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Does Prior Knowledge Matter? Comparing Gamified and Adaptive Platforms for Introductory Mathematics

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Abstract*– Basic concepts in introductory mathematics remain a persistent challenge in STEM education, particularly for students entering with heterogeneous levels of prior knowledge. Among technology-enhanced approaches, gamified learning environments and adaptive learning systems have shown promise; however, their differential effectiveness as a function of students' initial proficiency is not yet well understood. This study examines the impact of these two instructional strategies through a quasi-experimental pre-test–post-test design using intact classroom groups in introductory mathematics courses. A gamified learning platform and an adaptive learning platform were implemented over comparable instructional periods. Learning outcomes were assessed using normalized learning gain, while engagement-related behavior was examined through a normalized dedication metric. Statistical analyses included chi-square tests to examine pre-post performance transitions and one-way ANOVA to evaluate the effect of initial proficiency on learning gain within each instructional condition. Results indicate that both approaches led to improvements in post-test performance; however, distinct learning gain profiles emerged across proficiency levels. Gamified instruction was associated with higher gains among students with low initial proficiency, whereas adaptive learning produced more homogeneous gains across performance groups. Interpreted through an aptitude–treatment interaction framework, these findings suggest that gamified and adaptive learning approaches may serve complementary roles when aligned with learner characteristics. The study contributes empirical evidence to inform the design of personalized instructional strategies in introductory mathematics and motivates future research on integrated, aptitude-sensitive learning models.

***Keywords*- Gamification, Adaptive learning, Educational innovation, Higher education, Learning gain, Aptitude–treatment interaction**

I. INTRODUCTION

Introductory mathematics instruction at the upper high school and early university academic levels in engineering represents a persistent challenge in STEM education pathways. A substantial proportion of students enter introductory mathematics courses with insufficient mastery of foundational algebra, compromising their subsequent academic progression [1]. Two technology-enhanced instructional approaches have gained prominence as potential solutions: gamification and adaptive learning systems. However, the comparative effectiveness of these strategies, particularly as a function of students' initial knowledge levels, remains empirically underexplored.

Gamification, defined as the use of game design elements in non-game contexts [2], leverages motivational affordances such as rewards, progression systems, and narrative elements to enhance engagement and learning [3]. Adaptive learning systems, conversely, employ algorithmic personalization to dynamically adjust task difficulty and feedback based on real-time student performance [4]. While meta-analytic evidence supports positive effects for both approaches [3], [5], these studies typically report aggregate outcomes without examining aptitude–treatment interactions; the extent to which intervention effectiveness varies as a function of learner characteristics.

This study addresses this gap through a quasi-experimental pre-test – post-test comparison of two web-based platforms: a gamified learning environment (DuckMath Quest) implementing mastery-based progression with motivational game elements, and an adaptive learning platform (Realized it) implementing dynamic difficulty adjustment. We examine learning gains across different initial proficiency levels, measured via normalized gain scores [6], to identify whether instructional strategy effectiveness is moderated by students' prior knowledge.

II. BACKGROUND

A. Gamification in Mathematics education

Gamification has been theorized to enhance learning through mechanisms articulated by Self-Determination Theory [7]: game elements such as rewards, progression, and challenges can satisfy psychological needs for competence, autonomy, and relatedness. The meta-analysis by Sailer and Homner [3], synthesizing 38 studies, provides the most comprehensive evidence to date on gamification's effectiveness in educational contexts. Table I summarizes their key findings:

TABLE I
HEDGES' G

Learning Outcomes	Hedges' g	95% CI	k	Interpretation
Cognitive	0.49	[0.30, 0.69]	19	Small to medium positive effect
Motivational	0.36	[0.18, 0.54]	16	Small positive effect
Behavioral	0.25	[0.04, 0.46]	9	Small positive effect

Sailer and Homner identified substantial heterogeneity across studies, with moderator analyses revealing that gamification incorporating narrative elements and collaborative competition (rather than pure competition) produced larger effects. This heterogeneity suggests that effectiveness varies by implementation design and potentially by learner characteristics, a hypothesis explored in the present study.

