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Boosting Higher Education Learning Outcomes: The Structural Impact of Adaptive Gamified Environments on Students' Cognitive Skills

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ABSTRACT

Purpose—This study examines the effectiveness and structural impact of adaptive gamified learning environments on students' Computational Thinking and Real-World Problem-Solving in higher education. It specifically investigates whether Scratch-based Adaptive Gamification improves learning achievement and whether Computational Thinking enhances students' ability to solve authentic, complex problems.

Design/methodology/approach—This study employed a quasi-experimental nonequivalent control group design involving 60 undergraduate Informatics students, equally divided into an experimental group receiving Scratch-based adaptive gamified instruction and a control group receiving conventional instruction. Learning outcomes were assessed using pre-tests, post-tests, project-based assessments, and structured classroom observations. Descriptive statistics and Pearson's Chi-Square test were used to evaluate differences in academic achievement, while Partial Least Squares Structural Equation Modelling was applied to examine the structural relationships among Adaptive Gamification, Computational Thinking, and Real-World Problem-Solving.

Findings—The experimental group's mean score increased from 65.30 in the pre-test to 84.70 in the post-test, representing a gain of 19.40 points, whereas the control group's mean score increased from 64.90 to 72.50, representing a gain of 7.60 points. Pearson's Chi-Square test confirmed a statistically significant association between the instructional method and categorised academic achievement ($\chi^2(1, N = 60) = 5.690$, $p = .017$), with Cramér's $V = .308$. The structural model further showed that Computational Thinking positively affected Real-World Problem-Solving ($\beta = .301$, $p = .006$), while Adaptive Gamification exerted a stronger positive direct effect on Real-World Problem-Solving ($\beta = .553$, $p < .001$). However, the mediating role of Computational Thinking requires confirmation through a formally bootstrapped specific indirect-effect analysis.

Originality/value—This study integrates quasi-experimental evidence of instructional effectiveness with PLS-SEM-based structural validation in a unified analytical framework. It extends adaptive gamification research beyond motivation, participation, and general academic achievement by focusing on higher-order cognitive outcomes and positioning Computational Thinking as a potential cognitive pathway that connects adaptive learning experiences to real-world problem-solving.

Implications—The findings suggest that higher education institutions, lecturers, instructional designers, and educational technology developers should implement adaptive gamification as an integrated instructional system rather than as a superficial collection of rewards. Personalised challenges, progressive task difficulty, diagnostic feedback, repeated experimentation, and authentic project-based scenarios should be aligned with learning objectives to strengthen computational reasoning and transferable problem-solving capabilities.

1. Introduction

The accelerating digital transformation has led to heightened expectations that higher education should equip graduates not only to operate digital technologies but also to think systematically, adapt to unfamiliar situations, and formulate defensible solutions to complex problems. These expectations are becoming increasingly important as technology changes how jobs are done and what skills people need to get a job after they finish their studies (Jung et al., 2024; Lucas et al., 2022). In this professional context, it is clear that Computational Thinking (CT) and real-world problem-solving (RWPS) have become vital and highly transferable competencies. They have replaced narrowly defined technical skills as the preferred option. Conversely, CT enables learners to approach problems through decomposition, abstraction, generalisation, algorithmic design, and evaluation. In contrast, RWPS requires learners to interpret authentic situations (often ill-structured), select relevant information, develop feasible strategies, and evaluate the consequences of proposed solutions (Argelagós et al., 2022; Kang et al., 2023). However, ongoing skill gaps among graduates suggest that disciplinary knowledge alone is insufficient to ensure the transfer of conceptual understanding into technology-rich professional contexts (Jung et al., 2024; Scheuring and Thompson, 2025).

A significant source of this discrepancy can be attributed to pedagogical practices that persist in emphasising one-directional knowledge transmission, procedural replication, and predetermined answers. While these methods may assist in acquiring short-term content, they offer limited opportunities for learners to break down unfamiliar problems, compare alternative solutions, evaluate unsuccessful strategies, or apply knowledge in authentic contexts. Research in the field of CT education has demonstrated that the acquisition of these competencies is not a spontaneous consequence of exposure to programming or digital content. Instead, the literature suggests that intentionally designed learning activities integrating conceptual understanding, iterative practice, reflection, and problem-oriented application are more effective (Åkerfeldt et al., 2024; Lee et al., 2022). In the field of problem-solving education, students often encounter difficulties in defining complex problems, identifying relevant information, planning solution procedures, and transferring prior knowledge to new situations without adequate instructional support (Argelagós et al., 2022). Active and project-oriented pedagogies provide a stronger foundation for higher-order learning, yet the effectiveness and rigour of educational interventions vary (Chang et al., 2022; Martella et al., 2023).

