An Adaptive AI Framework for Personalized Gamification in Online Education

Tejaswini Gunagi[1], Sachin K[2], Kishore Kumar K[3], Monica K P[4]
[1,2,3,4] *KVG College of Engineering, Department of Computer Science and Engineering, Sullia, Dakshina Kannada*

***Abstract*— Online education offers flexible, large-scale access to learning, but sustaining student engagement and motivation in virtual environments remains a persistent problem. Gamification points, badges, leaderboards, and challenges is widely used to raise participation, yet most gamified systems apply the same mechanics to every learner and ignore individual behaviour and preferences. In parallel, AI-based adaptive learning systems personalize content and difficulty but rarely personalize the gamification layer itself. This paper proposes an Adaptive AI Framework for Personalized Gamification in Online Education that targets this gap. The framework continuously collects learner interaction and performance data, builds and updates a learner profile, and uses that profile as the context for an AI adaptation engine that selects which gamification element to deliver next. We frame this selection as a contextual multi-armed bandit problem, in which the learner profile is the context, the available gamification elements are the actions, and an engagement signal derived from the learner's response is the reward. A gamification management module delivers the chosen elements, and learner responses feed back into the loop. We describe the architecture, specify a concrete decision mechanism, and define an evaluation methodology dataset, metrics, baselines, and hypotheses through which the framework can be tested. The work is presented as a conceptual framework with a validation plan; empirical results are identified as future work.**

***Index Terms*—Adaptive learning; personalized gamification; online education; learning analytics; contextual bandits; student engagement.**

I. INTRODUCTION

Online education has expanded access to learning through learning management systems (LMS), massive open online courses, and other virtual platforms. Despite this reach, sustaining student engagement, motivation, and completion remains difficult. Many learners reduce their participation or drop out because online study can feel impersonal and weakly interactive [1], [3].

Gamification is a common response. Adding game elements such as points, badges, leaderboards, rewards, and challenges to a course can raise participation and motivation [1], [7]. However, most gamified systems use fixed mechanics: every learner receives the same badges, the same challenges, and the same rewards, regardless of differing preferences, behaviour, and needs. The same incentive does not motivate every learner equally.

Artificial intelligence has enabled adaptive learning systems that personalize content, difficulty, and feedback from learner performance and behaviour [2], [6]. These systems improve personalization, but they focus mainly on adapting the learning content. The gamification layer is usually left static.

Although combining AI with gamification has attracted attention, recent reviews report that the evidence is fragmented and that few systems dynamically adapt gamification elements to individual behavior, motivation, and engagement [3], [4], [5]. Most approaches personalize content while keeping a single, fixed gamification strategy, which limits their ability to sustain engagement.

To address this, we propose an Adaptive AI Framework for Personalized Gamification in Online Education. The framework uses learner performance data, behavioural analytics, and engagement indicators to choose which gamification element each learner should receive next, and it treats that choice as an explicit online decision problem. The objective is a more engaging and personalized experience that supports motivation, participation, and achievement.

The contributions of this paper are:

1) We propose an adaptive AI framework that personalizes gamification elements not only content using learner behaviour and engagement analytics.
2) We specify the adaptation decision as a contextual multi-armed bandit, making explicit the context, the action set, and the reward signal that earlier conceptual frameworks leave undefined.
3) We define an evaluation methodology dataset, metrics, baselines, and hypotheses for testing the framework.
4) We discuss limitations and risks, including the extrinsic-motivation trap and the cold-start problem, that adaptive gamification must address.

II. RELATED WORK

This section reviews work on gamification in online education, AI in personalized learning, and the integration of the two, and then states the research gap.

A. Gamification in Online Education

Gamification improves engagement and motivation by adding game elements to learning. Studies report gains in participation, retention, and performance when points, badges, and challenges are introduced [1], [7]. The common limitation is that game mechanics are fixed and identical for all learners, which reduces their effectiveness across diverse preferences.