In mathematics specifically, Huang [8] found that gamified flipped learning enhanced both task completion rates and cognitive test scores among undergraduate students. However, studies have also reported null or inconsistent findings. Alt [9] noted that while gamification improves motivation and engagement, cognitive gains are not universally observed. Pehlivan [10] found no significant differences in mathematics achievement between gamified and non-gamified conditions in a high school sample. These mixed results underscore the importance of examining moderating variables, including baseline proficiency, a variable rarely disaggregated in prior research.

B. Adaptative Learning Systems and Prior Knowledge

Adaptive learning platforms personalize instruction by continuously adjusting content difficulty based on student responses, a feature theorized to optimize challenge level and prevent cognitive overload [11]. Ma [5] meta-analyzed intelligent tutoring systems (ITS) in mathematics and found that students with low prior knowledge exhibited significantly larger effect sizes compared to those with medium or high prior knowledge. This pattern aligns with the expertise reversal effect from Cognitive Load Theory [12], which posits that highly structured guidance benefits novices but becomes redundant for advanced learners.

However, more recent evidence complicates this narrative. Walkington and Bernacki [4] argued that adaptive systems' effectiveness depends on students' self-regulatory capacity—their ability to interpret automated feedback and adjust learning strategies accordingly. Lin [13] found that an adaptive mathematics platform improved self-regulation and achievement among medium- and high-performing students but showed limited benefits for low-performing students, who may lack the metacognitive skills to leverage algorithmic feedback effectively.

Yilmaz [14] similarly reported that while the ALEKS adaptive system improved overall mathematics achievement in middle school, the achievement gap between low and high performers did not narrow, suggesting that adaptive technology alone may be insufficient for students with profound conceptual deficits. These findings highlight a critical question: do low-performing students benefit more from algorithmic adaptivity (as suggested by Ma [5]) or from pedagogical scaffolding that addresses motivational and metacognitive barriers?

C. Aptitude- Treatment Interactions and Mastery Learning

The concept of aptitude–treatment interaction (ATI) posits that instructional methods exhibit a notorious different effectiveness depending on learner characteristics [16]. In mathematics education, prior knowledge is a canonical aptitude variable, yet comparative studies examining ATI effects between gamification and adaptive learning are scarce. Theoretical frameworks offer competing predictions:

- Expertise Reversal Effect [11] predicts that structured adaptive systems should benefit low-knowledge students more than high-knowledge students, who may experience redundancy.
- Self-Regulation Hypothesis [4] predicts that low-knowledge students may struggle with autonomous adaptive platforms due to metacognitive deficits, potentially benefiting more from scaffolded, gamified environments that embed motivational support.

Both platforms in this study incorporate elements of mastery learning, the principle that all students can achieve competence given sufficient time and appropriate instruction. The gamified platform implements mastery through progressive unlocking of content levels, while the adaptive platform adjusts difficulty based on correctional feedback loops. However, the operationalization differs: gamification combines mastery with extrinsic motivators (virtual rewards), whereas adaptive systems emphasize diagnostic precision. Whether these designs differences interact with prior knowledge remains an empirical question.

D. Learning Gain as an Outcome Measure

This study employs normalized learning gain (g) as the primary outcome metric [6], calculated as:

$$g = \frac{posttest(\%) - pretest(\%)}{100 - pretest(\%)}. \quad (1)$$

This metric controls ceiling effects and baseline variability, enabling fair comparison across students with different initial proficiency levels. Hake's classification, low gain ($g \leq 0.3$), medium gain ($0.3 < g \leq 0.7$), high gain ($g > 0.7$), provides interpretive benchmarks widely adopted in STEM education research [6]. By stratifying results by pre-test performance, we can identify whether instructional effectiveness is moderated by prior knowledge, addressing the ATI gap in existing literature.