Gamification offers a solution to these limitations by incorporating game-design elements, such as challenges, levels, feedback, progress indicators, points, narratives, and achievement systems, into non-game-based learning environments. Recent research suggests that well-designed gamification can positively impact learner engagement, knowledge acquisition, satisfaction, intrinsic motivation, and academic performance in higher education (Khaldi et al., 2023; Murillo-Zamorano et al., 2023; Xu et al., 2025). However, conventional gamification often uses the same game elements for all learners, despite differences in abilities, preferences, motivation, and learning progress. Adaptive gamification is a solution to this issue, in which challenges, feedback, game elements, and learning pathways are modified based on learners' characteristics as they develop. From the perspective of Self-Determination Theory, personalised challenges, meaningful choices, competency-oriented feedback, and supportive interaction can strengthen autonomy and competence as well as relatedness, thereby promoting continued engagement (Li et al., 2024). From a constructivist perspective, adaptive gamified environments also facilitate active knowledge construction by enabling learners to explore different solutions, receive immediate feedback, revise unsuccessful ones, and learn through interaction with meaningful problems (Seraji and olsadat Musavi, 2023).

While adaptive gamification has theoretical potential, it does not automatically produce uniform learning benefits. Personalised game elements have been shown to increase participation and enjoyment, but their effects on cognitive and emotional engagement, as well as higher-order learning, remain inconsistent across contexts and learner profiles (Oliveira et al., 2022; Xiao and Hew, 2024). Existing studies have focused mainly on factors such as motivation, engagement, satisfaction, and general academic performance. However, comparatively less emphasis has been placed on the joint development of multidimensional CT skills and authentic problem-solving abilities. Furthermore, intervention studies typically evaluate the efficacy of gamification in improving outcomes but offer limited insight into the cognitive processes underlying these improvements. Conversely, studies examining relationships among gamification, motivation, engagement, and learning effectiveness often rely heavily on learners' perceptions rather than combining perceptual evidence with demonstrated performance outcomes (Kırmacı and Kılıç Çakmak, 2025; Nguyen-Viet et al., 2025; Zhang et al., 2025). As a result, the literature is divided between studies that demonstrate educational effects and studies that explain relationships among the underlying constructs.

The present analysis addresses this gap by examining the role of adaptive gamification in CT and RWPS within an integrated conceptual framework. The key novelty of this work is the combination of evidence of instructional effectiveness and structural explanations of the relationships among adaptive gamification, CT and RWPS. This dual-validation perspective goes beyond simply assessing the efficacy of a gamified intervention; it also elucidates how adaptive gamification can enhance problem-solving capabilities, both directly and indirectly, by cultivating CT. This approach offers a more comprehensive overview than studies limited to comparing learning outcomes or to cross-sectional relationships among perceived constructs (Liengaard, 2024; Kurtaliqi et al., 2024). Accordingly, the study explores whether adaptive gamification strengthens CT, whether CT contributes to RWPS, and whether adaptive gamification directly supports RWPS.

This study significantly contributes to the gamification literature by integrating adaptive instructional design with multidimensional CT and authentic problem-solving outcomes. It extends the evaluation of adaptive gamification beyond motivation and participation to include higher-order cognitive skills. Additionally, it highlights CT as a key cognitive pathway connecting adaptive learning experiences to real-world problem-solving. The study also offers a combined empirical and structural perspective, addressing calls for more rigorous, theory-based, and learner-centred gamification research (Kang et al., 2023; Xiao and Hew, 2024; Xu et al., 2025). The rest of the article is organised as follows: Section 2 reviews the literature and develops the conceptual framework and hypotheses. Section 3 details the research methodology. Section 4 presents the findings, while Section 5 concludes the study, acknowledging its limitations and proposing future research directions.

2. Literature Review

2.1 Theoretical Foundation

The proposed framework combines Self-Determination Theory (SDT), constructivist learning theory, and experiential learning theory to explain how adaptive gamification, computational thinking (CT), and real-world problem-solving (RWPS) are connected through affective, cognitive, and practical mechanisms. SDT highlights how adaptive gamification can boost motivation by offering personalized challenges, meaningful choices, competency feedback, and supportive interactions that meet learners' needs for autonomy, competence, and relatedness. These elements can increase intrinsic motivation and engagement (Li et al., 2024; Oliveira et al., 2023). Constructivist theory shows how such engagement promotes CT by enabling active knowledge construction through problem exploration, algorithm testing, feedback, strategy revision, and meaning negotiation through interactive processes rather than the passive reception of solutions (Seraji and olsadat Musavi, 2023).

Experiential Learning Theory explains how CT is applied to RWPS through cycles involving concrete experience, reflection, conceptual understanding, and active experimentation with real tasks, enabling learners to turn abstract computational ideas into practical solutions to complex problems (Anderson-Gough et al., 2022). Overall, these theories create a unified framework where adaptive gamification motivates learners, supports active CT development, and promotes its real-world application.

2.2 Gamification in Education

Gamification refers to the purposeful integration of game-design elements into non-game contexts to enhance learners' motivation, engagement, and learning behavior. In educational environments, commonly used elements include points, badges, leaderboards, progress bars, challenges, narratives, and achievement systems that make learning activities more interactive and goal-oriented. Recent evidence indicates that gamification can strengthen intrinsic motivation, participation, knowledge acquisition, and academic performance when game elements are aligned with learning objectives rather than applied merely as external rewards (Khaldi et al., 2023; Li et al., 2024). A multilevel meta-analysis further demonstrates that appropriate combinations of game elements can improve cognitive, affective, and skill-based learning outcomes, although their effectiveness varies across instructional designs and learner characteristics (Xu et al., 2025). Conventional gamification, however, generally employs a one-size-fits-all configuration in which all learners receive identical challenges, rewards, and feedback. Adaptive gamification represents a more personalized evolution by dynamically adjusting game elements, task difficulty, feedback, content, and learning pathways based on learners' performance, preferences, and evolving needs (Oliveira et al., 2022; Xiao and Hew, 2024).

