Beyond One-Size-Fits-All: A Systematic Literature Review of Adaptive Gamification Strategies and Frameworks in the Age of AI

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Abstract. Adaptive gamification tailors gamified systems to individual users' characteristics and preferences to improve their effectiveness. Despite growing research interest, the field still lacks a cross-domain, multi-dimensional synthesis that reflects recent methodological and technological advances. Following the PRISMA guidelines, this systematic review examines studies on adaptive gamification published between January 2019 and December 2025, addressing the outcomes sought through adaptivity, the theoretical frameworks underpinning it, the game elements most frequently adapted, the adaptive strategies employed, and the limitations reported. The review is deliberately scoped to gamification proper, that is, to the tailoring of game elements applied to non-game contexts, rather than to the adaptation of full serious games or playful learning environments. Searching five academic databases (Web of Science, Scopus, IEEE Xplore, ScienceDirect and the ACM Digital Library) yielded 680 records, of which 39 met the inclusion criteria. Education was the dominant application domain (61.5%), and motivation (36.7%), engagement (22.8%), and performance (13.9%) were the most sought-after outcomes. The Hexad Player Types framework (25.4%) and Self-Determination Theory (19.7%) were the most common theoretical foundations, while points, badges, and leaderboards dominated the adapted elements, together accounting for 35.2% of all coded adaptations. Machine learning-based personalisation (33.3%) was the most frequent adaptive strategy, although static implementations remained prevalent. Notably, recommendation algorithms and large language models were almost entirely absent, despite their evident relevance. These findings indicate that adaptive gamification is maturing, yet significant

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gaps persist, particularly in the diversity of adapted game elements and the integration of emerging AI-driven personalisation.

Keywords: Adaptive gamification · Literature review · Algorithms · Rewards · Theoretical frameworks

1 Introduction

Gamification, broadly defined as the implementation of game elements and mechanics in non-game contexts to achieve a more game-like experience [7], has been recognised as a strategy for enhancing users' engagement, motivation and behavioural outcomes over a wide range of domains.

From its early theorisation to its current extensive adoption, gamification design has evolved, supported by a growing empirical body of evidence demonstrating its potential effectiveness [18,27,28,34]. Yet, despite this progress, the field continues to hold limitations that persist to this day, constraining the real-world impact of gamified applications [1,6,13].

Among those limitations, one that has been widely acknowledged is the *one-size-fits-all* approach [16,43], which implies adopting the same game elements, reward structure and progression mechanics, without taking into account individual differences, which can be due to personality traits, motivation, prior experience, or contextual factors, among others.

Scientific literature has broadly documented the consequences of this design approach: users who don't relate to the game elements and strategies adopted in the gamification design tend to lose motivation, feel less engaged and eventually drop out, thwarting the efficacy of the gamified solution [1,6,23].

An interesting strategy to address this limitation is represented by the implementation of adaptive gamification strategies. By *adaptive gamification strategies*, we mean an approach that aims to tailor the gamification design elements, like reward types or interaction modalities, among others. To craft an adaptive gamified system, a variety of approaches can be adopted, ranging from player-type profiling to fully data-driven personalisation [9]. In recent times, the improvements in artificial intelligence and machine learning offer an improved toolkit to implement such adaptive strategies, thus representing a turning point in the development of adaptive gamification.

Even though several recent literature reviews explored the adaptive gamification research field, it can be observed that the majority of these reviews were mostly focused on the educational field [9,10,35,37,43,44], or on specific technical aspects of adaptivity [37,41] or on users' profiling [26,42], without offering a comprehensive view of the field.

This paper addresses this gap in the literature through a systematic literature review (SLR) of adaptive gamification research, to map the current state of the art of adaptive gamification, while also highlighting the open challenges and new directions to be explored to guide future research.

The review is deliberately scoped to gamification, understood as the application of game elements to non-game contexts [7], and does not cover adjacent traditions such as personalised game-based learning, player modelling, or dynamic difficulty adjustment [17], which adapt the game itself rather than elements added to a non-game activity; this boundary is revisited in Sect. 5.

2 Related Work

As already mentioned in the previous paragraph, the adaptive gamification approach emerges as an answer to the need to design gamified systems capable of tailoring game elements, reward structure, or interaction modalities to individual users' preferences [3,14].

Advancements in technologies, especially in AI and machine learning fields, have shaped the contemporary scenarios of adaptive gamification. The first attempt in adaptive gamification design relied mostly on customisation based on static, rule-based mechanisms, built based on the results of pre-assessment questionnaires, administered to users at the beginning of the experience [11]. While these approaches were relatively inexpensive, they had, and still have, a limited ability to adapt to dynamic changes in user preferences over time.