E. Research objectives

The objective of this study is to examine the effectiveness of two technology-enhanced instructional strategies, gamified learning and adaptive learning, in supporting the acquisition of basic algebra skills, with particular attention to how their impact varies as a function of students' prior knowledge. To achieve this goal, the study is structured around the following specific objectives, explicitly linked to the study variables:

1. To compare the learning outcomes produced by gamified and adaptive learning platforms, using normalized learning gain, g, as the primary dependent variable, and instructional approach (gamification vs. adaptive learning) as the main independent variable.
2. To examine whether learning gains are moderated by students' initial proficiency level, operationalized through pre-test performance, in order to identify the presence of an aptitude–treatment interaction (ATI) between prior knowledge (aptitude variable) and instructional strategy (treatment variable).
3. To analyze engagement-related behavior under each instructional approach, using normalized dedication as an auxiliary variable, operationalized as points earned in the gamified platform and time-on-task in the adaptive platform, and to explore its relationship with learning gain.

By explicitly relating instructional approach, prior knowledge, learning gain, and dedication, this study seeks to clarify not only whether gamified and adaptive learning environments are effective, but for whom and under what conditions each approach yields greater educational benefit in introductory mathematics contexts.

III. METHODOLOGY

This study employed a quasi-experimental pre-test – post-test design to compare two web-based instructional platforms implementing distinct learning strategies: gamified learning and adaptive learning. Group assignment was determined by existing course enrollment, as students were assigned to instructors by the academic program before the intervention. Thus, the study employed a non-randomized, quasi-experimental design using intact classroom groups. The research was conducted during the August–December 2025 academic semester with students enrolled in introductory mathematics courses oriented toward STEM-related fields. In both cases, participants were between 17 and 18 years old.

A. Gamified Learning Platform

The DuckMath Quest platform (DMQ) was used as a gamified learning approach. The platform is currently deployed in a restricted beta version available only within the institutional context. DMQ is organized into thematic mathematical islands, each corresponding to a specific algebra topic, including numerical fractions, order of operations, laws of exponents, algebraic expressions, special products, factoring, algebraic fractions, equations and inequalities, systems of equations, and logarithms. Each island contains two or three levels of increasing complexity, with ten exercises per level, promoting mastery-based progression and gradual reinforcement of both conceptual understanding and procedural fluency. [17]

The platform provides immediate, real-time feedback after each response (correct or incorrect), enabling students to identify errors, reflect on their reasoning, and correct misconceptions during practice. Gamification elements include a virtual reward system, where successful task completion grants coins that can be used to customize an animated character, DuckMath, which accompanies learners throughout the experience. Pedagogically, DMQ is grounded in principles of gamification and active learning, emphasizing learner autonomy, self-regulated practice, and incremental challenges aligned with clearly defined learning objectives.

B. Adaptive Learning Platform

The web-based educational platform Realized it [18] was used to deliver exercises of varying levels of complexity. Based on students' performance on the pre-test, which served as a diagnostic instrument to assess their initial proficiency, the platform assigned a sequence of subsequent exercises. Each exercise was dynamically adjusted to be either more or less complex than the previous one. When a student answered an exercise correctly, the platform presented a more complex exercise; conversely, an incorrect response resulted in a subsequent exercise with lower complexity. As in the gamification platform, exercises were organized by topic, and an achievement level was assigned according to the extent to which students were able to solve exercises across the different topics available on the platform.

This adaptive methodology is consistent with the Mastery Learning approach, which posits that all students are capable of achieving mastery, although some may require more time and effort to do so [19, 20]. Within the adaptive platform, students were allowed to freely select the topics they wished to practice. No sequencing constraints were imposed on topic selection, as each exercise addressed a single topic exclusively and could therefore be completed independently of the others.