Adaptive gamification can support computational thinking (CT) through interconnected motivational and cognitive mechanisms. From the perspective of self-determination theory, personalized choices strengthen autonomy, performance-sensitive feedback reinforces competence, and socially meaningful game elements support relatedness, thereby encouraging intrinsic motivation and sustained engagement in cognitively demanding tasks (Li et al., 2024). Consistent with constructivist learning theory, learners actively construct CT knowledge by exploring problems, testing alternative procedures, receiving dynamic feedback, reflecting on errors, and revising ineffective strategies. Progressive challenges encourage the decomposition of complex problems into manageable components, while contextualized tasks facilitate pattern recognition, generalization, and abstraction. Immediate feedback further supports algorithmic iteration by enabling learners to continuously test, debug, evaluate, and refine procedural solutions (Kang et al., 2023; Zitouniatis et al., 2023). Adaptive gamification, therefore, creates a learner-responsive environment in which personalization, active experimentation, and formative feedback jointly facilitate the progressive development of CT (Seraji and olsadat Musavi, 2023; Xiao and Hew, 2024).

H1: Adaptive gamification positively affects computational thinking.

2.3 Computational Thinking

In today's business environment, computational thinking (CT) is an essential skill for professionals. It involves cognitive processes for the systematic formulation, representation, and solution of problems. These problems can be tackled by both humans and computers, making CT a crucial competency in the 21st century. Its four main pillars are decomposition, which breaks down complex issues into simpler parts; pattern recognition, which identifies recurring structures and connections; abstraction, which highlights important details while filtering out less relevant information; and algorithm design, which involves developing step-by-step solutions (Boom et al., 2022; Kang et al., 2023). CT is more than just programming or computer science; it is a versatile problem-solving skill applicable across scientific, professional, and daily contexts (Hurt et al., 2023; Lee et al., 2022). In higher education, CT serves as an intellectual framework that combines adaptive, gamified experiences with real-world problem solving (RWPS). Personalized challenges promote decomposition and pattern recognition, while iterative experimentation and feedback improve abstraction, algorithmic thinking, and solution evaluation. These processes help learners turn interactive experiences into structured methods for addressing unfamiliar and poorly defined problems. Therefore, developing CT through adaptive learning environments naturally enhances learners' ability to interpret, model, and solve real-world challenges.

2.4 Real-World Problem-Solving (RWPS)

Real-World Problem-Solving (RWPS) involves recognizing, interpreting, and addressing authentic, complex, and often ill-structured problems by combining conceptual knowledge with analytical thinking and practical judgment. Unlike routine tasks with preset steps, real-world problems require learners to define the issue, gather relevant data, develop alternative strategies, implement feasible solutions, and assess their impacts within specific contexts (Argelagós et al., 2022; Chang et al., 2022). Computational Thinking (CT) provides a cognitive framework for performing these tasks systematically. It includes decomposition, which breaks down complex problems into manageable parts; pattern recognition, which identifies recurring relationships; abstraction, which isolates key variables; and algorithmic reasoning, which organizes solutions into logical sequences. These skills help learners turn ambiguous situations into structured, actionable problem representations (Hurt et al., 2023; Kang et al., 2023). As a result, CT serves as a mental bridge between conceptual understanding and practical action, enabling the application of knowledge from learning environments to new professional and societal challenges. Research from problem-centered and project-based learning also shows that structured inquiry, iterative reasoning, and authentic application significantly enhance the development of transferable problem-solving skills (Santhosh et al., 2023; Zheng et al., 2023).

H2: Computational thinking positively affects real-world problem-solving.

Adaptive gamification can directly influence RWPS by creating interactive environments in which learners face increasingly complex challenges, receive performance-based feedback, and refine their strategies without the high stakes of actual failure. Personalized difficulty settings help keep challenges aligned with learners' abilities, while dynamic feedback enables learners to spot errors, compare approaches, and refine solutions through ongoing experimentation (Oliveira et al., 2022; Xiao and Hew, 2024). According to experiential