Technologies like AI and machine learning have opened new possibilities for dynamic, data-driven adaptation. Reinforcement learning allows the system to learn, through repeated interactions, which game elements are more effective based on users' behavioural feedback [22,33]. Recommendation algorithms, mostly used in commercial recommendation systems [15,29], can also represent an interesting technical tool to further develop the possibilities of adaptive gamification [39,40]. In more recent times, the emergence of Large Language Models (LLMs) has opened new avenues for experimentation [19]. In this regard, the period between 2019 and 2025 is particularly significant. In fact, it comprises both the strengthening of machine learning as a personalisation tool [15,29] and the rise of generative AI [4,25].

Systematic reviews that previously examined the adaptive gamification research corpus highlight that player-type frameworks mostly guided the design of adaptivity, that algorithms were for the most part static, and that the theoretical foundations were in an early-stage development [3,11,14]. More recent ones adopted a closer focus on educational applications [2,9,37] or on specific technologies [12]. Lastly, greater emphasis was placed on theoretical studies than on the empirical ones [9]. While these contributions improved the understanding of the field, several dimensions remain only partially explored, providing the motivation for the present study. It can be noticed that the majority of those studies investigate the educational context, leaving the broader field of adaptive gamification unmapped. Furthermore, they address specific aspects of the analytical dimensions like game elements or theoretical frameworks, but few examine those aspects in an integrated way, and none of them assess the influence of AI improvements in the 2019–2025 period. These gaps collectively point to the need for a cross-domain, multi-dimensional synthesis of adaptive gamification research that is up-to-date.

The present review has the specific aim of providing an integrated understanding of the field's current state, considering its design elements, theoretical foundations, adaptive strategies, and practical implications. To structure this inquiry, the following research questions were formulated:

RQ1: What are the most sought-after outcomes of adaptivity in gamified systems?
RQ2: Which theoretical frameworks underpin the design of adaptivity in gamified systems?
RQ3: Which game elements are most frequently adapted in adaptive gamified systems?
RQ4: What are the primary adaptive strategies used to make a gamified system adaptive?
RQ5: What are the main reported limitations of adaptive gamified systems?

3 Method

This systematic review was conducted in accordance with the PRISMA 2020 statement [24], following the methodological steps described below.

Specification of Eligibility Criteria. Drawing upon the previously defined research questions, the eligibility criteria guiding this systematic review were established, as presented in Table 1 below.

Table 1. Inclusion and exclusion criteria.

Criterion type	Criterion description
Language	Only papers in English were included.
Topic	Studies were included only if they focused on the design and/or implementation of adaptive gamification solutions.
Publication date	Only papers published from January 2019 until December 2025 were included.
Publication type	Only peer-reviewed publications were included. Conference papers were also considered eligible, given the emerging nature of the topic.
Research type	Only primary studies were included. Secondary studies (e.g., systematic reviews, mapping studies) were excluded.
Transparency	Studies were included only if their methodology was clearly and explicitly described.

Identification of Information Sources and Search Strategies. The search for this systematic review was performed on five scientific databases, selected as the most relevant for the field under review: Web of Science, IEEE Xplore, Science Direct, Scopus, and the ACM Digital Library.

To define the search string, an iterative process was implemented. Preliminary searches were carried out to explore the existing literature and refine the search string to address the RQs most effectively.

The final search string was the following:

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("adaptive gamif*" OR "tailored gamif*" OR "personali* gamif*")
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The search terms were applied to the title, abstract and keywords of the papers. The string was adapted to each engine's syntax, expanding wildcards into explicit variants where unsupported inside quotes. The search, conducted in January 2026 for January 2019–December 2025, returned 680 papers.

Selection Process. The study selection process was conducted with the support of the CADIMA software (https://www.cadima.info/index.php). Initially, an automatic screening process was carried out to identify and remove duplicates, resulting in a total of 611 papers.

In the next stage, papers were selected based on the inclusion and exclusion criteria previously identified. An initial screening was conducted by reviewing the titles and abstracts of the papers. This step involved three researchers in total, with each title and abstract independently reviewed by two researchers. In cases of inconsistencies during the selection process, the CADIMA software notified the reviewers, who then resolved conflicts collaboratively. This stage resulted in the exclusion of 481 articles.

Full texts were sought for the 130 remaining articles, of which 7 could not be retrieved; of the 123 assessed, 84 were excluded and 39 included. Risk of bias was not formally assessed given the mix of study designs; the synthesis below is descriptive rather than quality-weighted.

The entire selection process is summarised in Fig. 1. A complete list of the 39 included studies is available at https://doi.org/10.5281/zenodo.20999807.

