Integration of Adaptive AI and Collaborative Gamification: A Contextualized Personalization Model to Enhance Student Engagement in Cloud-Based Learning

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***Abstract*—This study evaluates the effectiveness of integrating adaptive Artificial Intelligence (AI) and collaborative gamification systems into a cloud-based learning platform to enhance learning personalization and student engagement in higher education. Through a quasi-experimental design with 225 students divided into three groups (AI + gamification, AI only, and control), the study examines the effects of the intervention on learning outcomes, engagement, and academic motivation. Data were collected through cognitive assessments, engagement and motivation instruments, platform analytics, and qualitative interviews. The results showed that the integration of AI and collaborative gamification significantly improved learning outcome scores ($F(2,220) = 42.68$, $p < 0.001$, $\eta^2 = 0.28$) and student engagement, particularly in the social and agency dimensions. Structural Equation Modeling analysis revealed positive direct and interaction effects of both technologies on learning engagement (CFI = 0.94; RMSEA = 0.048). This study also introduces a "Contextual Personalization" model that combines individual, social, and collaborative adaptation, and emphasizes the role of digital literacy and learning styles in moderating the effectiveness of interventions. These findings offer conceptual and practical contributions to the transformation of digital education to be more adaptive, collaborative, and student-centered.**

***Keywords*—cloud-based learning, adaptive artificial intelligence, collaborative gamification, learning personalization, student engagement, higher education**

I. Introduction

The digital transformation of higher education has led to a paradigm shift in learning models, characterized by the growing adoption of cloud-based learning platforms [1, 2]. These platforms offer flexibility and scalability, enabling students to access learning resources anytime and anywhere [3]. However, despite improving accessibility, cloud-based learning still faces two persistent challenges: limitations in providing personalized learning experiences and low levels of student engagement, particularly in remote learning contexts [4–6].

Various studies have attempted to address these issues through the application of adaptive Artificial Intelligence (AI) systems and gamification approaches. Adaptive AI systems deliver real-time, personalized learning paths based on students' learning behavior [7, 8]. While these systems have shown promise in enhancing cognitive learning outcomes, most implementations remain narrowly focused on individual characteristics, overlooking the social dimensions that are essential in higher education contexts [9, 10].

On the other hand, gamification has shown potential in increasing student motivation and engagement by incorporating game elements such as points, badges, and leaderboards [11, 12]. However, many gamification designs tend to be mechanical and overly focused on extrinsic rewards, which may obscure learning objectives and diminish intrinsic motivation [12, 13]. Recent approaches in collaborative gamification emphasize peer interaction and team-based challenges, which have been shown to foster social connectedness and collaborative skills [14, 15]. Nevertheless, empirical studies combining collaborative gamification with adaptive AI systems remain limited in both scale and context.

In online learning settings, gamification can be implemented not only individually but also through student collaboration in virtual groups. Online collaborative gamification facilitates social interaction, peer support, and collective motivation, all of which encourage deeper engagement in learning tasks. Therefore, this study focuses on implementing collaborative gamification integrated with adaptive AI systems in online environments at both individual and group levels.

Moreover, conceptual frameworks proposed in previous studies [16, 17] have emphasized the importance of synergy between adaptive technology and game-based elements. However, large-scale empirical validation, especially in cloud-based learning contexts, remains scarce.

To address these gaps, this study is grounded in three complementary theoretical frameworks: Social Constructivism [18], Self-Determination Theory [19], and the Technological Pedagogical Content Knowledge (TPACK) framework [20]. Social Constructivism highlights the importance of collaboration in knowledge construction, which underpins the design of team-based gamification [21]. Self-Determination Theory explains how learning system designs can fulfill basic psychological needs—autonomy, competence, and relatedness—to foster intrinsic motivation. Meanwhile, the TPACK framework guides the coherent integration of technology, pedagogy, and content.

By synthesizing these perspectives, this study proposes a new model called "Contextual Personalization," which views adaptive learning as the result of interactions among three dimensions: individual characteristics, social context, and collaborative dynamics. This model is empirically tested through the implementation of an integrated adaptive AI and collaborative gamification system within a cloud-based learning platform.

In this study, the term *Contextual Personalization* refers to a model of learning personalization that considers individual traits, social context, and collaborative dynamics in cloud-based learning. Meanwhile, *synergistic effects* describe the combined impact of integrating adaptive AI and collaborative gamification, which produces greater improvements in engagement and learning outcomes than the implementation of each technology in isolation.

Based on the theoretical background and objectives described in the introduction, this study aims to address the following research questions:

Q1. To what extent does the integration of adaptive AI and gamification influence students' cognitive learning outcomes?

Q2. How does the contextual personalization model affect student engagement across cognitive, social, and agency dimensions?

Q3. What is the relationship between adaptive technology, curriculum integration, lecturer support, and students' academic motivation?

Q4. How do collaborative interaction patterns differ between groups with and without gamification?

II. Literature Review

This literature review begins with the recognition that, despite the flexibility and broad accessibility offered by cloud-based learning technologies [1–3], significant challenges remain in the areas of personalization and student engagement. Previous studies have shown that the use of adaptive Artificial Intelligence (AI) systems can enhance learning outcomes by delivering real-time content tailored to students' learning behaviors [7, 8]. However, many of these AI applications still focus predominantly on individual cognitive aspects, neglecting the social dimensions that are critical in higher education settings [9, 10].

Conversely, gamification has been widely recognized for its potential to boost student motivation and engagement through game-like elements such as points, badges, and leaderboards [11, 12]. Yet, much of the existing gamification design tends to be overly mechanistic and driven by external rewards, which may diminish students' intrinsic motivation and obscure learning objectives [12, 13]. Emerging approaches such as collaborative gamification—emphasizing team-based challenges and peer interaction—have demonstrated promise in strengthening social connections and developing collaborative competencies among students [14, 15]. Despite this, studies that empirically combine adaptive AI and collaborative gamification remain scarce, both in terms of scale and contextual scope.