C. Implementation Procedure

The gamified learning intervention was implemented over a three-week period and consisted of three guided sessions. Prior to the intervention, a 40-minute multiple-choice diagnostic pre-test was administered to assess students' baseline knowledge of the content. During each session, students were guided to use DMQ for 40 minutes, with the objective of progressing through the corresponding thematic content. At the conclusion of the intervention, students completed a post-test identical to the pretest, enabling direct measurement of learning gains.

The adaptive learning intervention was conducted over a three-week period. On the first day of classes, students completed a multiple-choice pretest with a time limit of 40 minutes. This assessment served as the initial performance indicator for the adaptive platform. Over the subsequent three weeks, students were asked to use the adaptive platform for one hour per week, resulting in a total of three hours of intended practice. However, because the practice sessions were unsupervised and completed independently at home, students were free to use the platform for more or less time than the recommended duration. At the end of the third week, students completed a post-test, identical to the pre-test, and was likewise limited to 40 minutes.

The different implementation contexts (guided in-class sessions versus unsupervised autonomous practice) were intentionally preserved, as they reflect authentic use conditions of gamified and adaptive platforms in real educational settings. Rather than controlling for context, this study examines how each instructional approach performs under its typical deployment conditions.

D. Impact Measurement

Learning outcomes were assessed using objective pre-test and post-test instruments administered before and after each instructional intervention. In both the gamified and adaptive learning conditions, the assessments consisted of multiple-choice items aligned with the basic algebra content covered by the respective platforms, including conceptual understanding and procedural skills. The instruments were designed to ensure coherence between the instructional activities and the evaluated learning objectives.

Learning gain, g, was used as the primary outcome variable to quantify changes in students' conceptual understanding resulting from the instructional interventions. This metric allows for meaningful comparisons of learning outcomes by accounting for baseline variability and has been widely employed in educational research to assess the effectiveness of instructional strategies in mathematics and STEM-related domains [3, 6].

Another variable used to measure the intervention's impact was normalized dedication. In the gamified platform, dedication was operationalized through the points earned in the game, which are proportional to the time invested by the student. In the adaptive platform, dedication was measured using the total time the student spent interacting with the platform.

We calculated the normalized dedication according to the formula

$$d_k = \frac{1}{n}\sum_{i=1}^{n} 1(x_i < x_k), \qquad (2)$$

where $1(x_k)$ is the indicator function that gives a value of 1 when the inequality is true, and zero when it is false. Normalized dedication does not represent identical behavioral constructs across platforms, but rather a relative indicator of student engagement within each instructional environment. For simplicity, the term dedication is used throughout this paper to refer to normalized dedication.

Based on this methodological framework, the following section presents the results of the learning gain analysis obtained for both instructional platforms.

IV. RESULTS

The results are organized into three subsections: first, an analysis of pre-test and post-test score distributions across instructional platforms; second, an examination of normalized learning gain as a function of initial performance; and third, an analysis of students' dedication and its relationship with learning gain.

A. Scores

Students were classified in three different groups according to their performance in the Pre-Test. Low, for scores between 0 and 50; Medium, for scores between 51 and 75; and High, for scores greater than 75. As can be seen in Fig. 1, there exists improvement in students grades after interacting with any of both platforms, adaptive or gamification. In the case of students with Low performance, more than 25% of those students could achieve the minimum passing grade in the post-test. Similarly, for those students with a Medium performance, the adaptive platform allowed 100% of students to achieve a passing grade, while gamification slightly less than 50%.

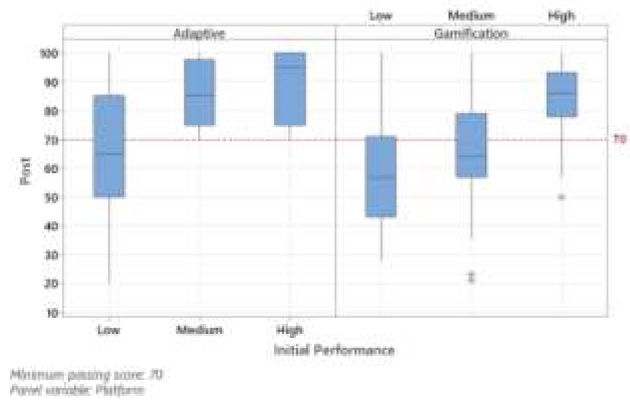

Fig. 1. Post – Test scores according to initial performance.