Data Collection Process. Three researchers analysed the 39 studies included at the end of the selection process. The analysis involved coding the data and assigning them to various categories with the support of the Atlas.ti software.

The initial categories were identified by two of the authors, drawing on existing literature. For example, to code the game elements adapted in the gamified systems described in the selected studies, the gamification elements taxonomy by Toda et al. [38] was employed. These preliminary categories were then presented to the entire research team for discussion, validation, and refinement.

Additional categories were introduced as necessary during the analysis, allowing for flexibility to capture emerging themes and patterns from the data.

Coding reliability varies across categories: adapted elements and frameworks are usually stated explicitly, so coding them was close to transcription, whereas adaptation outcomes (Table 3) had to be synthesised from per-variable results into a single verdict the studies themselves rarely gave, making that step interpretive. Coder agreement was accordingly reached through discussion.

4 Results and Discussion

This section presents the findings for each research question alongside their interpretation, preceded by a summary of the main characteristics of the 39 included studies.

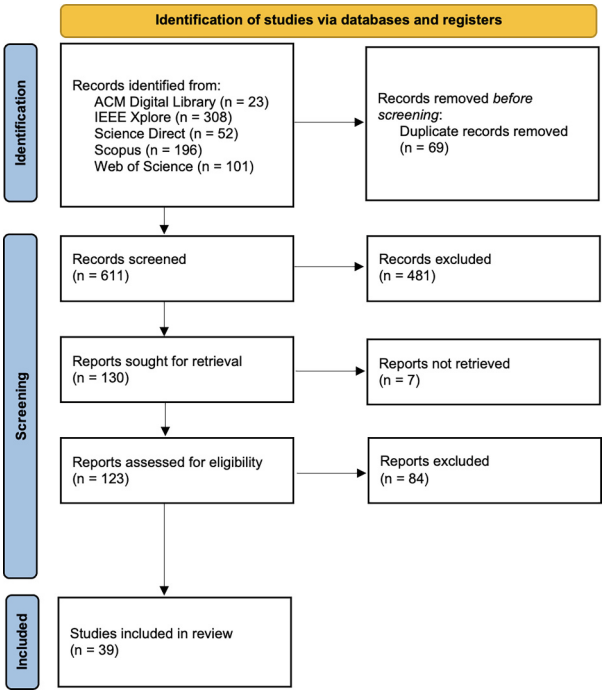
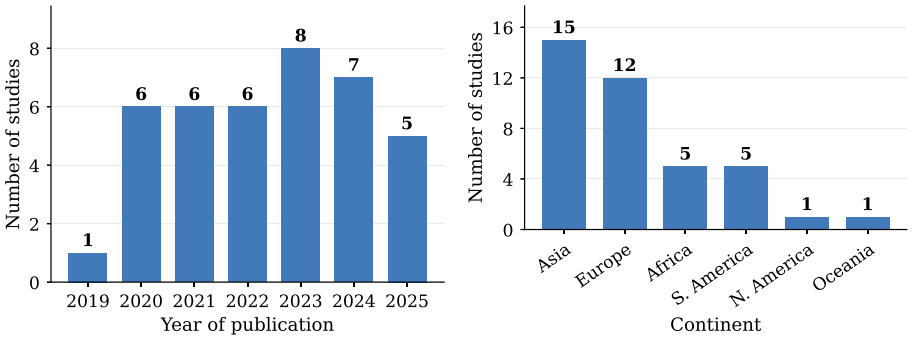


Fig. 1. Flow diagram of the article search and selection process.

Study Characteristics. As shown in Fig. 2a, interest in adaptive gamification grew steadily throughout the period examined, reaching a peak in 2023. Most studies (15 out of 39) were conducted in Asia (see Fig. 2b), with Malaysia (4 out of 15) contributing the highest number. The concentration of studies in a few regions, chiefly Asia and Europe, raises questions about cross-cultural generalisation that future research should address.

In terms of methodology, 18 studies adopted a quantitative approach, 3 combined qualitative and quantitative methods, and 18 focused on designing or implementing adaptive models without testing them with real users; fully qualitative studies are notably under-represented.

Empirical and theoretical work are almost evenly split (54% vs 46%), whereas earlier reviews found the literature weighted toward theoretical studies [9].



(a) per year of publication (b) per continent

Fig. 2. Distribution of the included studies (a) per year of publication and (b) per continent.

The field of application was predominantly educational: 61.5% of the studies (24 out of 39) addressed this domain, most often in digital or online learning (11 out of 24), followed by secondary school (5), higher education (3), primary school (2), and corporate training (1). This prevalence of education is consistent with previous reviews [2,3,9,11,37], and may be a structural feature of the field, given its diverse target populations, measurable outcomes, and suitability for longitudinal study.