Some conceptual works have stressed the importance of creating synergy between adaptive technologies and gamified elements [16, 17], but empirical evidence—particularly within cloud-based learning environments—is still limited. While studies confirm the effectiveness of AI in delivering personalized learning pathways, others caution that poorly designed gamification may hinder long-term engagement. Well-structured collaborative gamification, on the other hand, has been shown to reduce learner isolation and encourage social interaction in online environments.

To bridge these gaps, this study draws on three core theoretical frameworks: Social Constructivism [18], Self-Determination Theory [19], and the Technological Pedagogical Content Knowledge (TPACK) framework [20]. Social Constructivism underscores the role of collaboration in constructing knowledge, which serves as the basis for designing team-oriented gamification strategies [21]. Self-Determination Theory highlights that well-designed learning systems must fulfill learners' psychological needs for autonomy, competence, and relatedness in order to promote intrinsic motivation [19]. Meanwhile, TPACK offers a framework for harmoniously integrating technology, pedagogy, and content in the development of digital learning systems [20–23].

Vygotsky's concept of the Zone of Proximal Development (ZPD)-the gap between what a learner can do independently and what they can achieve with support-provides an important theoretical foundation for designing adaptive scaffolding. This principle has been applied in AI-driven learning platforms, such as E-Gotsky, which align instructional content to students' optimal challenge levels, accelerating mastery while promoting deeper engagement. In STEM and technology-based learning, ZPD is often used as a collaborative learning framework to enhance cognitive development through group scaffolding and peer interaction.

This review highlights several key gaps: the lack of systematic integration between adaptive AI and collaborative gamification in cloud-based learning environments; limited attention to social and collaborative dimensions in personalization studies; the scarcity of large-scale empirical studies evaluating their combined effects on learning outcomes; and the absence of a conceptual model that bridges individual adaptation with social and collaborative dynamics. This study addresses these issues by proposing the *Contextual Personalization* model, which integrates adaptive AI and collaborative gamification to create more adaptive, collaborative, and student-centered learning experiences.

In addition, global learning platforms such as Coursera and edX have started incorporating adaptive AI and gamification to enhance personalized learning. A study by [24] found that data-driven AI integration on edX improved learner retention by up to 25%, while [25] reported that collaborative gamification on Coursera significantly increased participant engagement in massive open online courses (MOOCs). These comparisons provide a broader global context for interpreting the findings of this research.

III. Materials and Methods

A. Research Design

This study employed a quasi-experimental design with a pretest-posttest control group format, combined with a mixed-methods approach. The primary objective was to evaluate the effectiveness of integrating adaptive AI and collaborative gamification within a cloud-based learning environment. Participants were divided into three groups:

1) **Experimental Group 1 (EG1):** Adaptive AI + Collaborative Gamification
2) **Experimental Group 2 (EG2):** Adaptive AI only
3) **Control Group (CG):** Standard cloud-based learning

without adaptive or gamification features

The term **AI + G** refers to the combined use of adaptive Artificial Intelligence and collaborative gamification modules. Quantitative data focused on cognitive learning outcomes, student engagement, and academic motivation, while qualitative data explored user experiences and implementation dynamics.

An outline of the research method can be seen in Fig. 1.

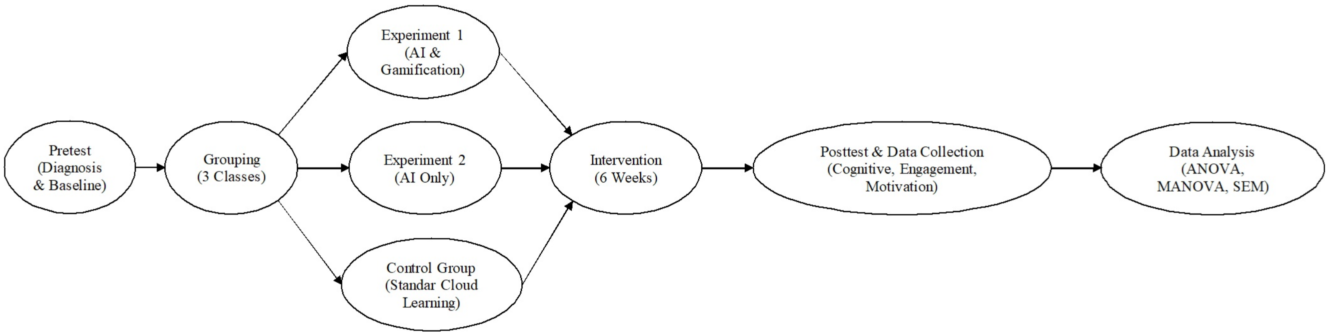

Fig. 1. Flowchart of research methods.

B. Population and Sample

The study involved 225 undergraduate students in their 4th semester from three faculties at a university in Indonesia. All participants were enrolled in blended-learning courses focused on basic programming and data analysis, integrating theoretical cloud computing concepts with practical assignments such as AI prediction simulations and database exercises. Demographically, 58% of students were female, and 42% male. Most came from middle socioeconomic backgrounds and received institutional financial support, creating relatively homogeneous conditions in terms of digital access and educational infrastructure.

A cluster random sampling technique was used to randomly select 9 classes (3 per group), each consisting of 75 students. One-way ANOVA confirmed no significant differences in academic performance (GPA) across groups prior to the intervention (p = 0.72), ensuring group equivalence.

C. Procedure

The intervention lasted 16 weeks. Students were required to access the learning platform for at least 3 h per week. The platform consisted of two core components:

1) **Adaptive AI Module:** Delivered personalized learning materials based on diagnostic quizzes and real-time analytics, built with TensorFlow.
2) **Collaborative Gamification Module:** Featured weekly team-based challenges, team points, and real-time leaderboards powered by Node.js APIs.

In the Collaborative Gamification Module, students were divided into small teams of five. Team formation was carried out randomly using the same cluster random sampling method as in the experimental group assignment. This strategy was chosen to minimize initial ability bias and to ensure that each team had a diverse composition in terms of digital and academic skills.

A pilot test was conducted over a period of four weeks involving 30 students to ensure system functionality and ease of use prior to full-scale implementation.