B. Artificial Intelligence in Personalized Learning

AI techniques analyse learner behaviour, monitor performance, detect knowledge gaps, and recommend learning paths. Adaptive platforms adjust content difficulty and sequencing to individual progress, and some use reinforcement learning to drive this adaptation [6]. These systems improve personalization, but they concentrate on content rather than on the gamification elements a learner receives.

C. AI-Driven Gamification

Combining AI with gamification has gained attention. Contextualized personalization models and adaptive designs use learner data to tune the experience [2], [7], and reviews synthesize the trends and reported benefits [3], [4], [5]. Even so, most systems adapt content while keeping the gamification strategy static or group-level, so learners often receive similar rewards and challenges regardless of their engagement. Reviews also note reward dependency and superficial “fast leveling” as risks of poorly designed gamification [3]. Table I contrasts representative approaches with the framework proposed here.

Table I. Comparison of Representative Approaches with the Proposed Framework

Work and focus	Personalizes gamification per learner?	Adaptation mechanism	Empirical validation
Idika and Saihi [1]: adaptive quiz with game elements	No (same elements for all)	Rule-based difficulty threshold	Pilot, small sample
Naatonis et al. [2]: adaptive AI with collaborative gamification	Partial (group level)	Contextualized personalization model	Empirical, higher education
Sayed et al. [6]: adaptive content with a gamification mode	Partial	Deep Q-Network (reinforcement learning)	Pilot, primary mathematics
Reviews [3], [4], [5]: surveys of AI and gamification	Identify this as an open gap	Various	Review (no built system)
This work: personalized gamification framework	Yes (per-learner element selection)	Contextual multi-armed bandit	Planned (future work)

D. Research Gap

Across these studies, content adaptation is relatively mature, but the gamification layer is usually static or only group-level, and reviews confirm fragmented evidence [3], [4], [5]. Two things are missing in most prior work: first, per-learner selection of gamification elements treated as an explicit, online decision; and second, a clear definition of the context, actions, and reward signal that drive that decision. This paper addresses both.

III. PROPOSED FRAMEWORK

The proposed framework enhances engagement by personalizing gamification, not only content. Unlike systems that give every learner the same rewards and challenges, it continuously analyses behaviour and adapts the gamification it delivers. It has four components a Data Collection Module, a Learner Profiling Module, an AI Adaptation Engine, and a Gamification Management Module that operate as a closed loop, as shown in Fig. 1.

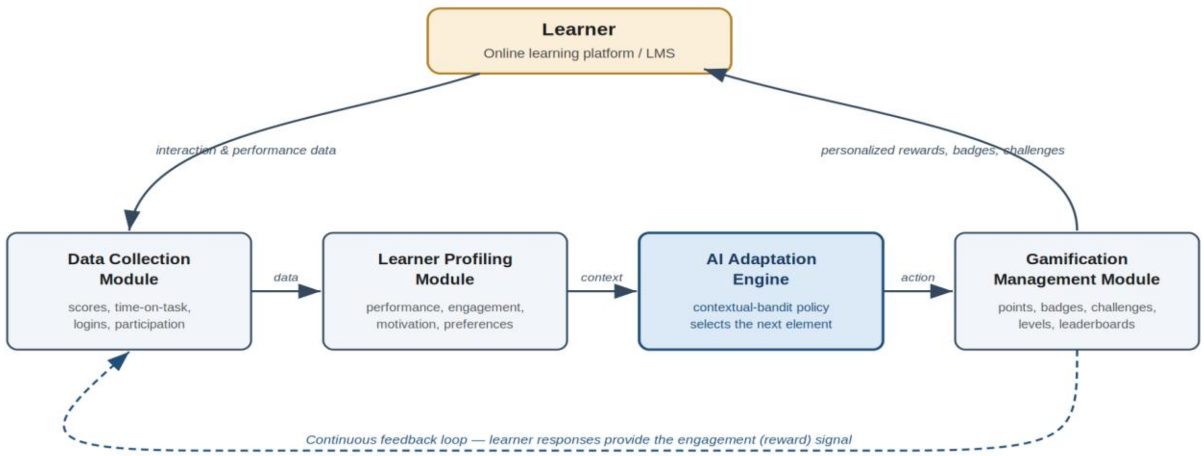

Fig. 1. Closed-loop architecture of the proposed framework: learner data is collected and profiled, the AI adaptation engine selects the next gamification element, the gamification module delivers it, and the learner's response returns as the engagement (reward) signal.

