game elements of 'performance' cluster provide information about users' performance in the gamified environment (e.g., reward, punishment); the 'personal' cluster is related to the learner who is using the gamified environment (e.g., personal goal); the 'social' one provides information about users' interaction in the gamified environment (cooperation, competition); the 'ecological' cluster provides users with the information about the gamified environment (e.g., time pressure); the 'fictional' one is a mixed dimension that is related to both the user (through narrative) and the environment (through storytelling), tying the users' experience with the context. Narrative refers to the larger story the user is working with and storytelling materializes this larger story with the aid of text, audio-visual and other sensorial stimuli to contextualize the narrative.

4. Results: studies overview

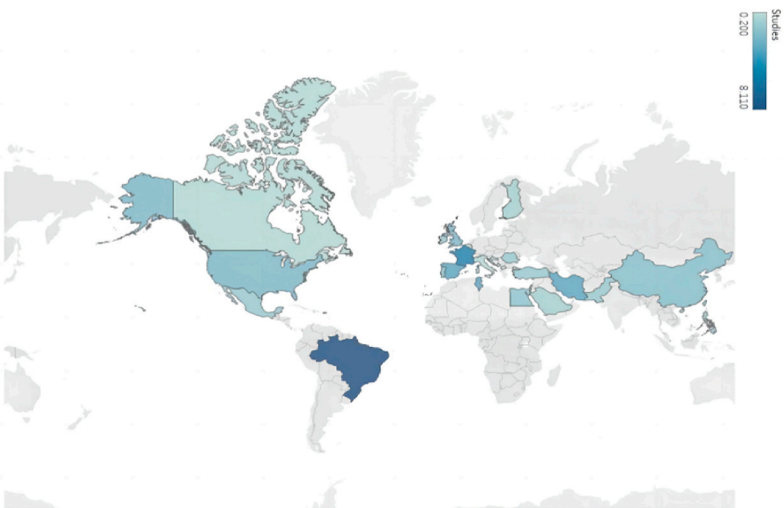
Tailored digital gamification is attracting global attention increasingly. As we can see in Fig. 2, compared with Asia (10.67), Europe assumed leadership in the number of publications with a total of 16.14 studies. On the other hand, South America, Africa, and North America contributed much fewer papers, and there were no publications found from Oceania. In terms of the authors' affiliation countries, Brazil (8.11) was the most published one, followed by France.

From the perspective of publication years, as shown in Fig. 3, the number of publications related to tailored digital gamification showed a fluctuating upward trend, with 2018–2021 witnessing the largest rise and the year 2021 reaching the top. It is worth mentioning that the decrease in 2022 could be not considered a trend, since this systematic review was conducted in the first half-year.

5. Results: approaches to tailor digital gamification in education

Table 4 of the Appendix gives an overview of the selected articles showing the approaches they employed in tailored digital gamified learning contexts. Table 2 calculates the number of publications using each tailored approach in this review study.

We can see that more than half studies (56%) focused on user modeling to explore what information could be collected to create personal user profiles. Even though it is a basis of tailoring gamified classes, the result implies that most articles in this review study only stayed in the preparation stages of tailoring, rather than concrete implementation in class (i.e., personalization, adaptation, recommendation). For example, Sezgin and Yüzer (2022) performed a four-round Delphi panel with twelve field experts and ultimately yielded a checklist of tailored gamification design principles for online courses. The authors stated that students' personal backgrounds, such as age, gender, education level, and learning styles, should be considered into user profiles when tailoring the gamified systems. However, this study did not include any further specification on whether and how the authors would tailor their classes.



Country	Studies
Brazil	8.11
France	5
Tunisia	3
Spain	3
Iran	3
United States	2
Britain	2
China	1.67
Portugal	1.33
Egypt	1.33
Israel	1
Romania	1
Philippines	1
Turkey	1
Ireland	1
Mexico	1
Pakistan	1
Singapore	1
Montenegro	0.8
Saudi Arabia	0.67
Croatia	0.67
Finland	0.64
Korea	0.33
Canada	0.25
Belgium	0.25
Italy	0.25
Macedonia	0.2

Fig. 2. Publication countries.

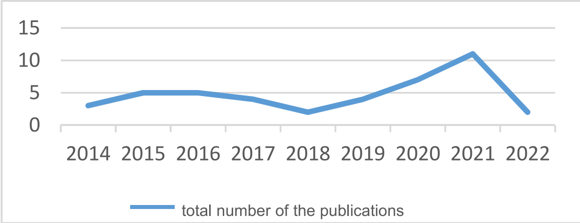


Fig. 3. Publication years.

Table 2
Tailored approaches.

Tailored approach	Studies	Total
User modeling (basis of the approaches)	Barata et al. (2015); Bennani et al. (2020); Codish and Ravid (2014); de la Peña et al. (2021); Dermeval et al. (2019); Dykens et al. (2021); Gil et al. (2015); González et al. (2016); Hammami and Khemaja (2019); Imre (2020); Klock, Gasparini, et al. (2015); Klock, da Cunha, et al. (2015); Knutas et al. (2019); Madrid and Jesus (2021); Monterrat et al. (2014); Monterrat et al. (2014b); Monterrat et al. (2015); Rodrigues et al. (2021); Santos et al. (2018); Santos et al. (2021); Sezgin and Yüzer (2022); Tenório, Dermeval, et al. (2020); Tenório et al. (2021); Zaric et al. (2017)	24 (56%)
Personalization	Abbasi et al. (2021); Buckley and Doyle (2017); Eder et al. (2021); Hallifax et al. (2020); Maher et al. (2020); Missaoui and Maalel (2021); Roosta et al. (2016); Shabihi et al. (2016)	8 (19%)
Adaptation	Daghestani et al. (2020); Hassan et al. (2021); Jagušt et al. (2018); Kolpikova et al. (2019); Maher et al. (2020); Missaoui and Maalel (2021); Monterrat et al. (2017); Rodríguez et al. (2022); Shi and Cristea (2016); Tan and Cheah (2021); Tenório, ChalcoChallco, et al. (2020); Xu et al. (2017)	12 (28%)
Recommendation	Su et al. (2016)	1 (2%)

5.1. Personalization

Table 2 shows that eight papers employed the personalized approach. It is a one-time adjustment, made according to students' user profiles that are determined by their static information (Klock et al., 2018). In the 'data sources' column, we show that students' static information could be collected using quantitative or qualitative methods, though quantitative methods were used more often. Several studies (i.e., Abbasi et al., 2021; Hallifax et al., 2020; Roosta et al., 2016; Shabihi et al., 2016) have explored various types of user profiles among students, like player types, personality traits, and motivation types, by using existing questionnaire modes quantitatively. For example, Hallifax et al. (2020) conducted two five-point Likert-scale questionnaire surveys to identify 258 participants' player and motivation types based on Hexad typology and Academic Motivational Scale before class. This study showed that combining these two types of student profiles for dual personalization reinforced the students' motivation for learning mathematics at a higher level better than using only one user profile.