D. Instruments and Validation

Data were collected through the following instruments:

1) Cognitive assessment

A set of 40 multiple-choice questions based on Bloom's Taxonomy (levels C1–C4), with an inter-rater reliability of 0.87. The questions were evenly distributed across four cognitive levels: 10 items for C1 (remembering), 10 for C2 (understanding), 10 for C3 (applying), and 10 for C4 (analyzing).

2) Student Engagement Inventory (SEI)

Adapted from [26], this instrument measures student engagement across three key dimensions: cognitive engagement, social engagement, and agency engagement. Each dimension consists of five items. Example items include: *"I think about how to connect what I learn with my personal experiences"* (cognitive), *"I actively contribute in group discussions"* (social), and *"I feel responsible for achieving my learning outcomes"* (agency). All items were rated on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree), and the instrument demonstrated strong internal consistency (Cronbach's Alpha = 0.91). Validity was assessed through content validity, construct validity, and reliability testing.

3) Academic Motivation Scale (AMS)

Based on [27], this instrument consists of 21 items grouped into three primary categories:

Intrinsic Motivation (7 items), e.g., "I study because I enjoy the process," "I feel satisfied when I succeed in understanding difficult material."

Identified Regulation (7 items), e.g., "I study because it is important for my future," "I'm motivated because I want to achieve personal goals."

Amotivation (7 items), e.g., "I study but I don't really know why," "I feel that this activity is pointless."

All items were rated on a Likert scale and the instrument showed good reliability (Cronbach's Alpha = 0.88). A full list of items can be found in Table 1.

Table 1. Items in the Academic Motivation Scale (AMS)

Category	Example Items (from a total of 7)
Intrinsic Motivation	I study because I enjoy the process I feel satisfied when I solve difficult problems.
Identifield Regulation	I study because it is important for my future I want to gain skills for my career
Amotivation	I'm not sure why I need to study this material I feel this activity is not relevant to me

The detailed results of instrument validity can be seen in Table 2.

Table 2. The detailed results of instrument validity

Bloom's Level	Number of Questions	Example Questions
C1-Remembering	10	(1) List three main components of a cloud-baesd learning system. (2) What is the definition of gamification according to [11]?
C2-Understanding	10	(1) Explain the difference between adaptive AI and traditional e-learning. (2) Why is collaboration important collaboration important in Social Constructivism [18]?
C3-Applying	10	(1) Provide a scenario that illustrates the use of AI to personalize learning content. (2) How would you apply Self-Determination Theory in designing a gamification module?
C4—Analyzing	10	(1) Analyze the impact of team-based gamification on students' intrinsic motivation. (2) Compare the learning outcomes of the AI + Gamification group with the AI-only

This mapping was conducted to ensure that the evaluation covered a range of cognitive skills from basic to analytical thinking. It includes conceptual understanding, application of simple algorithms, and analysis of short case studies related to cloud learning. Each question was validated by two subject-matter experts, with an inter-rater reliability score of 0.87.

The detailed results of instrument validity can be seen in Table 3.

Table 3. Instrument validity

Instrument	Construct	Cronbach's α	CFI	RMSEA	Interpretation
Student Engagement	Cognitive, Social, Agency	0.91	0.94	0.048	Excellent
Academic Motivation	Intrinsic, Identified Regulation	0.88	0.92	0.052	Good
Cognitive Assessment	Bloom's Taxonomy	0.87	0.93	0.050	Good

E. Data Analysis

Cognitive learning outcomes were analyzed using ANCOVA, while engagement and motivation were examined using repeated measures MANOVA. Synergistic effects were tested through Structural Equation Modeling (SEM), and moderating factors were analyzed using hierarchical regression. Qualitative data were analyzed thematically following the approach by [28].

F. Statistical Analysis

Prior to conducting ANOVA, MANOVA, and ANCOVA analyses, statistical assumption tests were performed. Normality was tested using the Shapiro–Wilk test, which indicated that most variables met the assumption of normal distribution ($p > 0.05$). Levene's test was used to assess homogeneity of variances across groups, and the results showed no significant violations ($p > 0.05$), supporting the appropriateness of using ANOVA and ANCOVA. For MANOVA, Box's M test yielded a non-significant result ($p > 0.001$), indicating that the covariance matrices across groups were homogeneous. Therefore, variance analysis approaches were considered suitable for this study.

IV. Result and Discussion

A. Implementation of the Platform and Student Activities

The following are the AI learning and gamification platforms and activities for students, as shown in Fig. 2 below.

Using the platform shown in Fig. 2, it was observed that during the 16-week intervention period, student participation and engagement levels differed significantly between groups. Data from the platform analytics indicate that Experimental Group 1 (AI + Gamification) had the highest level of activity, with 92% of students active, an average of 4.2 h per week, and an assignment completion rate of 85%. In contrast, the control group showed the lowest engagement, with 65% active students, an average of 2.4 h per week, and an assignment completion rate of 48%.

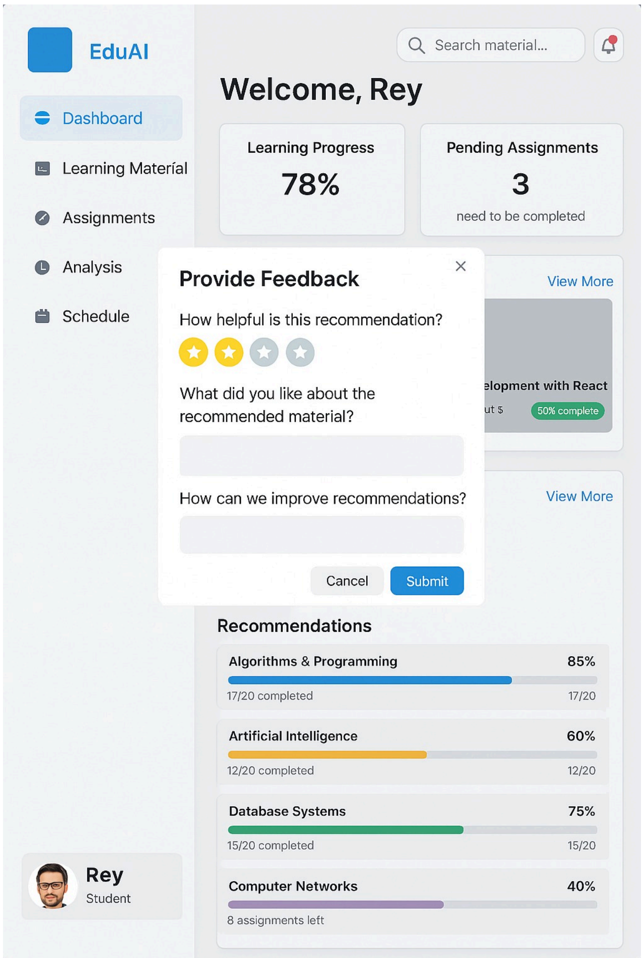

Fig. 2. AI learning and gamification platform.