RQ1: Sought-After Outcomes. Table 2 shows that motivation (36.7%), engagement (22.8%), and performance (13.9%) are the most common sought-after outcomes of adaptivity, confirming the objectives most commonly associated with gamification. This concentration suggests that future research might benefit from broadening the range of outcomes considered beyond these three dominant constructs.

Following the categories of Smith et al. [36] and Luo [20], the outcomes were largely positive where specified (35.9% positive and 10.3% mostly positive; Table 3), though this is not an effectiveness estimate: 43.6% report no outcome, the rest were not quality-appraised, and self-reported, short-term measures may overestimate real-world effects given gamification's tendency to diminish over time [8,32].

RQ2: Theoretical Frameworks. As shown in Table 4, the largest share of the studies (18 out of 39) base their adaptive gamification design on the Hexad Player Types framework, which classifies players into six motivational types: Socialiser, Free Spirit, Achiever, Player, Philanthropist, and Disruptor, each responding differently to various game mechanics [21]. Its prominence confirms a pattern established in previous reviews [3,11,14] and reflects the convenience of mapping player types directly onto game elements. However, such player-type taxonomies

Table 2. Outcomes of adaptivity.

Outcomes	N	%
Motivation	29	36.7%
Engagement	18	22.8%
Performance	11	13.9%
Enjoyment	5	6.3%
User experience	4	5.1%
Not specified	3	3.8%
Flow experience	2	2.5%
Permanence in the system	2	2.5%
Behaviour	2	2.5%
Satisfaction	2	2.5%
Interactions with other participants	1	1.3%
Total	79	100.0%

Table 3. Adaptation results frequency.

Results	Definition	N	%
Not applicable or not specified		17	43.6%
Mostly negative	Mostly adverse effects in some variables and improvements on others.	1	2.6%
Negative	Adverse impact of adaptive gamification on the observed variable(s).	1	2.6%
Neutral	Not positive nor negative effects noticed.	2	5.1%
Positive	Improvement in the observed variable(s) as a consequence of implementing adaptivity.	14	35.9%
Mostly positive	Mostly improvements in some variables and adverse effects on others.	4	10.3%
$N = 39$			

are by their nature static, and therefore ill-suited to capturing the dynamic changes users undergo over time.

Self-Determination Theory [31] follows, adopted by 14 of the 39 studies, leveraging its core principles of autonomy, competence, and relatedness to foster intrinsic motivation. Its growing presence may signal a shift towards richer theoretical foundations: SDT offers a more flexible and psychologically grounded basis for personalisation, focusing on the quality of the motivational experience rather than on a categorical classification of users.

The remaining frameworks, trailing by a wide margin, mostly categorise players according to their motivational profiles or play styles. The coexistence of

these two dominant models reflects a broader tension in the field between player-centred and needs-centred approaches to adaptation.

Table 4. Theoretical frameworks underpinning adaptivity.

Theoretical frameworks	N	%
Hexad player types	18	25.4%
Self-determination theory	14	19.7%
Motivation-based	7	9.9%
Brain Hex player types	5	7.0%
Bartle player types	4	5.6%
Learning styles (2 unspecified, 1 Felder–Silverman)	3	4.2%
Not specified	3	4.2%
Fogg behavioral model	2	2.8%
Big Five	2	2.8%
Learning dimensions	2	2.8%
Player behaviour	2	2.8%
Ferro player types	2	2.8%
Other frameworks, adopted by one study each (challenge completion likelihood, PEAS framework, player intent, NERIS personality traits, Hofstede's cultural dimensions, Cialdini's persuasion principles, Keirsey personality model)	7	9.9%
Total	71	100.0%

RQ3: Adapted Game Elements. Table 5 reports which game elements are most frequently targeted for adaptation, grouped into those covered by the taxonomy of Toda et al. [38] and those falling outside it. The 39 studies yielded 207 coded adaptations, since a single system typically adapts several elements at once.

Points, badges, and leaderboards (PBL) clearly predominate. Points alone account for 13.5%, while competition, acknowledgement, and progression together add a further 33%. Although PBL mechanics are measurable and easy to implement, their motivational effects have repeatedly been shown to be superficial and oriented towards extrinsic motivation [5]. Elements with richer motivational affordances, such as narrative, chance, or social pressure, appear far less often.

Table 5 also reports each element's taxonomy dimension: Performance/Measurement alone absorbs 89 of 207 coded adaptations (43.0%) against under 8% for Fictional, showing adaptation targets mainly the layer that quantifies the user.

Notably, 12.6% of the adapted elements fell outside the Toda et al. taxonomy, indicating that some researchers are beginning to move beyond standard classifications.