Apart from the quantitative methods, in some cases, qualitative methods relying on the interview transcripts were employed. For example, Eder et al. (2021) conducted an in-depth interview in a high school to define students' play-persona by including information from aspects of their demographics, academic skills, preferences, and learning contexts. The interviews were recorded to transcribe the comments of the interviewees and this facilitated the qualitative analysis.

The 'analyze' column in Table 4 shows that the static information collected by questionnaire and interview studies in 'personalization' was usually analyzed according to the existing literature and the instructors' judgment. Roosta et al. (2016) relied on the Achievement Goal Questionnaire (AGQ) to assess students' motivation types. For example, students in the 'Mastery Approach' emphasized 'skill acquisition' according to goal-oriented theory (Elliot & Murayama, 2008). Therefore, if a student chose a high Likert scale for the questionnaire item 'My goal is to learn as much as possible', then he/she was more likely to be a 'Mastery approach' student in motivation type. Apart from the literature, instructors' judgments on students' learning needs (e.g., pain points, goals, and aspirations) also played an important role in analyzing student data in the interviews.

5.2. Adaptation

Table 2 shows that twelve papers employed adaptive approaches to tailor the digital gamified learning activities. Compared with personalization, adaptation involves continuous adjustment, according to students' user profiles determined based on their dynamic information (Klock et al., 2018). This approach was used more often in the studies included in this review since more researchers began to realize that the static information students give may be inaccurate or change over time. For example, Rodríguez et al. (2022) stated that students' inner (static) player type achieved by the validated questionnaire may evolve slightly during the experience. Therefore, they recalculated students' player types by using the matrix multiplication method according to students' behaviors (dynamic) to adapt the game elements at any given moment. The results showed it achieved a low error considering both situations: when the user accurately and inaccurately answered the player-type questionnaires. In the 'data sources' column for adaptation, students' dynamic information was collected in five ways: observation, login frequency, time spent on quizzes, attempts at quizzes, and quiz scores.

Additionally, the observation included students' game speed, game duration and gamified action traces when interacting with the systems, and also the times they asked for instructors' scaffolding.

Combining the 'data sources' column with the 'analyze' column in Table 4, we can see that students' dynamic information could be fully or partially adaptive. First, all the dynamic information on a student in a gamified system could be recorded as a portfolio and, based on this, students' user profiles could be identified according to the action trajectory (e.g., Daghestani et al., 2020; Hassan et al., 2021; Monterrat et al., 2017). In this way, all of the subsequent gamified activities provided to the individual student would be fully adaptive (Böckle et al., 2017). For example, Daghestani et al. (2020) created an adaptive gamified learning system using AI to respond to students' player types. In this system, the students' integrated histories of the gamified action traces were analyzed to determine their player types.

In some cases, students' dynamic information was collected in real-time, which meant that one action on their part would result in one response from the systems or instructors, in order to respond to their needs in a timely way (e.g., Kolpikova et al., 2019; Shi & Cristea, 2016; Tan & Cheah, 2021; Tenório, ChalcoChallco, et al., 2020; Xu et al., 2017). Since each adaptive activity only focuses on a single aspect of the students' profiles, this kind of adaptation is regarded as partially adaptive (Böckle et al., 2017). In the studies of Kolpikova et al. (2019), Tan and Cheah (2021), and Xu et al. (2017), students had access to the timely intervention 'hints', which either referenced a particular section within the course materials or hinted that they ask their instructors if they had difficulties in problem-solving.

5.3. Recommendation

Only one paper in Table 2 employed recommendation as an approach to tailor digital gamified learning activities. Recommendation uses information about user characteristics to suggest to students game elements and activities that are preferred by people who had similar user characteristics in the past (Adomavicius & Tuzhilintake, 2005). Su et al. (2016) created an intelligent gamifying learning recommender system based on students' learning styles to recommend learners for the next learning content. This recommender system used repertory grid technology (RGT) to give distinct learning unit recommendations to students with different

Table 3
Game elements in each game element cluster.

Game element cluster	Game element	Definition	Total
Performance	Reward	Anything given to the player to praise his/her actions or success in the challenge, which could reinforce students to keep and strengthen their behaviors for achieving more rewards	30
	Progress	It enables the players to locate themselves and their real-time progress and demonstrates their growth and improvement during the gamified process	27
	Feedback	It acknowledges the player for his/her inquiry and the correctness or wrongness of his/her learning activities to encourage or discourage a particular behavior	13
	Punishment	It is imposed when students give an incorrect answer or break the rule of the gamified activity	1
	Voting	The process of soliciting user feedback to guide the development or progression of the gamified system	1
Personal	Challenge	A variety of situations or activities that the students need to conquer or make efforts to deal with, in order to achieve the learning goals	26
	Customization	It provides students with personal experiences by assigning challenges that perfectly fit their skill level, adjusting learning tasks moderated based on player feedback, or allowing students to change the gamified environment by creating their own identities	13
	Goal	A specific, clear, and defined goal serves as a guideline for student actions, and they can see the direct impact of their efforts	10
	Free to fail	It creates a low risk of submission for the players	2
	Novelty	New, updated information presented to the player continuously. Some examples and synonyms are changes, surprises, updates	2
	Sensation	Use of player senses to create new experiences. Some examples and synonyms are visual stimulation, sound stimulation	2
Social	Competition	A conflict between players towards a common goal and prompts the players to perform better than others	26
	Socialization	Social network allows users to create their profiles, add friends and interact with each other in it; Scaffolding allows the users to support others or ask for support from others; Social status is based on the user's social influence, such as the number of followers in the social networks; Social pressure is the pressure through social interactions with other players	13
	Cooperation	When two or more players collaborate to achieve a common goal	8
	Reputation	Titles that the player accumulates within the game	2
Ecological	Access	An exclusive content conditioned to an action of the user to be available	8
	Choice	It gives the users the possibility to have multiple routes to success, allowing them to decide how to complete the learning tasks	8
	Time pressure	It requires the players to complete one task in a determined time	7
	Chance	Any probability to take certain actions or increase outcomes within a gamified activity	5
	Trading	It represents the transaction in the gamified system	4
	Rarity	Limited resources and collectables	2
Fictional	Narrative	Order of events where they happen in a game, which is influenced by the player's actions.	5
	Storytelling	It is the way the story of the game is told (as a script). It is told within the game, through text, voice, or sensorial resources.	8

learning styles and was proven to enhance students' learning motivation and outcomes.