Moreover, when comparing the performance of post-test vs pre-test, a significant distribution change can be perceived in students. Fig. 2 shows how students located in the low section, moved into medium or high performance during the post-test. On the other hand, students located on a higher classification, did not go back to a lower performance, which represent a sustainable increase in students' scores.

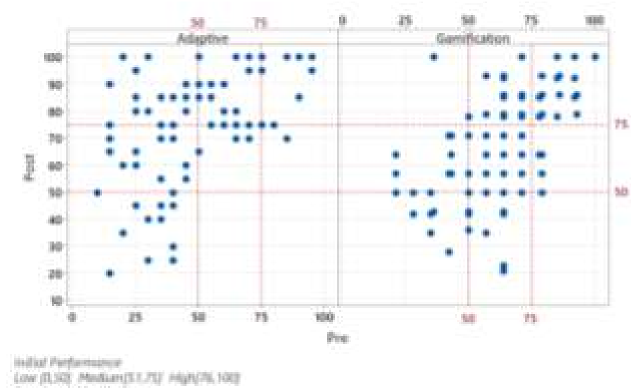

Fig. 2. Post–test vs Pre–Test scores comparison.

A Chi-Square Independence test was performed. Comparing pre- and post-performance of students in both experimental groups. In this test, the null and alternative hypotheses state the following:

H0: Scores in pre-test and post- test are independent
H1: Scores in pre-test and post- test are dependent

Tables II and III show a significant p −value, which allows us to infer statistical dependence of test performance results. A high probability of achieving a higher score for students with a low initial performance is perceived. For example, the probability of a student under adaptive platform to obtain a higher score when initially located in the low performance group is of 72%, while for a student who experienced the gamification platform the probability is 61%. In both cases, a significant increase in their performance was observed.

TABLE II
ADAPTIVE PLATFORM

	Low	Medium	High	All
Low	16	22	19	54
Medium	0	7	14	21
High	0	2	5	7
All	16	31	38	85
Chi-Square Independence test p −value = 0.011 Non independent P(Medium & High | Low) = 0.719				

TABLE III
GAMIFICATION PLATFORM

	Low	Medium	High	All
Low	15	21	2	38
Medium	12	31	20	63
High	1	4	20	25
All	28	56	42	126
Chi-Square Independence test p −value = 0.000 Non independent P(Medium & High | Low) = 0.605				

B. Learning gain

However, when analysing Learning Gain of students, Fig. 3 shows that, within the gamification platform, more than 50% of students with low initial performance achieved medium-to-high learning gains, while students with better initial performances demonstrated a low learning gain.

Students under the adaptive platform, on the other hand, despite their initial performance, showed similar learning gains, with most students in the Medium range.

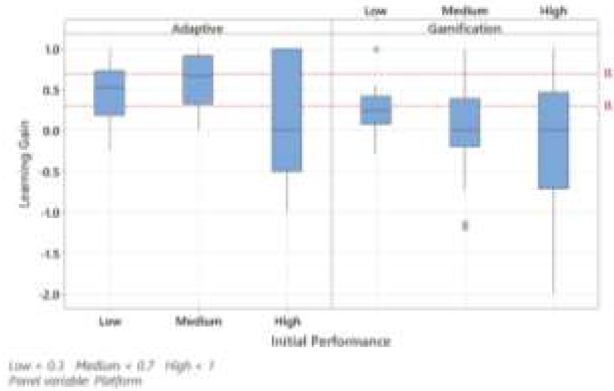

Fig. 3. Learning gain comparison

An ANOVA examining the effect of initial performance on learning gain indicates that a statistically significant effect is present only in the gamification condition (Table V, p = 0.007), as also illustrated by the corresponding confidence interval plot (Fig. 5). In contrast, no statistically significant effect was observed for the adaptive learning platform (Table IV; Fig. 4). In both cases, under adaptive and gamification approach, it can be seen a decrease in learning gain (Fig. 3), which states a limitation of both methodologies for reinforcing current knowledge, and focuses its application in developing new knowledge in students with large or medium gaps with respect to study plan.