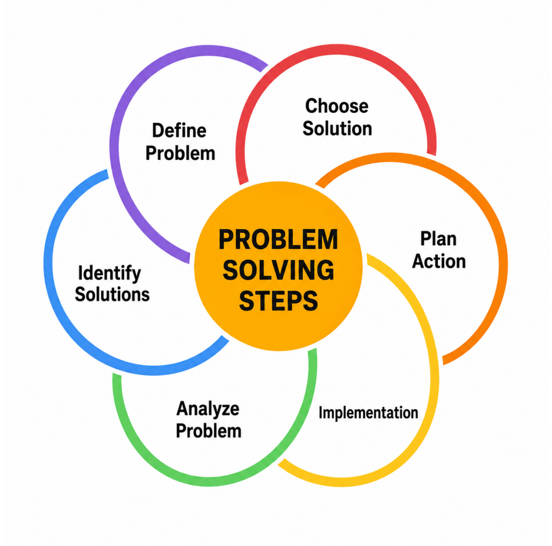

Fig. 1. Problem Solving Steps

learning theory, these cycles of action, feedback, reflection, and reapplication help transform abstract knowledge into practical problem-solving skills. Constructivist learning principles also indicate that learners gain deeper understanding when actively testing ideas and building solutions through meaningful interaction rather than simply reproducing procedures (Seraji and olsadat Musavi, 2023). Additionally, gamified challenges can boost persistence and intrinsic motivation, encouraging learners to stay engaged with difficult and uncertain problems (Li et al., 2024; Xu et al., 2025). Overall, adaptive gamification supports RWPS by maintaining engagement and offering repeated chances for authentic, iterative, and context-sensitive solution development.

H2: Computational thinking positively affects real-world problem-solving.

H3: Adaptive gamification positively affects real-world problem-solving.

2.5 Conceptual Framework

The conceptual framework positions adaptive gamification (AG) as the exogenous variable, computational thinking (CT) as the mediating variable, and real-world problem-solving (RWPS) as the endogenous variable. The model specifies three hypothesized paths: AG > CT (H1), CT > RWPS (H2), and AG > RWPS (H3), consistent with recent evidence on personalized gamification and multidimensional CT development (Kang et al., 2023; Oliveira et al., 2022). Figure 1 illustrates the problem-solving stages, while Figure 2 presents the complete research model.

3. Methodology

3.1 Research Design

This study used a quasi-experimental, nonequivalent control group design to assess the effectiveness of Scratch-based adaptive gamification in developing computational thinking (CT) and real-world problem-solving (RWPS). This approach was chosen because random assignment within intact classrooms wasn't feasible; however, pre- and post-intervention measurements allowed for systematic comparison while maintaining ecological validity. Establishing baseline equivalence is crucial in quasi-experimental research to prevent pre-existing group differences from confounding the results (Martella et al., 2023). The study involved two groups: an experimental group experiencing Scratch-based adaptive gamified instruction and a control group receiving traditional instruction, aligning with current educational intervention practices (Hwang et al., 2022; Qiao et al., 2022). Here, adaptive gamification was the independent variable, with CT and RWPS as the dependent variables.

3.2 Participants and Data Collection

The study involved 60 undergraduate students in an informatics program, divided equally into an experimental group and a control group. Students were selected intentionally to ensure comparable academic backgrounds and prior experience. Participation was contingent on active enrollment, informed consent, and completing all assessments. Since purposive sampling alone doesn't guarantee group equivalence, students' prior knowledge was assessed using a pre-test administered before the intervention. This approach minimized selection bias and allowed for a more valid comparison between the groups, aligning with recommendations for non-randomized educational studies (Hwang et al., 2022; Martella et al., 2023).

Data collection involved three complementary tools. First, parallel pre- and post-tests assessed changes in CT- and RWPS-related learning outcomes. Second, a project-based rubric assessed students' skills in identifying authentic problems, devising computational solutions, applying appropriate strategies, and evaluating the feasibility of those solutions. Third, structured classroom observations recorded behavioral engagement, participation, persistence, and interactions during activities. These instruments provided performance-based and observational evidence, supplementing self-reports. Employing multiple evidence sources facilitated methodological triangulation, allowing examination of convergence or divergence among test scores, project work, and observed behaviors. This approach improved interpretive validity and minimized bias from single methods (Maxwell, 2022; Qiao et al., 2022; Veldkamp et al., 2022).

3.3 Data Analysis

Means, standard deviations, and pre-test–post-test changes were used to summarize within-group learning progress through

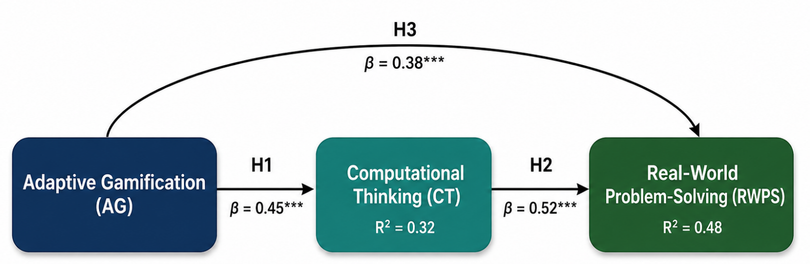

Fig. 2. Research Model of AG, CT, and RWPS Relationships

descriptive statistics. Pearson's chi-square test was then utilized to evaluate the association between instructional method and categorized academic achievement, with statistical significance set at 0.05 $p < .05$, and Cramér's V V employed to estimate association strength. PLS-SEM was subsequently applied as the model involved predicting direct and mediated relationships between adaptive gamification, computational thinking, and real-world problem-solving. The measurement model was evaluated through indicator reliability, composite reliability, and average variance extracted. This is consistent with contemporary PLS-SEM guidance. The structural model was assessed using collinearity, path coefficients, bootstrapping, confidence intervals, R^2, effect sizes, and indirect effects. This is also consistent with contemporary PLS-SEM guidance (Hair and Alamer, 2022; Sarstedt et al., 2022; Liengaard, 2024).