6. Results: clusters of game elements to tailor digital gamification in education

Since 6 among 43 articles (2 user modeling studies, 1 adaptation study, 1 recommendation study, and 2 studies using both the personalization and adaptation) had no specific information related to the game elements they used, only the remaining 37 articles were analyzed. In Table 3, we can see that twenty-three game elements were found in this review study, of which 'reward' was the most used with 30 papers employing it (around 81%). Then we grouped these game elements into five clusters, namely, performance, personal, social, ecological, and fictional cluster. These clusters had their own characteristics and the use of them in each tailored approach differed slightly (Fig. 4).

6.1. Performance cluster of game elements

From Fig. 4, the performance cluster was the most used in all the three kinds of tailored approaches (95% used in user modeling, 100% used in personalization and adaptation), with more than 97% of articles in this review study including game elements of this kind. Five game elements, namely, reward, progress, feedback, punishment, and voting belong to it. These game elements in this cluster allow students to get an environment response from the tailored gamifying systems. Response could be instant feedback (e.g., Eder et al., 2021; Kolpikova et al., 2019), voting (Dykens et al., 2021), a reward or punishment for student performance (e.g., Barata et al., 2015; Jagušt et al., 2018), or an indicator of progress in the student's learning trajectory (e.g., Dykens et al., 2021; Roosta et al., 2016). For example, Eder et al. (2021) employed feedback and reward as the responses to students' actions in the tailored gamifying system. During the gamification process, a help button was available to give students instant hints when they encountered problems and if they solved a challenge successfully, they would be rewarded with a point. Roosta et al. (2016) used a progress bar in their environment to display learners' progress through the grades achieved from all the course quizzes.

Among these five game elements, reward was the most used one (around 81%), whereas punishment (around 3%) and voting (around 3%) were the least. There were two main purposes for reward. First, in some cases, teachers or researchers praised students' learning performance by using rewards such as points, badges, certificates, and trophies (e.g., Hallifax et al., 2020; Santos et al., 2018, pp. 42–51). For example, Hallifax et al. (2020) rewarded students' progress by giving them badges for a quiz depending on how much of the quiz they got right (bronze for 70%, silver for 85%, and gold for 100%). This reward was for achievement and behavior and was demonstrated to motivate students in math. Second, reward (e.g., points, virtual goods) could help stimulate student extrinsic motivation to keep and strengthen their behaviors in the 'game' by providing them with scaffolding items. For example, Buckley and Doyle (2017) rewarded participants with virtual goods that they could use for their next games. The initial endowment of virtual cash was distributed for good performance in forecasting problems presented by the prediction market and students were allowed to use them to get more values in the next round of tasks in this market.

6.2. Social cluster of game elements

The social cluster was the second most used one for user modeling. It is related to the interactions between the learners in the environment. The game elements included competition, socialization, cooperation and reputation, providing information about users' interactions. Of the articles in this review study, 73% used this kind of game elements. For example, Daghestani et al. (2020) allowed students to share their ideas and solutions with others in the chat forum. Santos et al. (2021) had group missions that enabled students to cooperate to allow everybody to reach the end. Daghestani et al. (2020) displayed leaderboards that included the best students in the interface to stimulate students to compete for high rankings.

Among these game elements, competition (around 70%) was the most common. Compared with challenge which represents a conflict between players and gamified systems, competition is a conflict between players to motivate them to win. The studies reviewed in this study, used leaderboards, where the status of players depends on the number of points they achieve (e.g., de la Peña

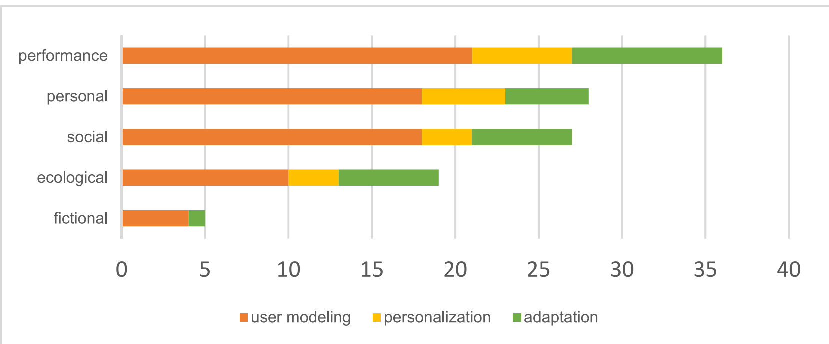


Fig. 4. Game element clusters in each tailored approach.

et al., 2021; Dermeval et al., 2019).

6.3. Personal cluster of game elements

The personal cluster as the second most used one in personalized approach (83%), involves six game elements totally, that is, challenge (around 70%), customization (around 35%), goal (around 27%), free to fail (around 5%), novelty (around 5%), and sensation (around 5%). The use of this cluster of game elements is directly related to characteristics of the learner using the environment. For example, Shabihi et al. (2016) defined clear goals as a guideline, which allowed students to see the direct impact of efforts and follow goals step by step. Hallifax et al. (2020) created a gamified activity, in which students could update their own avatars in different clothing or hold different items.

In this cluster, 'challenge' was the most often used for tailored gamification in learning (around 70%), with 26 among 37 papers applying it (e.g., Abbasi et al., 2021; Barata et al., 2015). First, in most cases, challenge was set up to assess and satisfy students' academic needs and learning goals, in the form of quizzes or tasks (e.g., Hammami & Khemaja, 2019; Klock, Gasparini, et al., 2015), puzzles or mysteries (e.g., Abbasi et al., 2021; Santos et al., 2021) and quests (e.g., Dykens et al., 2021; Hassan et al., 2021). For example, Hammami and Khemaja (2019) gave learning tasks to students who sensed a lack in their skills and were aiming to improve their competencies. Tan and Cheah (2021) assigned a difficulty value to the quizzes and presented them to the students in increasing order of difficulty. Students were allowed to choose them according to their learning abilities and seek help if necessary. Second, several studies used 'challenge' to assess and satisfy students' psychological needs. For example, Gil et al. (2015, pp. 568–572) required students to complete several assignments related to topics, working in different ways (alone, in pairs, or in teams) to identify their player types according to their actions. This study found that 'explorers' seldom spent time on assignments, while 'achievers' were motivated by this challenge. Mora et al. (2018, pp. 1925–1933) designed a game where students were assigned to different underwater stations with different exercises. For instance, A station was more competitive, while B was mostly collaborative. The decision was made according to students' player type questionnaire answers.