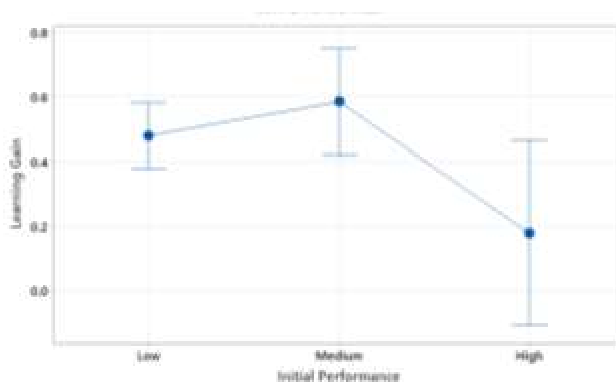

Fig. 4. 95% Confidence Interval Plot of Learning Gain vs Initial Performance in Adaptive Platform

TABLE IV
ANOVA ADAPTIVE PLATFORM

Source	**DF**	**SS**	**MS**	**F**	**P-value**
Initial Performance	2	0.8636	0.4318	2.98	0.056
Error	82	11.8820	0.1449		
Total	84	12.7456			

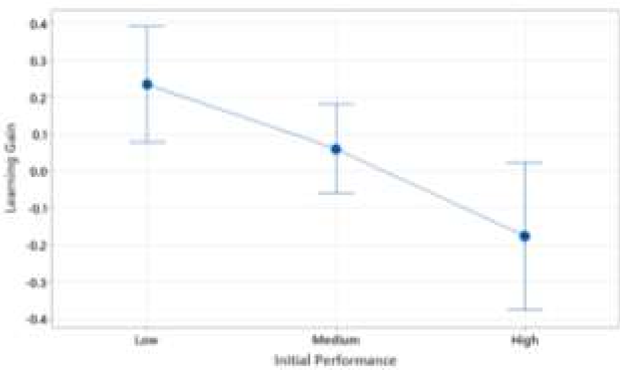

Fig. 5. 95% Confidence Interval Plot of Learning Gain vs Initial Performance in Gamification Platform

TABLE V
ANOVA GAMIFICATION PLATFORM

Source	DF	SS	MS	F	P-value
Initial Performance	2	2.424	1.2119	5.20	0.007
Error	121	28.188	0.2330		
Total	123	30.611			

C. Dedication

Nevertheless, an important difference among the dedication of students towards the activities on the platforms is appreciated in Fig. 6.

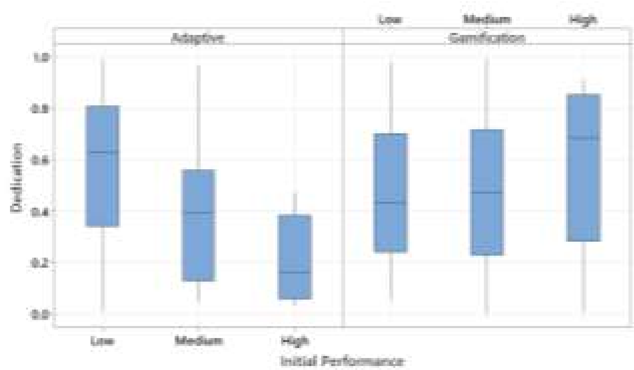

Fig. 6 Normalized dedication vs Initial Performance

As shown in Fig. 7, both instructional approaches exhibit substantial dispersion in learning gain across the range of normalized dedication. Although the gamified platform shows a slightly more positive association between dedication and learning gain compared to the adaptive condition, no statistical significant relationship between Dedication and Learning Gain can be stated.