The structural model proposed in Figure 2 links adaptive gamification, computational thinking, and real-world problem-solving. In the model, adaptive gamification is represented as the exogenous construct, computational thinking as the mediating construct, and real-world problem-solving as the final endogenous construct. Figure 2 illustrates three hypothesized relationships. These are as follows: adaptive gamification directly influences computational thinking. Computational thinking influences real-world problem-solving. Adaptive gamification directly influences real-world problem-solving. This structure reflects the theoretical assumption that adaptive gamified learning strengthens higher-order problem-solving by developing computational reasoning and providing direct experiential engagement with complex tasks.

4. Results

4.1 Descriptive Statistics

As shown in Table 1, both the experimental and control groups had very similar pre-test scores, measuring 65.30 and 64.90, respectively. This small difference of 0.40 points suggests a comparable baseline, though definitive baseline equivalence cannot be confirmed without standard deviations and an inferential pre-test comparison. After the intervention, the experimental group's post-test mean increased to 84.70, while the control group's mean was 72.50. The experimental group thus gained 19.40 points, representing a 29.71% increase over its initial score. In contrast, the control group improved by 7.60 points, or 11.71%. Overall, the improvement in the experimental group was about 2.55 times that of the control group, with a post-test difference of 12.20 points between the groups. These initial findings suggest that adaptive gamification may lead to greater learning gains than traditional instruction. Further inferential analysis will assess whether the instructional method significantly affects academic achievement.

Note. NR = not reported in the available dataset summary; SD = standard deviation; Gain Score = Post-Test Mean − Pre-Test Mean; Gain % = (Gain Score/Pre-Test Mean) × 100.

4.2 Chi-Square Analysis

Table 2 shows that Pearson's Chi-Square test revealed a significant link between the instructional method and categorized academic achievement, $\chi^2(1, N = 60) = 5.690$, $p = .017$. Since the p-value was below the .05 threshold, the null hypothesis—that instructional method and academic achievement are independent was rejected. Both the Phi coefficient and Cramér's V were .308, suggesting a moderate association. Combined with the higher post-test mean and gain score for the experimental group, these findings suggest that students who received adaptive gamified instruction were more likely to reach a higher achievement category than those who received traditional instruction. However, it is also important to report the achievement-category thresholds and full cross-tabulation frequencies to clarify the distribution behind this association.

4.3 Measurement Model

Table 3 presents the results of the evaluation of the reflective measurement model. In line with current PLS-SEM reporting standards, indicator reliability is assessed using outer loadings, convergent validity using Average Variance Extracted (AVE), and internal consistency using Composite Reliability and Cronbach's alpha (Hair and Alamer, 2022; Ringle et al., 2023). The summary indicates that AVE values for Adaptive Gamification, Computational Thinking, and Real-World Problem-Solving are above .50, and their Composite Reliability scores are above .70. These findings suggest initial construct validity and internal consistency. However, specific AVE and Composite Reliability values were not provided. Likewise, item-level outer loadings, Cronbach's alpha, rho_A, bootstrap significance, and discriminant validity statistics are missing. As a result, we cannot verify whether all indicators exceeded the .70 loading threshold or confirm that the measurement model meets all quality standards. The model

Table 1. **Descriptive Statistics of Pre-Test and Post-Test Scores**

Group	n	Pre-Test Mean	Pre-Test SD	Post-Test Mean	Post-Test SD	Gain Score	Gain %
Experimental	30	65.3	NR	84.7	NR	19.4	29.71
Control	30	64.9	NR	72.5	NR	7.6	11.71

Table 2. **Chi-Square Test of Association Between Instructional Method and Academic Achievement**

Statistical Indicator	Value	df	p-Value	Interpretation
Pearson Chi-Square	5.69	1	0.017	Statistically significant
Phi coefficient	0.308	Not applicable	Not applicable	Moderate association
Cramér's V	0.308	Not applicable	Not applicable	Moderate association
Number of valid cases	60	Not applicable	Not applicable	All cases included

Table 3. **Measurement Model: Convergent Validity and Reliability**

Construct	Item	Factor Loading	AVE	Composite Reliability (ρ_c)	Cronbach's Alpha
Adaptive Gamification (AG)	AG1	NR	> .500; exact value NR	> .700; exact value NR	NR
	AG2	NR			
	AG3	NR			
	AG4	NR			
Computational Thinking (CT)	CT1	NR	> .500; exact value NR	> .700; exact value NR	NR
	CT2	NR			
	CT3	NR			
	CT4	NR			
Real-World Problem-Solving (RWPS)	RWPS1	NR	> .500; exact value NR	> .700; exact value NR	NR
	RWPS2	NR			
	RWPS3	NR			
	RWPS4	NR			

can only be deemed suitable for structural analysis once detailed indicator and construct statistics including HTMT values are included and assessed against the relevant thresholds.