Table 4. Student activity level and task completion

Group	% Active Students	Average Hours/Week	% Assignment Completion
Experimental 1 (AI + G)	92%	4.2 ± 0.9	85%
Experimental 2 (AI only)	78%	3.1 ± 1.1	62%
Control	65%	2.4 ± 1.3	48%

Table 4 presents a comparison of three groups in the context of academic activities, showing significant differences in student engagement and performance. Experimental Group 1, working on the AI Prediction Simulation, performed the highest with 92% of students engaged, an average of 4.2 ± 0.9 h of weekly engagement, and an 85% task completion rate. In contrast, Experiment 2, which focused on Database Exercises, showed moderate results with 78% of students engaged, 3.1 ± 1.1 h of weekly engagement, and 62% task completion. The Control Group with basic tasks showed the lowest participation, with only 65% of students engaged, an average of 2.4 ± 1.3 h of weekly engagement, and 48% task completion, which consistently indicates that the special treatment in Experiment 1 substantially increased student engagement and productivity.

Average Platform Usage Hours per Week can be seen in Fig. 3.

Fig. 3 shows highest engagement in Experiment 1 (Artificial Intelegent + Gamification.

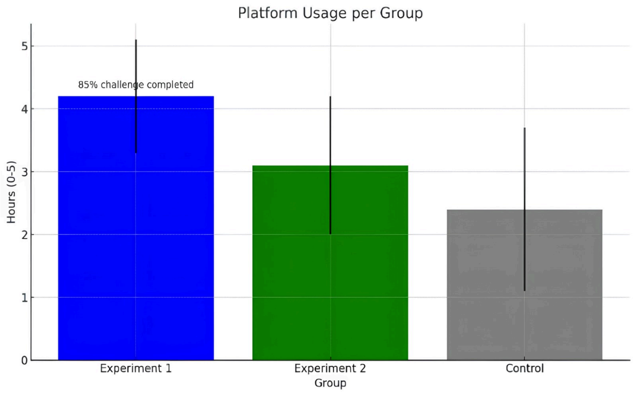

Fig. 3. Average platform usage hours per week.

1) Learner interaction patterns

Social Network Analysis (SNA) using Gephi on the discussion forum showed the following results:

Experimental Group 1: Density = 0.71, degree centrality = 52%, with 68% of interactions related to group challenges (120 posts for "Team Data Analysis").

Experimental Group 2: Density = 0.45, degree centrality = 38%.

Control Group: Density = 0.33, degree centrality = 29%.

The analysis also revealed that students in Experimental Group 1 frequently engaged in discussions due to group challenges, as reflected in feedback such as, The group challenge made me discuss with my team more often.

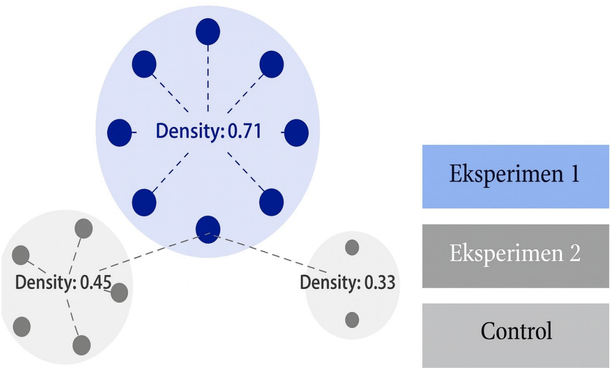

Fig. 4. SNA (Gephi) learner interaction patterns.

Fig. 4 presents the Social Network Analysis (SNA) visualization generated with Gephi, depicting the interaction patterns within the discussion forum for each experimental group.

The visualization of the discussion forum interaction network in Fig. 4, reveals communication patterns that significantly differentiate between the three groups. Experiment 1, represented by the large dark blue cluster containing 8 nodes, depicts a very dense and complex network structure, consistent with findings of a density of 0.71 and a degree centrality of 52%. In contrast, Experiment 2 (dark grey cluster with 5 nodes) shows looser but still structured interactions, reflecting a density of 0.45 and a degree centrality of 38%. The Control group, visualized by the smallest light grey cluster containing 4 nodes, clearly indicates the most restricted communication pattern with a density of 0.33 and a degree centrality of 29%, confirming that the intervention in Experiment 1 had the strongest and most centralized interaction network structure, indicating the intervention's success in improving team collaboration and communication.

B. Effects on Learning and Engagement

1) Cognitive learning outcomes

Analysis of cognitive learning outcomes was conducted using pretest and posttest scores measured on a scale of 0-100 based on 40 questions given to students. To evaluate the influence of variables on improving learning outcomes, data were analyzed using the ANCOVA (Analysis of Covariance) statistical method, the results of the analysis can be seen in Table 5.

Table 5. Pretest and posttest scores per group

Group	Pretest (M ± SD)	Posttest (M ± SD)	Average Increase	High level (M)
Experiment 1	62.4 ± 8.1	85.6 ± 7.2	23.2	87.3
Experiment 2	61.9 ± 7.9	78.3 ± 8.0	16.4	79.1
Control	63.1 ± 8.3	70.5 ± 9.1	7.4	71.8

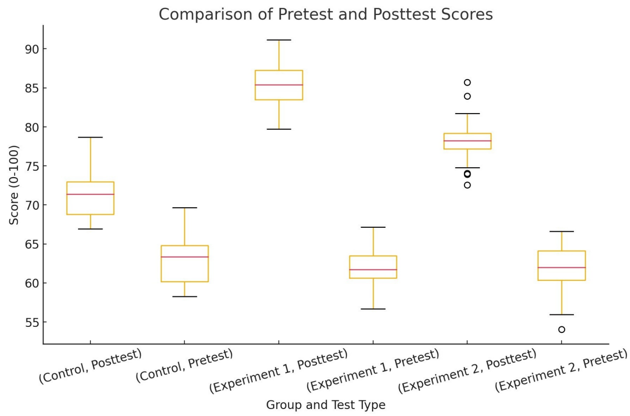

Fig. 5. Comparison of pretest and posttest scores.