6.4. Ecological cluster of game elements

The ecological and social clusters tied for the second place in the adaptive approach. In this review study, 49% of articles used the game elements of the ecological cluster, including access, choice, time pressure, chance, trading, and rarity with access and choice with the highest frequency (both around 22%). The ecological cluster acts as a property of the environment that can be implemented in a subtle way to engage the users to follow the desired behavior (Toda et al., 2019).

Access is exclusive content conditioned to an action of the user to be available (Klock et al., 2020). For example, in the study of Kolpikova et al. (2019), when students completed some tasks in a sequence, then they would access external resources to consolidate their knowledge. Rodríguez et al. (2022) designed the Easter egg, which was a mechanism that can respond to the player's specific action and then unlock hidden content. The interface of this Easter egg consisted of an image that allowed access to a mini game when it was pressed five times in a row. In addition, choice gives the users a possibility to have multiple routes to success, allowing them to decide how to complete the learning tasks, which included two types, namely, optional choice (e.g., Kolpikova et al., 2019) and imposed choice (Daghestani et al., 2020; Gil et al., 2015, pp. 568–572; Xu et al., 2017). Optional choice allows students to decide whether to implement a task or not, which does not influence the game completion. For example, students can accept the 'hints and tips' given by the gamified systems or just skip them (Kolpikova et al., 2019). Imposed choice is the decision that the user is obliged to make for completing the learning tasks, which means that if they do not choose a particular option, they cannot continue the tasks. For example, Daghestani et al. (2020) allowed students to choose any challenges to nail the game levels.

6.5. Fictional cluster of game elements

The fictional cluster of game elements was the least used one in all the approaches in this study. According to our findings, only two game elements 'storytelling' and 'narrative' were used in the fictional cluster. Storytelling is the way to tell the story of the environment (as a script). In this review, it was told by textual (e.g., Dykens et al., 2021; Monterrat et al., 2014) or audio information (e.g., Santos et al., 2021). For example, Dykens et al. (2021) established the theme, history, and context of the gamified environment textually at the beginning of the learning activities, while Santos et al. (2021) played an audio message when students were going through a forest to prevent them getting lost. Narrative can be understood as the process in which users build their own experience through a given content, exercising their freedom of choice in a given space and period of time, bounded by the system's logic (Palomino et al., 2019). As a content element, it could help make the content itself interesting and motivate students to focus on the learning content.

7. Discussion

Tailored digital gamification aims to increase student motivation and performance by considering individual differences in digital gamified classes. The number of publications on tailored digital gamification in educational settings has significantly increased since 2018. In this systematic review study, we examined the use of tailored digital gamification by exploring: (1) the approaches to tailor digital gamification in education; (2) the clusters of game elements used in tailored digital gamification. These two descriptive research questions were expected to help enhance the understanding of 'how to tailor' in digital gamified classes and bridge the gap between the one-size-fits-all gamification and the tailored one.

7.1. Approaches to tailor digital gamification

Most of the selected studies only focused on exploring what information can be used to create personal user profiles by user modeling. Personalization, adaptation, and recommendation could tailor gamification in class, relying on students' static data (personalization), dynamic data (adaptation), and suggestions from people with similar user profiles (recommendation). From this literature review it appears that the use of user modeling was examined in more than half of the studies, which is similar to the finding of a previous review by Klock et al. (2020). Personalization and adaptation were the two most frequently used approaches when implementing tailored digital gamifying classes in these reviewed studies. Although user modeling is a very significant step towards tailoring gamification (Klock et al., 2020), our findings imply that most studies focus on preparation instead of implementation of tailored gamification in class. This result is understandable since tailored gamification for learning is a rather new topic. In this review study, the first article in this field was in 2014 and the number of publications was limited, until the years 2018–2021 witnessing the largest rise. The research needs to first prioritize user modeling to analyze what information could be used to tailor, therefore building a solid basis for its implementation in class. Additionally, a long process is needed from preparation to implementation of a new educational technology. Although user modeling promotes the understanding of components for tailoring gamification in general, teachers must consider their own educational contexts for practice (Amiel & Reeves, 2008). In this review, most empirical studies only implemented tailored gamification for a limited time to test its effectiveness. The time constraints might result in a failure to detect some practical problems that would occur when teachers implement it in their classes. In order to promote the use of tailored gamification, we recommend future researchers conducting more design-based research that systematically refines tailored gamification through iterative analysis and design (Fishman et al., 2013). It can produce contextual design principles that provide similar researchers and teachers with clear guidance and solutions, so as to facilitate its implementation.

7.1.1. Personalization and adaptation

Personalization and adaptation are the adjustments to students' user profiles that are determined based on their static and dynamic information, respectively (Klock et al., 2018). In these studies, the questionnaire was the most used instrument for the personalization approach to collect student static data. Yet, if the information students give through the questionnaires is unintentionally or deliberately inaccurate or evolves slightly over time, the follow-up gamification class activities sometimes cannot respond appropriately to students' real types of user profiles. As for the adaptation approach, it can provide a continuous adjustment according to their real-time performance and needs, so it is regarded as a more accurate approach than the personalized one. Yet, capturing students' dynamic information relies heavily on the automation of tailored gamification systems such as the one described by Hassan et al. (2021). To adapt gamified activities accurately, future research is recommended to develop more automatic systems, so as to achieve a prompt response to student behaviors and to avoid overburdening teachers and curriculum designers.

Furthermore, this review found that adaptation was more commonly employed than personalization, which meant that students' dynamic information was used slightly more often than the static information in these works. This finding differs from Hallifax et al. (2019, pp. 294–307) who found that most tailored systems worked statically and there was more to be explored in the domain of students' dynamic information. This difference might be explained by a variety of reasons. First, this current study included almost twice as many articles as Hallifax et al. (2019, pp. 294–307) and thus it is possible to obtain different results. Second, there have been more studies of user modeling since the year 2020, which help create more useful automatic tailored gamification systems for teachers or researchers to use. For example, Tenório, Dermeval, et al. (2020) designed a gamification analytics model by integrating each key concept of tailored gamification for teachers. It enabled them to monitor students' interaction with the game elements easily to classify students and it also adapted the gamified missions to motivate students. Then Tenório, ChalcoChallco, et al. (2020) applied this existing gamified adaptive learning system in class to collect and analyze students' behaviors automatically. Third, more and more researchers believe that students' personal characteristics might change during gamified activities, so it is better and more accurate to identify their profiles in the process of a 'game', rather than before a 'game' (e.g., Hassan et al., 2021; Tan & Cheah, 2021).