Table 5. Adapted game elements frequency distribution.

Game Elements	Dimension	N	%
Points	Performance/Measurement	28	13.5%
Progression	Performance/Measurement	24	11.6%
Competition	Social	23	11.1%
Acknowledgement	Performance/Measurement	22	10.6%
Objectives	Personal	14	6.8%
Level	Performance/Measurement	11	5.3%
Novelty	Personal	9	4.3%
Cooperation	Social	8	3.9%
Chance	Ecological	7	3.4%
Narrative	Fictional	6	2.9%
Social pressure	Social	6	2.9%
Time pressure	Ecological	5	2.4%
Economy	Ecological	4	1.9%
Stats	Performance/Measurement	4	1.9%
Less frequent elements (reputation, storytelling, rarity, puzzle, sensation)	Mixed	10	4.8%
Other (outside Toda et al. taxonomy)	—	26	12.6%
Total		207	100.0%

RQ4: Adaptive Strategies. Both theoretical and empirical papers were examined to identify the adaptive strategies adopted. Each implementation was first recorded in the terms used by its own authors, then grouped by the mechanism deciding which element a given user receives, into four categories: **rule-based systems** (conditional decision trees, action grids, or a matching matrix of predefined affinities); **score-based and affinity methods** (a cumulative global score, or an affinity vector over categories); **machine learning-based personalisation** (deep learning, multinomial logistic regression, or matrix factorisation); and **user-controlled adaptation** (manually activated game design elements).

The 45 occurrences in Table 6 exceed 39 because some systems combine mechanisms and were coded under each; the categories classify decision mechanisms rather than systems, so boundaries are not watertight.

The landscape is technically more diverse than in previous analyses: machine learning-based personalisation (33.3%) is now the most common category, narrowly ahead of rule-based (28.9%) and score/affinity-based (26.7%) approaches.

Table 6. Frequency distribution of the four adaptive strategies categories.

Adaptive strategies	N	%
Machine Learning-Based Personalisation	15	33.3%
Rule-based Personalisation	13	28.9%
Score and Affinity-based Personalisation	12	26.7%
User controlled Personalisation	5	11.1%
Total	45	100.0%

This might seem to contradict the finding that adaptive algorithms remain predominantly static (as shown in Table 7). The tension, however, is only apparent, since many ML-based implementations operate in static or batch-update mode rather than adapting in real time. True dynamic adaptation is still rare (35.9% of studies) and typically relies on reinforcement learning [22,33]. The persistence of static and rule-based approaches reflects several converging factors: the high data requirements of dynamic ML models, the scarcity of large user datasets outside commercial settings, the interpretability and transparency of rule-based systems (particularly valued in education), and the technical skill needed to build and maintain ML pipelines. The shift from static to dynamic adaptation is therefore likely to be gradual and uneven across sectors and institutions.

Table 7. Nature of adaptive algorithms frequency distribution.

Adaptive algorithms' nature	N	%
Static	22	56.4%
Dynamic	14	35.9%
Both	3	7.7%
Total	39	100.0%

RQ5: Reported Limitations. Limitations were reported by 29 of the 39 studies; Table 8 summarises the 55 limitations they raised. The three most frequently cited are: findings not validated in other contexts (21.8%), small sample size (20%), and insufficient customisation specificity (18.2%). These limits are interlinked and point to a common underlying challenge: the profound individual variability in how users respond to gamified systems. Small samples limit the ability to model that variability; insufficient customisation reflects the current inability to capture it adequately; and the absence of cross-context validation leaves open whether findings generalise beyond their original setting. The recurring identification of static adaptation as a limitation, together with calls for advanced techniques such as Deep Reinforcement Learning, indicates that the field is aware of these technical limits and is seeking to overcome them.

Table 8. Study limits frequency distribution.

Limits	N	%
Findings not validated in other contexts	12	21.8%
Small sample size	11	20.0%
Insufficient customisation specificity	10	18.2%
Lack of long-term evaluation	5	9.1%
Lack of testing with real users	5	9.1%
Static (non-dynamic) adaptation	5	9.1%
Limited automation	3	5.5%
Other, cited once each (lack of data-driven strategies; limited range of game elements; absence of advanced ML techniques such as Deep Reinforcement Learning; self-evaluation questionnaire bias)	4	7.3%
Total	55	100.0%

Underexplored Frontiers. Cutting across the strategies identified above, a striking observation is that two mature families of AI technique are almost entirely absent from the corpus: recommendation algorithms and LLMs.