Table 5 shows data from the three groups (Experiment 1, Experiment 2, and Control) related to the change in scores between pretest and posttest. Experimental Group 1 experienced a significant increase with a mean change of 23.2, indicating the largest increase from pretest (62.4) to posttest (85.6). Experimental Group 2 also showed an increase, albeit smaller with a mean of 16.4, from pretest (61.9) to posttest (78.3). Meanwhile, the Control group only experienced a small increase, with a mean of 7.4, from pretest (63.1) to posttest (70.5). This shows that both experimental groups gained greater benefits compared to the control group, reflecting a positive effect of the intervention given to the experimental group.

A comparison of the pretest and posttest score distributions for each group is also visualized in Fig. 5, which shows the largest score improvement in the AI + Gamification group.

Next, an analysis was carried out to see the statistical significance, how much influence and differences there were between groups, which can be seen in Table 6.

Table 6. ANCOVA test results for high cognitive level questions and post test results

Source	df	F	p	Group	Average (M)	η²
Inter Group	2	45.32	< 0.001	Experiment 1	87.3	0.29
Error	220			Experiment 2	79.1	
Total	222			Control	71.8	

The results of the ANCOVA analysis in Table 6 show that: F (2,222) = 45.32, $p < 0.001$, $\eta^2 = 0.29$. Post-hoc: Experiment 1 > Experiment 2 > Control ($p < 0.001$). High cognitive level (10 analysis/creation questions): Experiment 1 M = 87.3, Experiment 2 M = 79.1, Control M = 71.8. while the visualization of the comparative analysis of pretest and posttest scores can be seen in Fig. 6.

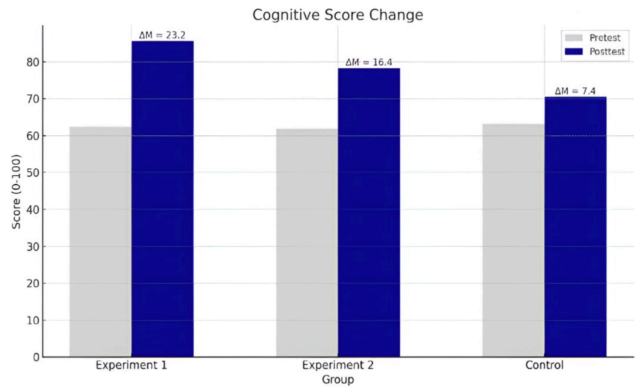

Fig. 6. Comparison of pretest and posttest scores.

2) Student involvement

To measure student engagement, researchers used the Student Engagement Inventory (SEI), a comprehensive instrument designed to measure student engagement across three key dimensions: cognitive, social, and agency. The instrument consists of 15 items rated on a 5-point Likert scale, allowing for in-depth measurement of multiple aspects of academic engagement.

The engagement dimensions analyzed in this study—cognitive, social, and agency—were selected based on the framework of Fredricks *et al.* (2004) and adapted to the context of collaborative and personalized learning. While behavioral and content engagement are also acknowledged conceptually, the instrument used (Student Engagement Inventory) explicitly focuses on students' internal and social engagement in the learning process, rather than solely on physical indicators such as attendance or platform activity. Therefore, emphasizing these three dimensions is considered most relevant for evaluating the impact of the Contextual Personalization model on active and reflective learning processes.

Table 7 presents the descriptive statistics of student engagement scores for each research group:

Table 7. Student engagement score

Group	Cognitive (M ± SD)	Social (M ± SD)	Agency (M ± SD)
Experiment 1	4.3 ± 0.5	4.5 ± 0.4	4.4 ± 0.5
Experiment 2	3.9 ± 0.6	3.7 ± 0.6	4.0 ± 0.6
Control	3.5 ± 0.7	3.4 ± 0.8	3.6 ± 0.7

Based on the data presented in Table 7, there are significant differences in the mean scores (M) and standard deviations (SD) on the three dimensions of measurement (cognitive, social, and agency) among the three groups - Experiment 1, Experiment 2, and Control. Experiment 1 showed the highest performance across all dimensions with a cognitive score of 4.3 ± 0.5, the highest social score of 4.5 ± 0.4, and the agency score of 4.4 ± 0.5, which were consistently higher than Experiment 2 and Control. Experiment 2 showed moderate scores ranging from 3.7–4.0, while the Control group had the lowest scores across all dimensions, ranging from 3.4–3.6, with slightly greater variability as indicated by the relatively high standard deviations. This pattern indicates that the intervention or treatment in Experiment 1 likely had the most substantial positive effect on participants' cognitive abilities, social skills, and agency capacity. The above data can be visualized in Fig. 7.

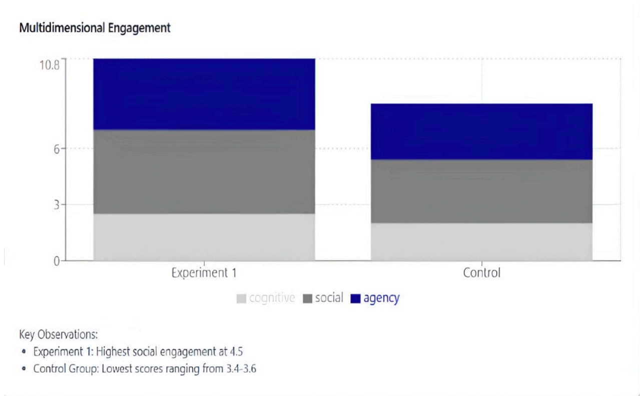

Fig. 7. Dimensions of student engagement.