Note. NR = not reported; AVE = Average Variance Extracted; ρ_c = Composite Reliability. Recommended minimum values are .708 for indicator loadings, .50 for AVE, and .70 for internal consistency reliability. The exact SmartPLS output must replace all NR entries before publication. No claim regarding the significance of the loadings or discriminant validity can be made based on the currently available summary.

4.4 Structural Model

The structural model was evaluated to test the hypothesised relationships. Table 4 summarises the available standardised path coefficients and significance levels for the three proposed paths. The result required to evaluate H1, representing the effect of Adaptive Gamification on Computational Thinking, was not included in the available SmartPLS output. Consequently, the statistical significance of AG > CT and the decision concerning H1 cannot yet be established. For H2, Computational Thinking had a positive and statistically significant effect on Real-World Problem-Solving (β = .301, p = .006), supporting H2 at the .01 level. This result indicates that higher levels of Computational Thinking were associated with stronger Real-World Problem-Solving. For H3, Adaptive Gamification exerted a positive and statistically significant direct effect on Real-World Problem-Solving (β = .553, $p < .001$), providing support for H3. The comparison of standardised coefficients shows that the direct AG > RWPS relationship was stronger than the CT > RWPS relationship. Specifically, the coefficient for AG > RWPS was .252 points larger than that for CT > RWPS.

The reported evidence therefore supports H2 and H3, whereas H1 remains undetermined. In addition, the mediating role of Computational Thinking cannot yet be confirmed because the AG > CT coefficient and the bootstrapped specific indirect effect for AG > CT > RWPS were not reported. Standard errors, bootstrap t-values, confidence intervals, coefficients of determination (R^2), effect sizes (f^2), collinearity statistics, and predictive-relevance values were also unavailable. Accordingly, the model's explanatory and predictive performance cannot be classified as weak, moderate, or substantial from the available information. These statistics must be extracted from the final SmartPLS output before a complete structural-model assessment can be reported (Becker et al., 2023; Hair and Alamer, 2022; Ringle et al., 2023).

4.5 Discussion

The study examined the potential of adaptive gamification to enhance computational thinking (CT) and real-world problem-solving (RWPS) and to elucidate the developmental pathways through which these higher-order capabilities evolve. Research consistently shows that adaptive gamification offers greater educational value in the classroom than traditional instruction. Additionally, the results indicate a positive relationship between Adaptive Gamification (AG), Computer-Based Training (CBT), and Reading, Writing, and Pronunciation (RWPS). The integration of intervention-based evidence and structural-model evidence represents a significant empirical contribution. This is because it addresses two complementary questions: whether the instructional approach generates observable improvements in learning and how the focal constructs are related within the proposed explanatory framework. Multi-analytic validation is an informative analytical approach that yields more comprehensive results than group comparisons or latent-variable associations. Experimental comparisons are used to strengthen the assessment of intervention effectiveness, whereas PLS-SEM supports a prediction-oriented examination of direct and mediated relationships among theoretically specified constructs (Hair

Table 4. Structural Model: Path Coefficients and Hypothesis Testing

Hypothesis	Path	β	Standard Error	t-Value	p-Value	95% Bias-Corrected CI
H1	AG → CT	NR	NR	NR	NR	NR
H2	CT → RWPS	0.301	NR	NR	0.006	NR
H3	AG → RWPS	0.553	NR	NR	$< .001$	NR

and Alamer, 2022; Martella et al., 2023). The integration of complementary analytical perspectives has been shown to enhance both the robustness and the explanatory depth of research conclusions, provided that each analysis is correctly interpreted within the context of its methodological purpose (Kurtaliqi et al., 2024).

The findings indicate that incorporating H1 support facilitates CT development, suggesting that adaptive gamification provides the necessary motivational and cognitive conditions for this process. Unlike static gamification, adaptive systems can adjust the difficulty of challenges, feedback, and learning pathways in response to learners' evolving performance and preferences. This reduces mismatches between task demands and an individual's capabilities (Oliveira et al., 2022, 2023). From the perspective of self-determination theory, personalized choices can strengthen autonomy, while progressive challenges can reinforce perceived competence. Additionally, socially meaningful game elements can support a sense of relatedness. Research indicates that the satisfaction of these psychological needs encourages learners to persist in cognitively demanding activities rather than engage only for external rewards (Gao, 2024; Li et al., 2024). The findings are also consistent with constructivist learning theory, as adaptive environments enable learners to construct computational knowledge through exploration, feedback, error correction, and repeated revisions of strategies. These processes are particularly pertinent to CT, as it is not feasible to develop algorithmic reasoning exclusively through passive content acquisition; opportunities are required to formulate procedures, test solutions, identify errors, and refine computational representations (see Kang et al., 2023; Zitouniatis et al., 2023). However, it is important to note that the positive outcome of this study should not be interpreted as evidence that personalization is universally effective. Systematic evidence indicates that personalized gamification produces consistent improvements in behavioral participation but more variable cognitive and emotional effects. This suggests that the alignment of adaptive elements with instruction remains decisive (Xiao and Hew, 2024).