Despite the rapid development and widespread adoption of recommendation algorithms, now well-established in commercial personalisation systems such as content streaming and e-commerce platforms [15,29], their application to adaptive gamification remains virtually unexplored in the literature reviewed. Collaborative filtering, content-based filtering and hybrid recommendation architectures offer technically mature solutions for inferring user preferences from behavioural data and mapping them onto tailored experiences; however, only one study in the corpus [30] explicitly frames its adaptive system as a recommendation system. This gap is particularly evident given that the motivational profiling underpinning most adaptive gamification approaches, the matching of user characteristics to preferences regarding game elements, is structurally analogous to the problem of item recommendation that recommendation systems are specifically designed to solve [39,40].

Equally absent is any use of large language models (LLMs), although 2022–2025 coincides with their widespread availability [4,25]. Two roles seem promising: as *profilers*, inferring motivational states from open-ended input in place of a Hexad or SDT questionnaire [19]; and as *generators* of the content carrying an adapted element (narrative, quests, feedback), exactly the material Table 5 shows least often adapted, plausibly because hand-authoring one variant per profile does not scale. The obstacle, that free-form text cannot feed an adaptation loop, is an engineering constraint rather than a conceptual one: schema-conditioned decoding and function calling can require the model to emit a structure the engine consumes directly, e.g. a JSON object of affinity scores over a taxonomy. What remains open is evaluation, since non-determinism and prompt sensitivity make it hard to isolate adaptivity's contribution against a

rule-based baseline, which, together with the usual lag between a technology's availability and its uptake, helps explain the corpus's silence here. The broader priority is to test whether adapting richer elements outperforms adapting points and badges, and to compare strategy families against a non-adaptive baseline rather than accumulating isolated prototypes [8,32].

5 Conclusion

This systematic review mapped the state of research on adaptive gamification between 2019 and 2025, examining the outcomes sought, the theoretical frameworks adopted, the game elements adapted, the strategies implemented, and the limitations reported. The 39 included studies confirm a field in active development, marked by growing empirical attention and an expanding technical repertoire.

Several patterns recur: application is predominantly in the educational context; motivation and engagement remain the primary targeted outcomes; the adapted game elements belong to the points–badges–leaderboards triad; and player-type frameworks remain central to the adaptation logic.

At the same time, significant shifts emerge: the rise of SDT as a complementary theoretical foundation, ML-based strategies as the most frequently adopted adaptive approach, and a gradual increase in dynamic algorithmic implementations compared to the static predominance reported in earlier reviews [11].

Taken together, these findings suggest that the sector may be at a turning point, with a broadening theoretical repertoire and recent AI advances laying the groundwork for real-time personalisation; realising this potential will depend in particular on integrating the recommendation algorithms and large language models that, despite their maturity, remain conspicuously underused.

Beyond these technological avenues, qualitative studies, which are currently scarce, could yield a deeper understanding of how adaptive gamification works, and further experimentation with a wider range of game elements may improve its efficacy.

Finally, this study has limitations of its own. The search terms delimit the corpus to work identifying itself as gamification, leaving out adjacent traditions such as personalised game-based learning and dynamic difficulty adjustment [17], where comparable problems are solved under different names. No formal quality appraisal was performed, so reported outcomes should not be read as evidence of effectiveness, and coding adaptation outcomes required interpretation rather than a computed reliability coefficient. Findings are further constrained by the uneven level of detail in the selected papers. Given the pace of technological change, the field warrants ongoing monitoring as new adaptive strategies are developed and tested.