3) Academic motivation

To measure motivation, researchers used the Academic Motivation Scale instrument to assess changes in student motivation before and after the intervention, with 21 items divided into three main dimensions: intrinsic motivation (e.g., "I study because I enjoy the process"), identified regulation (e.g., "I study because it is important for my future"), and amotivation (e.g., "I do not know why I study"). Each item is rated on a Likert scale of 1–7 (1 = strongly disagree, 7 = strongly agree), with high reliability (Cronbach's Alpha 0.88 based on previous studies). The results showed a significant shift in Experimental Group 1 (AI + Gamification), where intrinsic motivation increased from 4.2 to 5.8, identified regulation from 4.5 to 6.0, and amotivation decreased from 2.8 to 1.5, reflecting the positive impact of technology integration on internalization of motivation.

After conducting an assessment using the AMS instrument, a statistical analysis was then conducted using the Multivariate Analysis of Variance (MANOVA) statistical analysis to test the effect of the intervention on students' academic motivation, as measured by the Academic Motivation Scale (AMS). Where the statistical results of MANOVA were obtained: Wilks' $\lambda = 0.70$, $F(6,436) = 8.92$, $p < 0.001$, $\eta^2 = 0.19$. These data confirm the existence of a significant interaction between time (pre-test vs. post-test) and intervention group on academic motivation, the visualization results can be seen in Fig. 8.

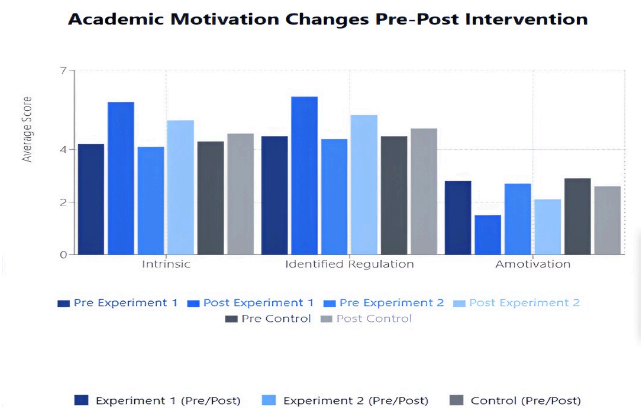

Fig. 8. Dimensions of student engagement.

C. Effectiveness of Technology Components

1) Effectiveness of adaptive AI systems

The TensorFlow-based adaptive AI system proved effective in reducing the performance gap between students with different digital literacy. In Experimental Group 1, the post-test scores of students with low ($M = 82.1$) and high ($M = 87.8$) digital literacy showed a smaller difference compared to the Control Group (low $M = 65.3$, high $M = 74.9$), with the t-test results indicating statistical significance. The adoption rate of AI recommendations was also higher in Experimental Group 1 (85%, e.g., "Learn Linear Regression") compared to Experiment 2 (70%), supported by chi-square analysis. Student quotes such as "The recommendations helped me focus" (Experiment 1) confirmed the positive perception of AI personalization.

2) Effectiveness of collaborative gamification

Collaborative gamification elements, such as group challenges (e.g. "Sales Prediction Simulation" with 5 students/group) and team rewards, were highly rated by students ($n = 30$) on a scale of 1-5: group challenges ($M = 4.6$), team rewards ($M = 4.4$), and individual points ($M = 3.9$). Correlations with learning outcomes showed that group challenges had a stronger relationship ($r = 0.62$, $p < 0.01$) than individual points ($r = 0.38$, $p < 0.05$), indicating that collaborative aspects had a greater impact on learning than individual elements.

3) Adaptive AI interaction and collaborative gamification

The synergy between adaptive AI and collaborative gamification is seen in three mechanisms:

Dynamic Adaptation: "Team Data Analysis" challenge was adjusted (e.g. group score 80 → difficulty 5/10, flow experience $M = 4.3/5$

Social Personalization: Role recommendation (e.g., "Analysis", for high score) was adopted by 88% vs. 72% ($p < 0.01$).

Gamification Reinforcement: Optional content exploration (e.g., "Database Tutorial")

Experiment 1 = 40%, Experiment 2 = 25%, Control = 15%.

Based on multivariate statistical analysis using Structural Equation Modeling (SEM) Analysis confirmed the direct effect ($\beta = 0.35$) and interaction ($\beta = 0.28$) on learning engagement, with a very good fit model (CFI = 0.95, RMSEA = 0.045). The details of the Effectiveness of Technology Components can be seen in Table 8.

Table 8. Statistical results of technology component effectiveness

Component	Statistical Test	Result	Interpretation
Adaptive AI System	t-test (Digital Literacy, Experiment 1)	$t(73) = 2.14$, $p = 0.03$	Low vs. High Score Difference Smaller
	t-test (Digital Literacy, Control)	$T(73) = 4.82$, $p < 0.001$	Larger Disparity in Control Group
Collaborative Gamification	χ^2 (Recommendation Adoption)	$\chi^2 = 6.45$, $p < 0.01$	Higher Adoption in Experiment 1
	Correlation (Group-Level)	$r = 0.62$, $p < 0.01$	Strong Correlation with Learning Outcomes
	Correlation (Individual Points)	$r = 0.38$, $p < 0.05$	Moderate Correlation with Learning Outcomes
AI + Gamification Interaction	χ^2 (Social Personalization)	88% vs. 72%, $p < 0.01$	Role Recommendations More Accepted
	SEM (Direct Effect)	$\beta = 0.35$, $p < 0.01$	Direct Effect on Involvement
	SEM (Interaction Effect)	$\beta = 0.28$, $p < 0.01$	Synergy Increasing Involvement
	SEM (Model Fit)	CFI = 0.95, RMSEA = 0.045	Model Highly Compatible with Data

D. Factors Affecting Effectiveness

1) Individual variables

To identify individual factors that moderate the effectiveness of the intervention, a hierarchical regression analysis was conducted with cognitive post-test scores as the dependent variable. The independent variables tested included digital literacy (scale 1-5 based on the pre-test), learning styles (visual, auditory, kinesthetic, measured by the VAK questionnaire), and personality (cooperative-competitive scale, 1–5). Hierarchical regression was chosen to allow for control of demographic variables (age, gender) at an early stage, before entering the main variables hypothesized to influence learning outcomes. The following are the results of the analysis using Regression, Table 9 is a summary of the hierarchical regression process.