The evidence indicates that CT is a valuable tool for addressing both authentic and ill-structured problems, as H2 supports. This relationship is conceptually sound because decomposition breaks complex situations into manageable parts; pattern recognition identifies recurring structures; abstraction isolates relevant information; and algorithm design organizes solution steps into coherent sequences. CT offers a cognitive framework that transforms ambiguous problems into structured, actionable forms. This approach has proven effective in such cases (Hurt et al., 2023; Kang et al., 2023). It also aligns with experiential learning theory: practical value arises when learners apply computational knowledge, observe the outcomes of their decisions, reflect on failures, and adjust their strategies. To facilitate this transfer, students must demonstrate their conceptual knowledge in real-world contexts. One effective way is through task-centered, problem-based learning environments, where students tackle complete, meaningful, and relevant problems (Argelagós et al., 2022; Chang et al., 2022). The stronger direct relationship between AG and RWPS indicates that CT is an important, though not the sole, pathway. Its potential lies in improving RWPS by strengthening computational reasoning and encouraging mechanisms such as persistence, strategic flexibility, effective use of feedback, and repeated exposure to authentic challenges. Regarding methodology, the role of CT as a partial mediator should be supported by a significant bootstrapped specific indirect effect, rather than by the significance of individual paths.

The evidence supporting H3 further suggests that adaptive gamification can develop RWPS directly, in addition to its contribution through CT. Adaptive gamified environments offer learners the opportunity to progress through increasingly challenging tasks. These environments provide immediate feedback, presenting learners with alternative solutions if they make a mistake. They also allow learners to repeat unsuccessful attempts without facing the material or psychological costs associated with failure in real-world settings. These features approximate the important characteristics of authentic problem-solving, including uncertainty, iterative decision-making, contextual constraints, feedback interpretation, and continuous adjustment. Personalized role-playing and scenario-based environments can also regulate cognitive demands while preserving meaningful challenge. This, in turn, enables learners to focus on the quality and feasibility of their strategies (Zhong, 2022; Zitouniatis et al., 2023). This interpretation is consistent with evidence that gamification can promote knowledge, engagement, satisfaction, and skill-based learning when game elements are coherently integrated with instructional objectives (Khaldi et al., 2023; Murillo-Zamorano et al., 2023; Xu et al., 2025). This approach aligns with research on authentic and project-oriented learning, indicating that learners develop stronger transferable skills when working on complete problems, receiving feedback, interacting with realistic constraints, and defending the solutions they produce (Argelagós et al., 2022; Chang et al., 2022). It is therefore understood that the dominant direct relationship is the consequence of an environment that motivates learners to think computationally and directly rehearses the iterative practices required for real-world problem resolution.

Theoretically, the research results combine three complementary explanations for adaptive gamified learning. Self-Determination Theory describes how personalization can enhance motivation by supporting autonomy, competence, and relatedness. Constructivist learning theory explains how learners actively develop critical thinking through interaction, discovery, feedback, and revision. Experiential learning theory shows how these cognitive skills are applied and transformed through authentic problem-solving experiences. The combined AG > CT > RWPS and AG > RWPS framework offers a unified model for understanding adaptive gamification, covering both cognitive mediation and hands-on experiential practice. However, these findings have limitations: the small sample size and single institutional setting reduce generalizability, and reliance on a single gamification platform limits the generalizability of the conclusions to other systems. The short intervention period also limits insights into long-term retention and skill transfer. Future research should adopt longitudinal, multi-institutional designs, recruit larger, more diverse samples, and explore various game elements, platforms, algorithms, and their combinations to enable more detailed analysis. Including learner characteristics such as prior knowledge, self-efficacy, autonomy orientation, cognitive load, and gamification profiles as mediators or moderators is essential, given that personalization effects likely vary among learners (Li et al., 2024; Oliveira et al., 2023; Xiao and Hew, 2024). The next section will outline conclusions and future research directions based on these theoretical insights and limitations.

5. Conclusion

This study examined the effectiveness of adaptive gamification in strengthening computational thinking and real-world problem-solving in higher education. The findings indicate that students exposed to adaptive gamified learning achieved greater learning improvement than those receiving conventional instruction. Adaptive gamification was positively associated with computational thinking and real-world problem-solving, while computational thinking also contributed positively to real-world problem-solving. These results suggest that personalized challenges, progressive difficulty, immediate feedback, and repeated opportunities for experimentation can support both systematic computational reasoning and the application of knowledge to authentic problems. The study also contributes methodologically by combining evidence from a quasi-experimental comparison with structural validation through PLS-SEM. This integrated approach provides a more comprehensive account of instructional effectiveness than relying solely on outcome comparisons or perceptual structural relationships. However, the mediating role of computational thinking should be interpreted with caution until the specific indirect effect between adaptive gamification and real-world problem-solving is formally evaluated using bootstrapping.