In the selected studies, we found two articles using personalization and adaptation simultaneously (Maher et al., 2020; Missaoui & Maalel, 2021). They tailored digital gamification according to students' user profiles that were determined based on both their static and dynamic information. The two studies in this review indicate that the combination of personalization and adaptation approaches has a potentially positive impact on student learning outcomes and motivation. Extracting static and dynamic student data simultaneously could allow curriculum designers and teachers to understand individual differences comprehensively and thus to create highly efficient student profiles. Not only can the gamified system collect students' static data such as age and gender that might influence their preferences, but it can also provide insight into how they behave while 'gaming', such as their game duration and speed. This could help reveal to what extent learners are engaged and allow the gamification activities to be effectively modified according to student preferences and needs during the gamified activities. However, the combination of the personalized and adaptive approaches was used in two studies only, which means more research is needed to capture diverse student data in the tailored digital gamified systems (e.g., questionnaire answers, login data, gamified action traces, behavior and interaction with the environment and others) to identify the effects of single and combined approaches on student learning performances. Recent studies using data mining (e.g., Imre, 2020) and machine learning (e.g., Rodrigues et al., 2021) provide a good opportunity to evaluate student data and analyze their performance in tailored gamifying learning contexts.

7.1.2. Recommendation

Recommendation was the least used approach in tailored digital gamified classes in the articles reviewed in this study. A recommendation system recommends gamified activities that most people who have similar profiles have often taken before. We found that it received little attention in the reviewed research regarding tailored gamification, with only Su et al. (2016) reporting this approach. A possible reason for this may be the lack of empirical studies in educational settings and the need for sufficient student data to establish a 'user profile type - preferred gamified activity database. Nevertheless, this approach was found to improve the learning motivation and outcomes of different students with various learning styles (Su et al., 2016). Additionally, the widespread use of recommendation systems in the marketing domain, such as the 'guess you like' system from Amazon, has boosted consumer purchasing considerably, reflecting its great potential to improve user motivation (Xu & Tang, 2015).

7.2. Game element clusters

The literature review revealed twenty-three game elements, with reward the most used when tailoring digital gamification. Rewards could be given to players to praise their actions and success such as points, credits, and badges, or given to scaffold them for the next round of the game such as virtual goods. When it comes to the game elements in each cluster, we can see that reward and challenge were the most used performance and personal elements, respectively. Competition was the most used game element of the social cluster. Access and choice shared the largest proportion of ecological game elements. In the fictional cluster, the number of narrative and storytelling game elements equaled. A clear understanding of the clusters of game elements allows an easier selection of them, therefore contributing to the success of tailored gamification classes, even to the development of using tailored approaches in other 'game' related areas, such as serious educational games and game-based learning. Even though serious educational games and game-based learning present fully fledged games, which differ from gamification (Deterding et al., 2011), all these concepts share the idea of using positive gameful experiences to educate and thus the use of game elements are all necessary in these three learning contexts (Krath et al., 2021).

Besides, it was clear from the literature review that the performance cluster was the most used in each of the tailored approaches, which meant that most studies on tailored digital gamification in this review study focused on giving students instant responses to their actions. This result provides cues on the design of the future gamified systems whatever tailored approaches they use, by highlighting the importance of the interaction between the systems and players. As Toda et al. (2019) stated the performance cluster must always be present so users can get feedback on their actions and thus enhance their engagement in the gamified systems they are using.

On the other hand, the fictional cluster was the least applied. The lack of it may cause the learning context to lose its meaning, which is, why students must take actions within the gamified system, therefore directly influencing the quality of the tailored user experiences (Toda et al., 2019). This finding is consistent with that of Palomino et al. (2019) who state that it is not common to consider the fictional cluster when designing and using a gamified environment. According to Toda et al. (2019), one possible reason for its uncommon use is that there is no clear differentiation between narrative and storytelling, causing the fictional cluster to be often misunderstood and underused. Both narrative and storytelling are necessary for the fictional cluster, but most existing frameworks of gamification see narrative as the same as storytelling, which means that they often only use storytelling and seldom include narrative elements when attempting to use the fictional cluster (i.e., Dykens et al., 2021; Monterrat et al., 2014; Tenório, Dermeval, et al., 2020b; Zaric et al., 2017).

In addition, we found that only four articles reported on all five clusters when preparing and implementing tailored digital gamification. Toda et al. (2019) stated that each cluster is associated with one aspect of the gamified environment and all of them are important for enhancing student motivation during gamified classes. However, few empirical studies have examined whether integrating all of them would lead to a higher level of learning motivation and performance. We would therefore encourage more empirical research on the impact of using all the game element clusters when tailoring gamification for learning.

8. Limitations and future research

We would like to mention three limitations of this review study and suggestions for future research that address these limitations. Firstly, it is noteworthy that a significant proportion (more than 50%) of the reviewed articles in this study did not mention the educational level of the students who participated. Most studies were aimed at university students, leaving insufficient information for gamification with students at other levels, particularly primary school students. Information about the educational level in which gamification has been implemented could allow researchers to delve deeper into related fields and provide teachers in different learning contexts with empirical foundations to design and implement their pedagogical strategies for gamified classes.

Secondly, most selected articles focused on the preparation of tailored digital gamification rather than its implementation. To bridge the gap between preparation and implementation, we suggest future researchers conduct design-based studies to develop and evaluate tailored gamification as part of teachers' instructional practice. In this way, more information will be available about teachers' considerations about approaches and game elements, how they implement these in their teaching, and how stakeholders evaluate gamified classes. In addition, experimental designs with non-tailored gamification classes as comparisons might help to examine the student outcomes in a rigorous way. As stated by Wei et al. (2021), the assessment of learning outcomes plays an essential role in the evaluation of students' actual achievements and the effectiveness of teaching practices. In these experimental research designs, not only approaches and combinations of game elements of gamified classes can be examined, but also the relative effect of each game element by comparing outcomes in student groups in which game elements are varied.