Based on the hierarchical regression analysis shown, the control variables (age and gender) in the first step only explained 3% of the variance ($R^2 = 0.03$) with a significance of $p = 0.035$. In the second step, with the addition of the main variables, the model was able to explain 18% of the variance (an increase of 15%) with a stronger significance ($p < 0.001$). Among the main variables, digital literacy ($\beta = 0.22$, $p = 0.015$) and visual learning style ($\beta = 0.18$, $p = 0.034$) emerged as significant predictors, while auditory, kinesthetic, and cooperative-competitive learning styles did not show significant effects. These results indicate that digital literacy and visual learning preferences have a significant positive impact on the dependent variable.

Table 9. Individual variable regression analysis

Steps and Variables	β (Standard Coefficient)	*t*	*p*	R^2	ΔR^2	*F* (*df*)	*p* (Model)
Step 1: Control Variables				0.03	-	*F*(2,222) = 3.41	0.035
Age	0.11	1.62	0.107				
Gender	0.09	1.34	0.181				
Step 2: Main Variables				0.18	0.15	*F*(7,217) = 6.82	< 0.001
Age	0.08	1.19	0.235				
Gender	0.07	1.05	0.295				
Digital Literacy	0.22	2.45	0.015*				
Visual Learning Style	0.18	2.13	0.034*				
Auditory Learning Style	0.06	0.78	0.437				
Kinesthetic Learning Style	0.04	0.52	0.604				
Personality (Cooperative-Competitive)	−0.12	−1.68	0.094				

2) Contextual variables

The process of obtaining quantitative data began with the preparation of a survey given to 75 lecturers involved in the study, assuming one lecturer per student group for three groups (Experiment 1, Experiment 2, and Control). The survey was designed using a Likert scale of 1-5, with three items to measure lecturer support (e.g., "I feel capable of assisting students in using the platform") and three items for curriculum integration (e.g., "This platform is easy to integrate into my course curriculum"), each with high reliability (Cronbach's Alpha around 0.85 and 0.82). The survey was collected in week 16, the end of the intervention period, via Google Forms to facilitate data processing. The mean score was calculated from the lecturer responses, resulting in lecturer support $M = 4.5$ (SD ≈ 0.6) and curriculum integration $M = 4.3$ (SD ≈ 0.7). The results of the survey analysis can be seen in Table 10.

Table 10. Survey analysis results

Variable	Number of Items	Item Examples	Mean (M)	Standard Deviation (SD)	Reliability (Cronbach's Alpha)
Lecturer Support	3	"I feel capable of assisting students in using the platform"	4.5	0.6	0.85
Curriculum Integration	3	"This platform is easy to integrate into my course curriculum"	4.3	0.7	0.82

Next, a Pearson correlation was run using SPSS to test the relationship between these contextual variables (combined as one mean score) with student engagement from the Student Engagement Inventory. The data were paired per group, and the results showed $r = 0.48$. The significance test yielded a *t* value ≈ 4.56 (with df = 73), $p < 0.01$, confirming that faculty support and curriculum integration significantly influenced student engagement, explaining about 23% of the variance ($r^2 \approx 0.23$). The results of the Pearson correlation analysis can be seen in Table 11.

Table 11. Pearson correlation analysis results

Variable	Correlation Coefficient (*r*)	Coefficient of Determination (r^2)	Nilai *t*	*df*	*p*-value
Lecturer Support and Curriculum Integration (combined) with Student Involvement	0.48	0.23	4.56	73	< 0.01

SemMeanwhile, qualitative data were collected through semi-structured interviews with 15 lecturers, purposively selected (five from each group) to reflect a variety of experiences, conducted in weeks 17–18 post-intervention. Interviews, lasting 20–30 min per lecturer, included questions such as "How did the training impact your ability to manage the platform?" and were recorded for transcription. The AWS training mentioned consisted of three sessions (2 h each, totaling 6 h), covering an introduction to AWS, use of the QuickSight dashboard, and management of gamified APIs. Thematic analysis [26] was applied: transcripts were re-read, coded (e.g., "confidence," "effective training"), and grouped into themes such as "Impact of Training." A key theme that emerged was increased confidence, with a representative quote: "Amazon Web Services (AWS) training (3 sessions, 6 h) increased confidence in managing the platform." A total of 12 lecturers mentioned that the training made technical navigation easier, and 9 others reported smoother curriculum integration, providing qualitative context to support the high quantitative scores and significant correlation with student engagement.

E. Discussion

The results of this study confirm that the integration of adaptive AI systems and collaborative gamification has a significant impact on improving students' learning outcomes, engagement, and academic motivation in cloud-based learning. In general, the greatest effect was found in the group that received the combined intervention of both, both in cognitive and affective dimensions.

The improvement in learning outcomes in Experimental Group 1 shows that AI is not only able to personalize content, but also encourage meaningful learning through continuous adaptation. This finding extends previous literature that focuses on adaptation [29]; by showing that social interactions facilitated by collaborative gamification strengthen the effects of AI.

Specifically, students' social engagement and agency increased significantly in the collaborative gamification group. This supports the principle of Social Constructivism [30], that social interaction facilitates the construction of deeper knowledge. In addition, students' intrinsic motivation experienced a significant increase, strengthening the validity of Self-Determination Theory [19] which emphasizes the role of autonomy, competence.

The SEM model shows that there is a strong synergistic effect between AI and gamification, explaining how adaptive personal technology and interactive social mechanisms can complement each other. This model provides a conceptual basis for the development of a more comprehensive learning system, and is the main theoretical contribution of this study, namely the proposal of the Contextual Personalization model, an approach that balances individual adaptation, social dynamics, and collaborative support in digital learning.