A. Learner Data Collection Module

This module gathers learner data from the platform: quiz and assignment scores, course-completion progress, time spent on activities, login frequency, participation in discussions, and activity history. These signals are the raw input for profiling.

B. Learner Profiling Module

This module turns the raw data into a structured, continuously updated learner profile. The profile captures the learner's performance level, engagement level, estimated motivation, learning preferences, and activity patterns. This profile is the context that the adaptation engine uses to make decisions.

C. AI Adaptation Engine

The AI Adaptation Engine is the core of the framework. It decides which gamification element each learner should receive next. We frame this as a contextual multi-armed bandit. The context is the current learner profile. The action set is the catalogue of gamification elements, for example a new badge tier, a harder challenge, a streak reward, a leaderboard placement, or an encouraging message. After an element is delivered, the learner's subsequent behaviour produces a reward, such as a normalized change in session time, task completion, or return frequency.

The engine learns a policy that maps the profile to the element expected to maximize the reward, while still exploring elements whose effect is uncertain. A linear contextual-bandit method such as LinUCB, or Thompson sampling, balances this exploration and exploitation and updates online as new responses arrive. Reinforcement learning, such as the Deep Q-Network approach of Sayed et al. [6], is an alternative when the effect of an element unfolds over a longer sequence of interactions. Challenge difficulty is adapted in the same loop: high-performing learners receive harder challenges, while struggling learners receive simpler tasks and supportive rewards.

D. Gamification Management Module

This module applies the engine's decision inside the learning environment by issuing the selected points, badges, challenges, levels, leaderboard positions, or missions. It also records what was delivered to each learner so that the response can be attributed to the element and fed back into the loop.

E. Framework Workflow

The framework operates as a continuous loop:

1) Learner interaction and performance data are collected from the platform.
2) The Learner Profiling Module updates the learner profile.
3) The AI Adaptation Engine evaluates the profile and selects a gamification element.
4) The Gamification Management Module delivers the element.
5) The learner's response is observed and converted into a reward signal.
6) The reward updates the engine, and the loop repeats.

IV. EVALUATION METHODOLOGY (PROPOSED)

Because the framework is conceptual, this section specifies how it should be validated rather than reporting results.

A. Study Design

We propose a controlled comparison. A control group uses static gamification, where all learners receive the same elements, and a treatment group uses the adaptive framework. Learners are randomly assigned, and both groups take the same course on an LMS such as Moodle over roughly eight to twelve weeks. Related pilots used pre-test and post-test designs within a course [1], [6].

B. Data and Deployment

The framework is deployed as an LMS plug-in or service that logs the features listed in Section III-A. The cold-start problem the engine has little data for a new learner is handled by a short rule-based warm-up that supplies default elements until enough responses are available for the bandit to personalize.

C. Metrics

Engagement is measured by active days, session time, task completion, and return rate. Learning outcomes are measured by pre-test to post-test gain and course-completion rate. Motivation and satisfaction are measured with a validated survey. A fairness check tests whether adaptation helps initially low-performing learners, an effect reported by Sayed et al. [6]. The bandit's cumulative reward and regret are also reported to show whether the policy improves over time.

D. Hypotheses

H1: the treatment group shows higher engagement than the control group. H2: the treatment group shows higher course-completion and post-test gains. H3: gains for initially low-performing learners are at least as large as for other learners.

V. EXPECTED OUTCOMES AND DISCUSSION

The outcomes below are anticipated from the design and from related empirical work. They are hypotheses to be tested using the methodology in Section IV, not measured results.