Third, our study focuses mainly on describing the tailored approaches and the game elements in digital gamified educational contexts. Although information about approaches and elements is a necessary step for understanding how to tailor digital gamified classes, the motivating effects of each game element on each student type must be also considered since individual needs and preferences are key to tailor. To maximize the potential of tailored digital gamification for student learning, we thus recommend that future research explore the relationship between student types and the game elements, which can provide a solid theoretical foundation for developing tailored digital gamifying systems, and thus facilitate the use of this innovative teaching method. In recent years, some frameworks and typologies have been proposed to differentiate students from different perspectives, such as the Hexad typology for student player types, Big Five model for student personality traits, and Felder & Silverman model for student learning styles. These frameworks and the clear definitions of various game elements provide a great possibility to build the relationship between each student type and each game element, therefore supporting the gamification users to design tailored digital educational environments capable of satisfying student individual needs and preferences.

9. Conclusion and practical implications

This systematic review study examined 43 articles and investigated the application of tailored digital gamification in the educational context. Three approaches, namely, personalization, adaptation, and recommendation, were employed to implement tailored digital gamification in class, with user modeling as their basis. Furthermore, this study characterized game elements using five clusters: performance, social, personal, ecological, and fictional, with the performance and fictional one as the most and least frequently used in all tailored approaches, respectively. This review identified the combined application of personalized and adaptive approaches in two selected articles, which expands upon the research focus of Klock et al. (2020) on the types of tailored approaches in gamified learning. These findings hold some implications for teachers who would like to gamify their classes.

First, teachers should introduce tailored digital gamification comprehensively along with illustrative examples (e.g., videos of tailored gamification lessons) before their class, because tailored digital gamification is a new technology and has not been widely adopted for learning. Furthermore, the implementation of three tailored approaches relies heavily on user modeling to create individuals' user profiles. Therefore, students' acceptance of collecting their personal data is of great importance for teaching effectiveness. Before class, teachers need to provide students with insight into this approach and enable them to understand why their personal data is being collected. Secondly, as shown in our study, automatic systems could adapt suitable gamified activities by identifying students' real-time needs and preferences. Without the pressure to design tailored tools themselves, teachers can focus on the content students should learn. Since the gamification in class is aimed at 'learning' rather than 'entertainment', the potential of tailored gamification can be maximized by tailoring both game elements and learning content. Thirdly, during class, teachers should give scaffolding and instant feedback to students. Our results show that game elements of performance cluster were applied in almost all of the selected studies. It implies that immediate responses to students are important for their engagement in class, regardless of teachers' tailored approach. Teachers need to pay close attention to students' actions, especially if they encounter difficulties in using gamified systems.

CRediT authorship contribution statement

Yujia Hong: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Visualization, Writing – original draft, Writing – review & editing. **Nadira Saab:** Conceptualization, Formal analysis, Methodology, Project administration, Supervision, Writing – review & editing. **Wilfried Admiraal:** Conceptualization, Formal analysis, Methodology, Project administration, Supervision, Writing – review & editing.

Data availability

Data will be made available on request.

Appendix

Table 4
An overview of tailored approaches for digital gamification in the studies reviewed

Authors(year)	Country	Discipline	Educational level	Tailored approach	Data sources	Analyze	Research description
Barata et al. (2015)	Portugal	Engineering	University	Modeling	Observation	Machine learning	Player type-based gamification model
Bennani et al. (2020)	Tunisia	No info	No info	Modeling	Observation	Literature	AGE-Learn ontology program
Codish and Ravid (2014)	Israel	Industrial management and engineering		Modeling	Questionnaire	Literature	Personality-based gamification model
de la Peña et al. (2021)	Spain	Science, education, business management and economy, technical sciences and engineering	University	Modeling	No info	Scientific triangulation methodology	Player type-based Distance learning gamification model
Dermeval et al. (2019)	Brazil, Canada	No info	University	Modeling	Observation	Automated reason	GaTO ontology program
Dykens et al. (2021)	USA	No info	No info	Modeling	No info	No info	Unified gamification and motivation model
Gil et al. (2015)	UK	Computer science	University	Modeling	Questionnaire, observation	Literature	Player type-based model
González et al. (2016)	Spain	No info	No info	Modeling	User data, observation: login times, game duration, gamified action traces	Data mining	Gamified intelligent tutorial system based on students' multiple characteristics
Hammami and Khemaja (2019)	Tunisia	System and Data Integration	University	Modeling	Observation	Agile methodology	Skill, competency and learning goal-based model
Imre (2020)	Romania	Computer science	No info	Modeling	No info	Data mining	Ontology based automatic gamified program
Klock, Gasparini, et al. (2015)	Brazil	No info	No info	Modeling	Observation, form, survey, user data, interview	Human-computer interaction	Adapt Web program
Klock, da Cunha, et al. (2015)	Brazil	Computer science	University	Modeling	Questionnaire	Literature	Adapt Web program
Knutas et al. (2019)	Finland, Belgium, Italy	No info	No info	Modeling	Survey	Literature	Player type-based model
Madrid and Jesus (2021)	Philippines	No info	No info	Modeling	No info	Literature	Player type-based model
Monterrat et al. (2014)	France	No info	No info	Modeling	Observation	Machine learning	Player type-based model
Monterrat et al. (2014b)	France	No info	No info	Modeling	User data, observation	Trace analysis	Tailored gamified system based on multiple characteristics
Monterrat et al. (2015)	France	No info	No info	Modeling	Test, questionnaire	Linear relation	Player type-based model
Rodrigues et al. (2021)	Brazil, Canada	No info	No info	Modeling	Questionnaire	Machine learning (decision tree)	Automated tailoring gamified system model

Authors(year) Country Discipline Educational level Tailored approach Data sources Analyze Research description

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Table 4 (*continued*)