The results of this study indicate that the integration of adaptive AI and collaborative gamification (AI + G) has a significant impact on improving cognitive learning outcomes. This finding is consistent with the study by [23], which reported that the use of adaptive AI systems in programming courses led to an 18% increase in exam scores compared to the control group. Furthermore, the observed increase in cognitive, social, and agency engagement dimensions in this study supports the findings of [29], who demonstrated that socially contextualized gamification design can enhance deep learning engagement.

In terms of academic motivation, the findings of this study align with those of [24, 30], which showed that gamification elements can enhance intrinsic motivation and foster a sense of ownership over the learning process. However, not all motivation dimensions exhibited equally significant improvements, suggesting that contextual factors such as instructor support and curriculum relevance continue to play an important role [31–34]. These findings highlight the importance of an approach that not only focuses on technology but also incorporates social and institutional elements in digital learning.

Although the proposed "Contextual Personalization" model demonstrates synergy between adaptive AI and collaborative gamification, it has not yet been tested in cross-cultural or cross-institutional contexts. This raises questions about the extent to which our findings can be generalized to other educational ecosystems with different social dynamics and infrastructures. Several studies have also highlighted the potential negative effects of gamification, such as a decline in intrinsic motivation when game elements focus solely on external rewards [25, 26, 35]. Therefore, this study recommends further research to evaluate the long-term sustainability of motivation generated by gamification.

In terms of implementation, the success of this system is also influenced by moderator factors such as students' digital literacy and institutional support from lecturers. Therefore, these results provide clear practical implications: higher education institutions need to provide supporting infrastructure, technical training for lecturers, and flexible but structured systems so that learning technology can be optimally adopted.

Although the quasi-experimental design with cluster random sampling provides internal strength to this study, it carries the risk of group-level confounding variables that may not be fully controlled, such as differences in instructors' teaching styles or classroom dynamics. Furthermore, the study's context, which is limited to a university in Indonesia, restricts the external validity of the findings. Therefore, generalizing these results to international contexts should be approached with caution, and further research is recommended to include samples across institutions or countries.

V. Research Limitations

The limitations of this study include its scope, which is restricted to a national context and a single discipline. Although the sample size was adequate (N = 225), it was drawn from only one higher education institution in Indonesia, which may affect the external validity of the findings. In addition, experimental grouping was conducted at the class level (cluster sampling), creating the potential for uncontrolled inter-group biases such as differences in instructor characteristics, classroom atmosphere, or learning habits.

The short-term duration of the intervention (one semester) also limits the ability to measure long-term effects on engagement, motivation, and the development of non-cognitive competencies such as collaboration, creativity, and digital literacy. Furthermore, experimental conditions were not entirely uniform, particularly regarding device access and internet connection quality, which could have influenced interactions on the cloud-based learning platform.

Future studies are recommended to explore the application of this model in international contexts, over longer periods, and to assess its effectiveness in fostering non-cognitive competencies more comprehensively.

The limitations of this study include the scope that is still limited to a specific national and disciplinary context, and the short-term duration of the intervention. Further studies are recommended to explore the application of this model in an international context and over a longer period of time, as well as to test the effectiveness of the system in developing non-cognitive competencies such as collaboration, creativity, and digital literacy.

In the implementation of adaptive AI, particular attention was given to ethical considerations, including potential algorithmic bias, data privacy, and the risks of learner surveillance. Student data were anonymized and used solely for aggregate analysis, while AI-generated recommendations were manually monitored to prevent unfair decisions. The system was also designed with transparency in mind, allowing students to view and adjust their learning recommendations. These measures were taken to minimize bias and ensure compliance with data privacy principles.

With cluster random sampling, there is a potential for group-level confounding variables such as differences in classroom dynamics or instructors that may not be fully controlled. Second, the study's context, which is limited to a university in Indonesia, constrains the generalizability of the findings to international settings or institutions with different cultures and infrastructures. In addition, the sustainability of student engagement after the intervention was not measured longitudinally, so the long-term effects of combining AI and gamification on motivation and engagement cannot yet be confirmed.

VI. Conclusion

This study concluded that the integration of adaptive AI systems and collaborative gamification significantly improved cognitive learning outcomes, student engagement, and academic motivation in cloud-based learning in higher education. The group receiving the combined intervention performed the highest in higher-order learning outcome indicators, social engagement, and intrinsic motivation.

These findings support a learning approach that is not only oriented towards individual adaptation, but also strengthens social interaction and student agency. The "Contextual Personalization" model developed in this study is an important conceptual contribution, because it combines individual, social, and collaborative dimensions in an integrated manner in one cloud-based digital learning system.

In addition to its strengths, this model requires external validation through cross-context trials and an evaluation of the long-term motivational effects of gamification elements. This study also has several limitations. First, the quasi-experimental design with cluster random sampling carries the risk of group-level confounding variables such as differences in classroom dynamics or instructors that may not be fully controlled. Second, the study's context, which is limited to a university in Indonesia, restricts the generalizability of the findings to international contexts or institutions with different cultures and infrastructures. Furthermore, the sustainability of student engagement after the intervention was not measured longitudinally, meaning the long-term effects of combining AI and gamification on motivation and engagement remain uncertain.

VII. Recommendations

Based on the findings of this study, several practical recommendations can be made to enhance the quality of technology-based learning:

Integration of adaptive AI and collaborative gamification: Educational institutions should consider incorporating adaptive AI modules combined with collaborative gamification to enhance personalization and student engagement.

Data-driven instructional strategies: Instructors and curriculum developers are encouraged to use learning platform analytics to dynamically adjust teaching strategies.

Professional development for educators: Training should be strengthened for educators on the use of learning data and the design of instruction grounded in motivational theory and personalization, ensuring that technology interventions are sustainable and have a tangible impact.

Conflict of Interest

The author declares no conflict of interests.

Author Contributions

In this article, each author contributed to the completion of this article, namely Remerta Noni Naatonis conducted the research and wrote the draft of the article; Sumarlin and Edwin Ariesto Umbu Malahina helped conduct research focusing on AI, Gamification, and Claud technology; Skolastika Siba Igon and Meliana Oktavia Meo conducted data analysis and assisted in editing; and Franki Yusuf Bisilisin provided additional studies related to statistical literacy. All authors have approved the final version.

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