Matching the gamification element to the learner profile should sustain engagement better than a one-size-fits-all scheme. High-performing learners can be given advanced challenges, while learners who need support can be given simpler tasks and motivational rewards; similar adaptive behaviour improved outcomes in prior pilots [1], [6]. Because the framework is delivered as a service over standard LMS data, it is intended to be added to existing platforms without redesigning the course.

A. Limitations and Risks

Several limitations must be stated plainly. First, the framework has no empirical validation yet; every benefit above is expected and depends on the study in Section IV. Second, the cold-start problem means the engine personalizes poorly until it has collected enough responses, and warm-up rules are only a partial fix. Third, the reward is a noisy proxy: engagement metrics can be inflated and do not always equal learning. Fourth, heavy external rewards can crowd out intrinsic motivation, and reviews flag reward dependency and superficial progress as real risks [3]; the policy must be tuned to avoid them. Fifth, continuous behavioural logging raises data-protection, consent, and fairness obligations. Finally, effects may vary by subject, learner age, and platform, so cross-context studies are needed before the framework is assumed to generalize.

VI. CONCLUSION AND FUTURE WORK

This paper proposed an Adaptive AI Framework for Personalized Gamification in Online Education. Its distinguishing move is to treat per-learner gamification-element selection as an explicit online decision, framed as a contextual multi-armed bandit with a defined context, action set, and reward signal. The contribution is a framework, a decision formulation, and an evaluation plan; empirical validation is future work and is not claimed here.

Future work will implement the framework on an LMS and run the controlled study described in Section IV. Further work may compare the contextual bandit with reinforcement learning for longer-horizon effects, add emotion-aware signals, improve the explainability of the engine's decisions, and validate the framework across institutions and subjects.

REFERENCES

[1] S. Idika and S. Saihi, "Enhancing Student Engagement through AI-Driven Adaptive Learning and Gamification," *British Journal of Education*, vol. 13, no. 12, pp. 57–103, 2025.

[2] R. N. Naatonis, S. S. Igon, Sumarlin, E. A. U. Malahina, F. Y. Bisilisin, and M. O. Meo, "Integration of Adaptive AI and Collaborative Gamification: A Contextualized Personalization Model to Enhance Student Engagement in Cloud-Based Learning," *International Journal of Information and Education Technology*, vol. 16, no. 2, pp. 546–556, 2026.

[3] P. N. Adi, Priyanto, T. Köhler, S. A. Handayani, M. B. Triyono, and R. F. Maruanaya, "AI-Enhanced Gamification in Education: An Integrative Review of Trends, Impacts, and Corrective Role Potential," *Journal of Computers in Education*, 2026, doi: 10.1007/s40692-026-00387-0.

[4] Kassenkhan, V. Serbin, R. Beisembekova, A. Abshukirova, and B. Mendekina, "AI-Supported Gamification in E-Learning: A Systematic Review of Adaptive Architectures and Cognitive Outcomes," *Information*, vol. 17, no. 3, Art. no. 282, 2026, doi: 10.3390/info17030282.

[5] M. Kassenkhan, A. N. Moldagulova, and V. V. Serbin, "Gamification and Artificial Intelligence in Education: A Review of Innovative Approaches to Fostering Critical Thinking," *IEEE Access*, vol. 13, pp. 98699–98728, 2025, doi: 10.1109/ACCESS.2025.3576147.

[6] W. S. Sayed, A. M. Noeman, A. Abdellatif, M. Abdelrazek, M. G. Badawy, A. Hamed, and S. El-Tantawy, "AI-Based Adaptive Personalized Content Presentation and Exercises Navigation for an Effective and Engaging E-Learning Platform," *Multimedia Tools and Applications*, vol. 82, no. 3, pp. 3303–3333, 2023, doi: 10.1007/s11042-022-13076-8.

[7] S. Sezgin and T. V. Yüzer, "Analysing Adaptive Gamification Design Principles for Online Courses," *Behaviour & Information Technology*, vol. 41, no. 3, pp. 485–501, 2022, doi: 10.1080/0144929X.2020.1817559.