Authors(year)	Country	Discipline	Educational level	Tailored approach	Data sources Analyze Research description		
Santos et al. (2018)	Brazil, Canada	No info	No info	Modeling	Observation	Statistical tests (Shapiro-Wilk, Kolmogorov-Smirnov, Skewness, Kurtosis)	Player type-based model
Santos et al. (2021)	Brazil, Finland	No info	No info	Modeling	Survey	Storyboard	Player type-based model
Sezgin and Yüzer (2022)	Turkey	Education	University	Modeling	Delphi panel	Content analytics	Design principles in tailored online course
Tenório, Dermeval, et al. (2020)	Brazil	No info	No info	Modeling	Observation	Literature	Gamification analytics model
Tenório et al. (2021)	Brazil	No info	No info	Modeling	Observation	Literature	Gamification analytics model
Zaric et al. (2017)	Montenegro, Macedonia	No info	University	Modeling	Questionnaire	Literature	Learning style-based model
Abbasi et al. (2021)	Iran	Math	High school	Personalization	Questionnaire	Literature	Motivation and personality trait-based pretest-posttest experimental study
Buckley and Doyle (2017)	Ireland	Accounting and finance	University	Personalization	Questionnaire	No info	Learning style and personality trait-based experimental study
Eder et al. (2021)	Mexico	No info	High school	Personalization	Interview	Instructors' judgment, literature	Player-Persona-based case study
Hallifax et al. (2020)	France	Math	High school	Personalization	Questionnaire	Literature	Player type and motivation type-based comparative study
Maher et al. (2020)	Egypt	No info	No info	Personalization	User data, observation: gamified action traces	Learning analytics	Experimental study based on students' multiple characteristics
Missaoui and Maalel (2021)	Tunisia	No info	No info	Personalization	Registration Form, questionnaire, observation: gamified action traces	Machine learning	Case study about SPOnto ontology based on students' multiple characteristics
Roosta et al. (2016)	Iran	Language	University	Personalization	Questionnaire	Literature	Motivation type-based experimental study
Shabihi et al. (2016)	Iran	Language	University	Personalization	Questionnaire	Literature	Two personality trait-based personal experimental studies
Daghestani et al. (2020)	Saudi Arabia, Egypt	Data structure	No info	Adaptation	Observation: gamified action traces	Data mining	AI-enabled gamified case study based on students' player type in BrainHex typology
Hassan et al. (2021)	Pakistan	Math	No info	Adaptation	Observation: gamified action traces	Instructors' judgement, literature	FSLSM Learning style-based experimental studies
Jagušt et al. (2018)	Croatia, Korea	Math	Elementary	Adaptation	Game score, observation: gamified action traces	No detailed-algorithm	Comparative study based on students' timely behaviors and performances
Kolpikova et al. (2019)	USA	Biology	University	Adaptation	Quiz score, observation: scaffolding times	Instructors' judgment	Comparative study about adaptive pre-class quizzes based on students' timely behaviors and performances
Authors(year)	Country	Discipline	Educational level	Tailored approach	Data sources Analyze Research description		

(*continued on next page*)

Table 4 (*continued*)

Authors(year)	Country	Discipline	Educational level	Tailored approach	Data sources	Analyze	Research description
Maher et al. (2020)	Egypt	No info	No info	Adaptation	User data, observation: gamified action traces	Learning analytics	Experimental study based on students' multiple characteristics
Missaoui and Maalel (2021)	Tunisia	No info	No info	Adaptation	Registration Form, questionnaire, observation: gamified action traces	Machine learning	Case study about SPOnto ontology based on students' multiple characteristics
Monterrat et al. (2017)	France	Language	Secondary school	Adaptation	Observation: gamified action traces	Linear variation	BrainHex Player type-based exploratory study
Rodríguez et al. (2022)	Spain	No info	Secondary school	Adaptation	Observation: game speed, game duration, gamified action traces	Matrix multiplication method	Experimental study based on students' player type
Shi and Cristea (2016)	UK	Computer science, management	University	Adaptation	Observation: gamified action traces	Literature	SDT Motivation type-based gamified case study
Tan and Cheah (2021)	Singapore	Physics	University	Adaptation	Quiz score, time spent in quizzes, attempts for quizzes, login frequency,	Instructors' judgment, literature	AI-enabled gamified case study based on students' timely behaviors and performances
Tenório, ChalcoChallco, et al. (2020)	Brazil	Gamification in education	No info	Adaptation	Observation: gamified action traces	Literature	Case study about a gamification analytics tool based on students' class timely behaviors and performances
Xu et al. (2017)	China, Portugal	Computer science	University	Adaptation	Observation: bullet and shake requests for stating questions and help	Instructors' judgement, literature	Gamified case study based on students' timely behaviors and performances
Su et al. (2016)	Taiwan (China)	Math	No info	Recommendation	No info	Delphi method	A learning style-based recommendation system used experimental study

Table 5
An overview of game element clusters for tailored digital gamification in the studies reviewed

Authors(year)	Tailored approach	Game element clusters	Game elements	Game mechanics
Barata et al. (2015)	Modeling	Performance	Reward	Point, badge
			Progress	Level, leaderboard
		Ecological	Time pressure	
		Social	Competition	Leaderboard
		Personal	Challenge	Task
Bennani et al. (2020)	Modeling	No info	No info	No info
Codish and Ravid (2014)	Modeling	Performance	Reward	Point, badge
			Progress	Leaderboard, progress bar
de la Peña et al. (2021)	Modeling	Performance	Reward	Point
			Progress	Card, point, level
		Ecological	Access	External resource, power
			Chance	
		Social	Competition	Point, leaderboard (scoreboard, comparison table)
			Cooperation	
		Personal	Customization	
Dermeval et al. (2019)	Modeling	Performance	Reward	Badge, point
			Progress	Level
			Feedback	
		Social	Competition	Point, leaderboard
		Personal	Customization	Avatar
			Challenge	Boss fight
Dykens et al. (2021)	Modeling	Performance	Reward	Badge, gift, award
			Progress	Progress tracker, badge
			Voting	
		Social	Competition	Leaderboard
			Socialization	Social comparison
		Personal	Customization	Player generated content, task complexity
			Challenge	Quest, solution identification & application
		–	Storytelling/story	Avatar
Gil et al. (2015)	Modeling	Performance	Reward	Point, badge, certificate, gift
			Progress	Level
		Ecological	Choice	
			Economy/trading	
			Access	
		Social	Competition	Point
			Socialization	Social status, social networking, social discovery, mutual help and sharing
			Cooperation	Teamwork
		Personal	Challenge	Assignment, quest
González et al. (2016)	Modeling	Performance	Reward	
			Progress	
		Ecological	Access	
		Personal	Challenge	
Hammami and Khemaja (2019)	Modeling	Performance	Reward	Point
		Ecological	Choice	
		Social	Competition	Point, leaderboard
			Cooperation	
		Personal	Goal	
			Customization	Role
			Challenge	Task
Imre (2020)	Modeling	Performance	Reward	Point, badge
			Progress	Level
			Feedback	
		Social	Competition	Leaderboard
		Personal	Challenge	
		Fictional	Storytelling/story	
			Narrative	
Klock, Gasparini, et al. (2015)	Modeling	Performance	Reward	Point, badge
			Progress	Progress bar, level

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Table 5 (*continued*)