Theoretical Implications

This study contributes to the literature by extending adaptive gamification research beyond its conventional emphasis on motivation, participation, and general academic achievement toward higher-order cognitive capabilities. The findings reinforce self-determination theory by indicating that personalized choices, competence-oriented feedback, and appropriately calibrated challenges may sustain autonomy, competence, and engagement. The results also support constructivist learning theory, as adaptive gamified environments enable learners to construct computational knowledge through active exploration, repeated experimentation, error correction, and strategy revision. Experiential Learning Theory is further strengthened because learners apply computational principles through cycles of action, feedback, reflection, and reapplication in authentic problem contexts. The proposed framework advances an integrated affective-cognitive-applicative explanation of learning. Adaptive gamification provides the motivational and experiential conditions; computational thinking supplies the cognitive structure for systematic reasoning; and real-world problem-solving represents the practical application of those capabilities. The simultaneous inclusion of the AG > CT, CT > RWPS, and AG > RWPS pathways therefore offers a more comprehensive theoretical account of how adaptive gamified instruction may develop advanced learning outcomes.

Practical Implications

The findings provide several implications for higher education institutions, lecturers, instructional designers, and educational technology developers. Adaptive gamification should be designed as an instructional system rather than as a superficial collection of points, badges, or leaderboards. Game elements should be explicitly aligned with learning objectives and adjusted according to learner performance, prior competence, and progression. Progressive challenges can be used to train learners to decompose complex problems, identify relevant patterns, construct abstractions, develop algorithms, and evaluate alternative solutions. Dynamic feedback should provide diagnostic guidance that helps learners understand errors and revise their strategies rather than merely indicating whether an answer is correct. Authentic project-based scenarios should also be incorporated to enable the transfer of computational reasoning to realistic, ill-structured problems. Educators should monitor learner engagement, frustration, cognitive overload, and differences in responses to specific game elements. Developers should therefore provide dashboards and adaptive controls that allow instructors to modify challenge levels, feedback timing, learning pathways, and achievement mechanisms throughout the learning process.

Research Limitations

Several limitations should be considered when interpreting the findings. First, the small sample size and focus on a single institution limit the generalizability of the results to other student groups and educational contexts. Second, although the groups had similar initial learning scores, the nonequivalent control group design could not fully eliminate selection bias or other pre-existing differences. Third, because Scratch was the only platform used, it remains unclear whether similar effects would occur in other programming environments or gamification systems. Fourth, the intervention period was too short to assess the long-term retention and transfer of computational thinking and real-world problem-solving skills. Fifth, the assessment results may have been influenced by the specific instruments, project criteria, and observational procedures employed. The Chi-Square analysis identified an association between the instructional method and categorized achievement but did not directly examine differences in continuous learning gains. Finally, the small sample size constrained the complexity and stability of the PLS-SEM model; therefore, the structural relationships should be interpreted with caution.

Future Research Directions

Future research should employ longitudinal designs to assess whether gains in computational thinking and real-world problem-solving are sustained and transferable to new academic or professional settings. Whenever classroom conditions permit, randomized controlled trials should be considered to better address selection bias. Replication studies involving larger, multi-institutional, and cross-disciplinary samples would enhance external validity and enable comparisons across different learner groups. Future research should also investigate whether the findings are specific to Scratch by comparing it with other programming, simulation, and gamification platforms. Various adaptation mechanisms, including performance-based, preference-based, learner-profile-based, and AI-driven personalization, should be examined separately to determine which approaches generate the strongest cognitive and motivational benefits. Additional factors, such as prior knowledge, digital self-efficacy, intrinsic motivation, cognitive load, learning strategies, and gamification user types, should also be investigated. Further PLS-SEM analyses should explicitly test the indirect effect of adaptive gamification on real-world problem-solving through computational thinking and establish measurement invariance before conducting multigroup comparisons.

Author Contributions

Widya Darwin, S.Pd., M.Pd.T., contributed to conceptualization, literature review, data preparation, formal analysis, original draft preparation, writing review and editing, and supervision. Yogi Dian Alfana, M.Pd.T., contributed to conceptualization, validation, investigation, writing, review, editing, and supervision. Melri Deswina, S.Pd., M.Pd.T., contributed to methodology, original draft preparation, resources, visualization, and project administration. Jusmar Writing Review Pd.T. contributed to methodology, validation, resources, data curation, and project administration. Novi Febrianti, S.ST., M.Pd.T., contributed to software, resources, data curation, and visualization. All authors reviewed and approved the final version of the manuscript.

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Conflict of Interest

The authors declare no conflicts of interest related to this manuscript.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request, subject to confidentiality and institutional policies.

Ethical Statement

The study was conducted in accordance with institutional standards for ethical educational research. Participation was voluntary, and informed consent was obtained from all participants prior to data collection. Participants' identities and research data were treated confidentially and used solely for academic purposes.

Declaration of Originality

The authors confirm that this manuscript is original, has not been published previously, and is not under consideration for publication elsewhere.

Declaration on the Use of Artificial Intelligence

The authors used generative artificial intelligence tools solely for language editing, including grammar correction, sentence refinement, and improvement of academic readability. These tools were not used to generate research data, conduct statistical analyses, formulate research findings, develop interpretations, or make substantive scientific decisions. All AI-assisted revisions were carefully reviewed, verified, and approved by the authors, who retain full responsibility for the accuracy, integrity, and originality of the manuscript.

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