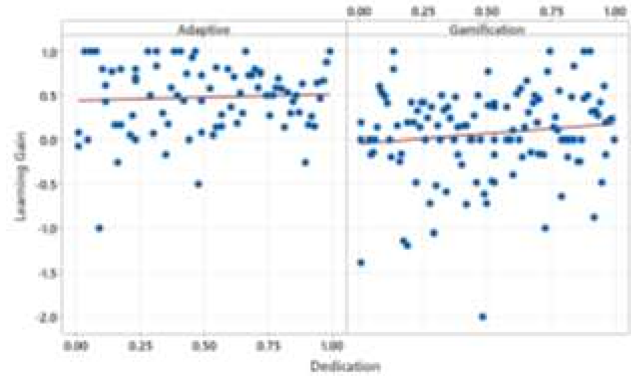

Fig. 7. Learning Gain vs Normalized Dedication comparison

V. DISCUSSION

The results of this study provide evidence that both instructional approaches, gamified learning and adaptive learning, positively impacted students' mathematical performance, as reflected by improvements from pre-test to post-test across all initial proficiency levels. As shown in Fig. 1, and 2, students in both experimental groups exhibited higher median post-test scores and upward transition from lower to higher performance categories, particularly among those initially classified as Low performers. This pattern is further supported by the Chi-square independence tests reported in Table II (adaptive platform, $p = 0.011$) and Table III (gamified platform, $p < 0.001$), which indicate a statistically significant dependence between pre-test and post-test performance in both instructional conditions.

Students with low initial performance exhibited a high probability of improving their classification under both instructional approaches. Specifically, the probability of a Low-performing student achieving a Medium or High classification in the post-test was 72% for the adaptive platform and 61% for the gamified platform (Tables II and III, respectively). These results indicate that both platforms function as effective remediation tools for foundational algebra skills when learning outcomes are analyzed at the level of score categories. However, while these pre-test – post-test improvements demonstrate gains in overall performance, they do not fully capture differences in the magnitude of learning achieved by students with different initial performance levels. As shown in the subsequent analysis of normalized learning gain (Fig. 3; Tables IV and V), more differentiated patterns emerge when learning outcomes are examined through a gain-based metric rather than categorical score transitions.

As illustrated in Fig. 3, students in the adaptive learning condition exhibited relatively homogeneous learning gains, predominantly concentrated in the medium range, regardless of their prior performance classification. This observation is consistent with the absence of a statistically significant effect of initial performance on learning gain in the adaptive platform, as indicated by the one-way ANOVA results (Table IV, $p =$

0.056). In contrast, the gamified platform exhibited learning gains that varied as a function of prior knowledge. Students initially classified as Low performers achieved medium to high normalized gains, while those with Medium and High initial performance showed progressively lower gains (Fig. 3). This interaction is statistically supported by the ANOVA for the gamified condition (Table V), which revealed a significant effect of initial performance on learning gain ($p = 0.007$). Together, these results provide quantitative evidence of an aptitude–treatment interaction, whereby the effectiveness of gamified instruction is moderated by students' baseline performance.

The analysis of dedication further contextualizes these learning gain patterns. In both learning conditions, regardless of whether student practice was supervised or not, the relationship between dedication and learning gain was weak, as shown by the broad dispersion of data points in Fig. 7 and the absence of a clear positive trend. This suggests that increased exposure to practice did not consistently translate into higher conceptual gains. However, the gamified platform exhibited a slightly more structured alignment between engagement and learning outcomes.