Authors(year)	Tailored approach	Game element clusters	Game elements	Game mechanics
		Social	Competition	Point, ranking
		Personal	Challenge	Task
Klock, da Cunha, et al. (2015)	Modeling	Performance	Reward	Badge, goods
			Progress	Level, leaderboard
		personal	Customization	
			Challenge	
Knutas et al. (2019)	Modeling	Performance	Reward	Point, badge
		Social	Competition	
			Socialization	
			Cooperation	
		Personal	Challenge	
Madrid and Jesus (2021)	Modeling	Performance	Reward	Point
			Progress	Milestone
		Ecological	Economy/trading	Badge
		Social	Socialization	Social status
		Personal	Customization	Avatar
			Challenge	Quest
		Fictional	Storytelling/story	
			Narravitve	
Monterrat et al. (2014)	Modeling	Performance	Feedback	Tooltip
		Social	Competition	Leaderboard
			Socialization	Tip, social network, chat
		Personal	Customization	
			Goal	
			Challenge	Badge, cup
		–	Storytelling/story	
Monterrat et al. (2014b)	Modeling	Social	Competition	Leaderboard
			Socialization	Share button
Monterrat et al. (2015)	Modeling	Performance	Reward	Point
			Progress	Avatar
		Ecological	Access	
			Time pressure	Timer
		Social	Socialization	Tip
			Competition	Leaderboard
Rodrigues et al. (2021)	Modeling	Performance	Reward/acknowledgement	Point
			Progress	Level
		Ecological	Choice	
			Chance	
			Rarity	
			Time pressure	
			Economy/trading	
		Social	Competition	
			Socialization	Social pressure
			Reputation	
			Cooperation	
		Personal	Free to fail/renovation	
			Novelty	
			Sensation	
			Goal/objectives	
			Challenge	Puzzle
		Fictional	Storytelling/story	
			Narrative	
Santos et al. (2018)	Modeling	Performance	Reward	Point, badge, trophy
			Progress	Progress bar, level
		Social	Competition	Ranking
		Personal	Customization	Avatar
Santos et al. (2021)	Modeling	Performance	Reward	Point, trophy
			Progress	Level, progress bar, stats
		Ecological	Choice	
			Chance	
			Rarity	
			Time pressure	
			Economy/trading	
		Social	Competition	

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Table 5 (*continued*)

Authors(year)	Tailored approach	Game element clusters	Game elements	Game mechanics
Authors(year)	Tailored approach	Game element clusters	Game elements	Game mechanics
			Socialization	Social pressure
			Reputation	Title
			Cooperation	
		Personal	Free to fail/renovation	
			Novelty	
			Sensation	
			Goal	
			Challenge	Puzzle
		Fictional	Storytelling/story	
			Narrative	
Sezgin and Yüzer (2022)	Modeling	No info	Info	No info
Tenório, Dermeval, et al. (2020)	Modeling	Performance	Reward	Point, badge
			Progress	Level
			Feedback	
		Social	Competition	Leaderboard
		Personal	Challenge	
		–	Storytelling/story	
Tenório et al. (2021)	Modeling	Personal	Customization	
			Goal	
			Challenge	Mission
Zaric et al. (2017)	Modeling	Performance	Reward	Badge
			Progress	Progress bar
			Feedback	
		Ecological	Time pressure	
		Social	Competition	
		Personal	Challenge	
		–	Storytelling/story	
Abbasi et al. (2021)	Personalization	Performance	Reward	
			Progress	Map
			Feedback	
		Personal	Challenge	Puzzle
Authors(year)	Tailored approach	Game element clusters	Game elements	Game mechanics
Buckley and Doyle (2017)	Personalization	Performance	Reward	Point, badge, virtual goods
		Ecological	Access	
		Social	Competition	Leaderboard
			Cooperation	
			Socialization	Social network
		Personal	Customization	
			Goal	
			Challenge	
Eder et al. (2021)	Personalization	Performance	Reward	Point
			Feedback	
		Social	Competition	
		Personal	Customization	Avatar
			Challenge	
Hallifax et al. (2020)	Personalization	Performance	Reward	Point, badge
			Progress	Level
		Ecological	Time pressure	Timer
		Social	Competition	Point, badge, leaderboard
		Personal	Customization	Avatar
Maher et al. (2020)	Personalization	No info	No info	No info
Missaoui and Maalel (2021)	Personalization	No info	No info	No info
Roosta et al. (2016)	Personalization	Performance	Progress	Progress bar
			Feedback	
Shabihi et al. (2016)	Personalization	Performance	Reward	Point, badge
			Progress	
			Feedback	
		Personal	Goal	
Daghestani et al. (2020)	Adaptation	Performance	Reward	External resources
			Progress	
		Ecological	Choice	
			Access	
		Social	Competition	Leaderboard
			Socialization	Forum chatting
Authors(year)	Tailored approach	Game element clusters	Game elements	Game mechanics
		Personal	Goal	Navigation interface
			Challenge	

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Table 5 (*continued*)

Authors(year)	Tailored approach	Game element clusters	Game elements	Game mechanics
Hassan et al. (2021)	Adaptation	Performance	Reward	Point, badge
			Progress	Progress bar, level
			Feedback	
		Social	Competition	Leaderboard
		Personal	Challenge	
Jahušt et al. (2018)	Adaptation	Performance	Reward	Point
			Punishment	Point
		Ecological	Time pressure	
		Social	Competition	
		Personal	Goal	
			Challenge	Fight
		Fictional	storytelling/story	Avatar
			Narrative	
Kolpikova et al. (2019)	Adaptation	Performance	Reward	Point
			Feedback	Hint
		Ecological	Choice	
Maher et al. (2020)	Adaptation	No info	No info	No info
Missaoui and Maalel (2021)	Adaptation	No info	No info	No info
Monterrat et al. (2017)	Adaptation	Performance	Progress	Level
		Ecological	Choice	
			Access	New task
		Social	Competition	Leaderboard
Rodríguez et al. (2022)	Adaptation	Performance	Reward	Point, badge
			Progress	Level
		Ecological	Access	Mini-game, Easter egg
			Chance	Lottery, development pool
		Social	Competition	Leaderboard
			Cooperation	

Authors(year)	Tailored approach	Game element clusters	Game elements	Game mechanics
			Socialization	Social network, social status
		Personal	Challenge	
Shi and Cristea (2016)	Adaptation	Performance	Feedback	Reminder system
			Progress	
		Ecological	Choice	
			Access	
			Chance	
		Social	Competition	
			Socialization	
		Personal	Goal	
			Challenge	
Tan and Cheah (2021)	Adaptation	Performance	Reward	Point
			Progress	Progress bar
			Feedback	Hint
Tenório, ChalcoChallco, et al. (2020)	Adaptation	Personal	Goal	
			Customization	
			Challenge	Mission
Xu et al. (2017)	Adaptation	No info	No info	No info
Su et al. (2016)	Recommendation	No info	No info	No info

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