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References

1. Ahmad, A., Zeeshan, F., Marriam, R., Samreen, A., Ahmed, S.: Does one size fit all? Investigating the effect of group size and gamification on learners' behaviors in higher education. J. Comput. High. Educ. **33**(2), 296–327 (2021). https://doi.org/10.1007/s12528-020-09266-8
2. Bennani, S., Maalel, A., Ben Ghezala, H.: Adaptive gamification in e-learning: a literature review and future challenges. Comput. Appl. Eng. Educ. **30**(2), 628–642 (2022). https://doi.org/10.1002/cae.22477
3. Böckle, M., Novak, J., Bick, M.: Towards adaptive gamification: a synthesis of current developments. In: Proceedings of the 25th European Conference on Information Systems, ECIS (2017)
4. Busch, P.A., Hausvik, G.I., Nielsen, J.A.: The early wave of ChatGPT research: a review and future agenda. Comput. Hum. Behav. Artif. Hum. **6**, 100213 (2025)
5. Chou, Y.K.: Actionable Gamification: Beyond Points, Badges, and Leaderboards. Packt Publishing, Birmingham (2019)
6. Dah, J., Hussin, N., Zaini, M.K., Helda, L.I., Ametefe, D.S., Aliu, A.A.: Gamification is not working: why? Games and Culture, pp. 1–24 (2024). https://doi.org/10.1177/15554120241228125
7. Deterding, S., Dixon, D., Khaled, R., Nacke, L.: From game design elements to gamefulness: defining "gamification". In: Proceedings of the 15th International Academic MindTrek Conference: Envisioning Future Media Environments, pp. 9–15 (2011). https://doi.org/10.1145/2181037.2181040
8. Dumas Reyssier, S., Serna, A., Hallifax, S., Marty, J.C., Simonian, S., Lavoué, E.: How does adaptive gamification impact different types of student motivation over time? Interact. Learn. Environ. **32**(10), 6043–6062 (2023). https://doi.org/10.1080/10494820.2023.2248220
9. Hong, Y., Saab, N., Admiraal, W.: Approaches and game elements used to tailor digital gamification for learning: a systematic literature review. Comput. Educ. **212**, 105000 (2024). https://doi.org/10.1016/j.compedu.2024.105000
10. Ishaq, K., et al.: Level up your coding: a systematic review of personalized, cognitive, and gamified learning in programming education. PeerJ Comput. Sci. **10**, e2310 (2024). https://doi.org/10.7717/peerj-cs.2310
11. Kamunya, S., Oboko, R.O., Maina, E.: A systematic mapping of adaptive gamification in e-learning. Open J. Inf. Technol. **2**(2), 53–68 (2019). https://doi.org/10.32591/coas.ojit.0202.04053k
12. Khakpour, A., Colomo-Palacios, R.: Convergence of gamification and machine learning: a systematic literature review. Technol. Knowl. Learn. **26**(3), 597–636 (2021). https://doi.org/10.1007/s10758-020-09456-4
13. Klein, G.: Viewing gamification design limitations and weaknesses through a pandemic lens. Societies **11**(4), 137 (2021). https://doi.org/10.3390/soc11040137
14. Klock, A.C.T., Gasparini, I., Pimenta, M.S., Hamari, J.: Tailored gamification: a review of literature. Int. J. Hum Comput Stud. **144**, 102495 (2020). https://doi.org/10.1016/j.ijhcs.2020.102495
15. Ko, H., Lee, S., Park, Y., Choi, A.: A survey of recommendation systems: recommendation models, techniques, and application fields. Electronics **11**(1), 141 (2022)
16. Lavoué, E., Monterrat, B., Desmarais, M., George, S.: Adaptive gamification for learning environments. IEEE Trans. Learn. Technol. **12**(1), 16–28 (2019). https://doi.org/10.1109/TLT.2018.2823710

17. Lemoine, B., Laforcade, P., George, S.: A domain-independent, extensible framework for generators of training game activities on declarative knowledge. J. Comput. Assist. Learn. (2025). https://doi.org/10.1111/jcal.70082, early view
18. Liu, D., Li, X., Santhanam, R.: Digital games and beyond: what happens when players compete? MIS Q. **37**(1), 111–124 (2013). https://doi.org/10.25300/MISQ/2013/37.1.05
19. Liu, J., et al.: A survey of personalized large language models: progress and future directions. arXiv preprint arXiv:2502.11528 (2025)
20. Luo, Z.: Determinants of the perceived usefulness (PU) in the context of using gamification for classroom-based ESL teaching: a scale development study. Educ. Inf. Technol. **28**(4), 4741–4768 (2023)
21. Marczewski, A.: Even Ninja Monkeys Like to Play: Unicorn Edition. Gamified UK (2018)
22. Nikolopoulos, I., Tzouveli, P., Karpouzis, K., Kollias, S.: A reinforcement learning system for adaptive gamification and hexad user profile tracking. In: 2024 IEEE Gaming, Entertainment, and Media Conference (GEM), pp. 1–6 (2024). https://doi.org/10.1109/GEM61861.2024.10585391
23. Ntelia, R.E.: Merits of gamification: transmediality and spatiality of Walden, a game. In: ACM International Conference Proceeding Series (2023). https://doi.org/10.1145/3582437.3582464
24. Page, M.J., et al.: PRISMA 2020 explanation and elaboration: updated guidance and exemplars for reporting systematic reviews. BMJ **372**, n160 (2021). https://doi.org/10.1136/bmj.n160
25. Peres, R., Schreier, M., Schweidel, D., Sorescu, A.: On ChatGPT and beyond: how generative artificial intelligence may affect research, teaching, and practice. Int. J. Res. Mark. **40**(2), 269–275 (2023)
26. Phosanarack, M., Avril, E., Lepreux, S., Wallard, L., Kolski, C.: User-centered personalized gamification: an umbrella review. User Model. User-Adap. Inter. **35**(1), 3 (2025). https://doi.org/10.1007/s11257-024-09423-z
27. Putz, L.M., Treiblmaier, H., Pfoser, S.: Using gamification for sustainable transport education: results from an empirical study. In: Proceedings of the World Conference on Transport Research (2018). https://doi.org/10.5281/zenodo.1451345
28. Rahman, R.A., Ahmad, S., Hashim, U.R.: The effectiveness of gamification technique for higher education students engagement in polytechnic Muadzam Shah Pahang, Malaysia. Int. J. Educ. Technol. High. Educ. **15**(41) (2018). https://doi.org/10.1186/s41239-018-0123-0
29. Raza, S., et al.: A comprehensive review of recommender systems: transitioning from theory to practice. Comput. Sci. Rev. **59**, 100849 (2026)
30. Rodrigues, L., et al.: GARFIELD: a recommender system to personalize gamified learning. In: Rodrigo, M.M., Matsuda, N., Cristea, A.I., Dimitrova, V. (eds.) AIED 2022. LNCS, vol. 13355, pp. 666–672. Springer, Cham (2022). https://doi.org/10.1007/978-3-031-11644-5_65
31. Ryan, R.M., Deci, E.L.: Intrinsic and extrinsic motivations: classic definitions and new directions. Contemp. Educ. Psychol. **25**(1), 54–67 (2000). https://doi.org/10.1006/ceps.1999.1020
32. Serna, A., Hallifax, S., Lavoué, E.: Investigating the effects of tailored gamification on learners' engagement over time in a learning environment. Proc. ACM Hum.-Comput. Interact. **7**(CHI PLAY), 264–288 (2023). https://doi.org/10.1145/3611030