As shown in Fig. 6, students using the gamification platform across all initial performance levels demonstrated higher and more consistent dedication values. This structured relationship can be attributed to the design of the gamified environment, in which progression through levels required sustained interaction and successful task completion, supported by immediate feedback and incremental challenges. Collectively, these findings indicate that while both instructional approaches foster learning, gamification more effectively converts engagement into learning gains for students with substantial initial deficiencies, whereas adaptive learning promotes more uniform, though less differentiated, progress across proficiency levels.

The results of this study align with prior research employing learning gain as a comparative metric in introductory mathematics, while offering evidence of an aptitude–treatment interaction [16]. As discussed by Henderson in [21], learning gains tend to be largest among students with lower initial proficiency and diminish as students approach ceiling performance, a pattern observed here in the gamified condition, where low-performing students achieved higher gains than their medium- and high-performing peers. In contrast, the adaptive learning platform produced more homogeneous gains across proficiency levels, partially echoing the findings of Ma [5], but without the disproportionately large benefits for low-performing students reported in meta-analytic studies of adaptive systems.

From an ATI perspective [16], these results indicate that the effectiveness of instructional strategies is moderated by prior knowledge. Gamified, mastery-based environments tend to benefit learners with substantial conceptual gaps, whereas adaptive systems yield more stable, moderate gains across a wider range of performance levels. Read in this way, the findings suggest an instructional design that integrates gamified and adaptive learning strategies in a complementary manner, with their deployment guided by students' initial proficiency to maximize learning outcomes.

This interpretation is consistent with the adaptive instructional framework proposed by Rincon-Flores et al. [15], which emphasizes that learning technologies are most effective when aligned with learners' cognitive and contextual needs rather than applied uniformly. From this perspective, the present findings point toward the potential value of a phased or blended instructional methodology, in which gamification is initially leveraged to foster engagement and foundational understanding, followed by adaptive learning systems to refine and individualize learning trajectories. Such a design-oriented interpretation reinforces the ATI principle that instructional effectiveness depends on the alignment between learner aptitude and pedagogical treatment and provides a conceptually grounded basis for future research on evidence-based personalization in mathematics education.

VI. CONCLUSIONS

The present work examined the comparative effectiveness of gamified and adaptive learning platforms in supporting basic algebra learning, with particular attention to how their impact varies as a function of students' prior knowledge. The results indicate that while both instructional approaches lead to measurable improvements in mathematical performance, their effectiveness differs when learning outcomes are analyzed through normalized learning gain and interpreted within an aptitude–treatment interaction framework.

The findings show that gamified environments are especially effective for students with low initial proficiency, who achieved higher normalized learning gains than their medium- and high-performing peers. This suggests that the combination of structured progression, immediate feedback, and motivational reinforcement inherent to gamification provides a tool to close substantial conceptual gaps. In contrast, adaptive learning systems yielded more homogeneous learning gains across proficiency levels, offering a stable learning pathway for students with moderate or higher prior knowledge, but without disproportionately amplifying gains among low-performing students.

Overall, this study contributes evidence to the growing body of research on personalized learning in introductory mathematics, indicating that learning gains derived from technology-enhanced instruction vary as a function of students' initial skill levels. Rather than favoring a single instructional solution, the findings highlight the importance of selecting and sequencing instructional strategies in ways that respond to learner heterogeneity. By characterizing the distinct learning gain profiles associated with gamified and adaptive platforms, this work contributes evidence that can guide the future design of instructional models that strategically integrate multiple learning technologies to support diverse student needs in early STEM education.

VII. Future work

Future work will focus on the design and evaluation of an instructional strategy that intentionally integrates gamified and adaptive learning approaches as complementary components within a single learning sequence. Building on the differentiated learning gain profiles identified in this study, such a strategy would explore phased or hybrid implementations in which gamified environments support early engagement and foundational skill development, followed by adaptive systems to individualize practice and consolidate learning. Additionally, future studies will aim to strengthen the empirical robustness of these findings by involving larger and more diverse student samples, enabling more comprehensive analyses of aptitude–treatment interactions and increasing the generalizability of the results across introductory STEM contexts.

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