33. Shabadurai, Y., Chua, F.F., Lim, T.Y.: A reinforcement learning-based dynamic adaptive gamification (DAG) method for online employee training. In: 2025 14th International Conference on Information Technology in Asia (CITA), pp. 66–71 (2025). https://doi.org/10.1109/CITA66455.2025.11198710
34. Sharma, W., Lim, W.M., Kumar, S., Verma, A., Kumra, R.: Game on! A state-of-the-art overview of doing business with gamification. Technol. Forecast. Soc. Chang. **198**, 122988 (2024). https://doi.org/10.1016/j.techfore.2023.122988
35. Sheejamol, P.T., Chacko, A.M., Kumar, S.M.: Beyond the one-size-fits-all: a systematic review of personalized and gamified e-learning for neurodivergent learners. Electron. J. e-Learn. **23**(3), 101–119 (2025). https://doi.org/10.34190/ejel.23.3.4051
36. Smith, A., Legaki, Z., Hamari, J.: Games and gamification in flipped classrooms: a systematic review. In: Proceedings of the 6th International GamiFIN Conference, pp. 33–43 (2022)
37. Suresh Babu, S., Dhakshina Moorthy, A.: Application of artificial intelligence in adaptation of gamification in education: a literature review. Comput. Appl. Eng. Educ. **32**(1) (2024). https://doi.org/10.1002/cae.22683
38. Toda, A.M., et al.: Analysing gamification elements in educational environments using an existing gamification taxonomy. Smart Learn. Environ. **6**(1), 16 (2019). https://doi.org/10.1186/s40561-019-0106-1
39. Tondello, G.F., Orji, R., Nacke, L.E.: Recommender systems for personalized gamification. In: Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization, pp. 425–430. ACM (2017)
40. Vasconcelos, G.F.X.D., Santos, W.O.D., Santos, A.C.G., Hamari, J.: ReGammend: a method for personalized recommendation of gamification designs. In: Proceedings of the 6th International GamiFIN Conference (2022)
41. Vijay, M.M., Jayan, J.P., Rose, R.I.: A systematic review on artificial intelligence based adaptive gamification in knowledge engineering. KSII Trans. Internet Inf. Syst. **19**(8) (2025). https://doi.org/10.3837/tiis.2025.08.009
42. Xiao, Y., Hew, K.F.: Personalised gamification enhances student participation but produces mixed effects on emotional and cognitive engagements: a systematic review. Interact. Learn. Environ. **32**(10), 7014–7040 (2024). https://doi.org/10.1080/10494820.2023.2299977
43. Xiao, Y., Hew, K.F.: Personalized gamification versus one-size-fits-all gamification in fully online learning: effects on student motivational, behavioral and cognitive outcomes. Learn. Individ. Differ. **113**, 102470 (2024). https://doi.org/10.1016/j.lindif.2024.102470
44. Zairon, I.Y., Wook, T.S.M.T., Salleh, S.M., Dahlan, H.A.: User model for virtual learning based on adaptive gamification. IEEE Access **13**, 24028–24040 (2025). https://doi.org/10.1109/ACCESS.2025.3537599