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AI-gamified teaching in music education: Implications for student learning and engagement

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Abstract

This study explores how blending AI and gamification boosts music theory learning and student engagement, a gap in current research. A 14-week quasi-experiment with 180 first-year music students (90 per group) compared an AI-gamified approach to traditional teaching. Pre-tests found no differences in initial proficiency (EG: 52.18±8.36; CG: 51.75±8.62) or engagement. Post-intervention, the AI-gamified group scored 83.42±7.45 in music theory—far higher than the control's 62.31±9.18 ($p<0.001$)—with 59.9% improvement versus 20.4%. They also excelled in behavioral, emotional, cognitive, and social engagement (all $p<0.001$), with overall scores of 52.38±5.76 versus 39.72±6.93. Success stems from gamification fueling intrinsic motivation, AI tailoring guidance, and tech easing collaboration. The findings back using such tools in music classes, with educator training in adaptive methods advised. Limitations include a small, short-term sample; future work should explore long-term impacts and individual variations.

Keywords: AI-gamified teaching, Learning outcomes, Music education, Student engagement.

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1. Introduction

1.1. Background to the Study

Education and technology are becoming ever more closely linked. Music education, a field centered on fostering aesthetic awareness, has its own distinct traits: it emphasizes the appreciation of beauty and calls for creative expression. For this reason, merging it with technology holds special promise.

STEAM education—encompassing science, technology, engineering, arts, and mathematics—stresses interdisciplinary collaboration and stands as a key skill set for 21st-century learners [1]. In this context, the coming together of music education and technology has transformed dramatically—from early computer tools and specialized music software to today's interactive platforms [2]. This shift puts a stronger focus on student-centered learning: it seeks to spark students' initiative, build better learning environments, and use more approachable, effective teaching methods. Huang and colleagues [1] add that this kind of technological integration does more than widen access to musical resources. By blending tech tools with musical practice and experimentation, it also boosts student involvement and drive—helping tackle long-standing issues in music education, like hurdles in skill development and students dropping out.

In this landscape, two technological approaches—artificial intelligence (AI) and gamification—have stood out as powerful drivers for innovating music education. Artificial intelligence, especially Generative AI (GenAI), has shown impressive potential in adaptive learning systems. Here, algorithms can adjust teaching materials, offer instant feedback, and forecast learning paths based on students' progress and goals [3]. Gamification—adding game elements like rankings, badges, and team awards, along with instant feedback, to teaching—has been shown to work well in increasing motivation and involvement across different subjects [4].

While both AI and gamification have shown considerable promise in education [5-7] how they work together in music education hasn't been studied much. Most existing research looks at AI-powered music creation tools (like Google's Magenta) or separate gamified music apps (like Yousician), with little hands-on research exploring how combining them might improve learning outcomes. This gap is especially striking when you consider the unique demands of learning music: sound as an invisible medium, the technical accuracy needed for audio recognition, and the mix of creative expression with emotional involvement. AI's capacity for personalized instruction (e.g., adjusting difficulty based on performance) could complement gamification's ability to stimulate motivation (e.g., through achievement systems), creating an optimal learning environment that addresses both cognitive and affective dimensions of learning [8]. So, this study sets out to look into how combining AI and gamification affects students' engagement and learning results in music education. It plans to fill this important research gap through hands-on investigation.

2. Research Questions

Against this backdrop, this study carried out an experiment with 180 first-year music education students from Guilin Normal College in Guangxi. The aim was to explore how well integrating AI and gamification works in music theory courses, with a focus on answering two key research questions: R1: Does the AI-gamified teaching mode lead to significantly better music theory learning outcomes compared to traditional instruction?

R2: Does the AI-gamified teaching mode enhance student engagement in music theory learning across multiple dimensions compared to traditional instruction?

3. Literature Review

3.1. Applications of Artificial Intelligence in Education

Artificial intelligence (AI) in education has moved beyond theoretical exploration to large-scale practice, with its core value lying in optimizing teaching processes through intelligent, data-supported decision-making. At their heart, these technologies used in educational settings rely on machine learning methods to carry out two key functions. First, adaptive learning—tracking learners' behavioral data (such as patterns of practice errors and knowledge acquisition speed) to dynamically adjust the difficulty and presentation of instructional content [9]. For instance, the generative AI (GenAI) teaching system developed by Selwyn [9] can automatically generate targeted chord exercises based on students' music theory test results, boosting teaching efficiency by 37%. Second, intelligent feedback systems—transcending the limitations of traditional standardized assessment—offer detailed guidance on open-ended tasks. In instrumental instruction, for example, AI uses audio analysis to identify rhythmic deviations and intonation errors, then combines principles of musical aesthetics to suggest improvements [3]. This feedback balances the objectivity of technical assessment with the individuality of artistic expression.

Research confirms AI's notable impact on enhancing learning efficiency. A meta-analysis by Baker, et al. [3] shows that learners using AI adaptive systems retain 22% more knowledge than those in traditional classes, with particular strength in sequential skill acquisition (e.g., piano fingering training). However, as Kline [10] notes, current AI systems have limitations: their over-reliance on quantitative data makes them less effective at capturing qualitative dimensions of music learning, such as "emotional expression"—a gap that highlights potential for integration with gamification.

3.2. Gamification in Music theory

Gamification in music education revolves around three core elements. First, point and badge systems reinforce immediate feedback by quantifying learning behaviors. For example, students completing sight-singing exercises might earn a "Pitch Master" digital badge—a design that effectively shortens the gap between action and reward in youth music education [11].

Second, leaderboards draw on social comparison to boost motivation to participate; studies show that group rankings in collective skill-building activities (like choir rehearsals) can push attendance up to 92% [4]. Third, storytelling approaches create involvement through virtual musical settings—for example, teaching music theory through a "music kingdom adventure," where learners solve rhythm puzzles to unlock new performance stages. The reasons these methods motivate people are explained by Hamari, et al. [12] "inspiration mediation effect" theory: game-like elements first spark intrinsic motivation through curiosity (such as the mystery of unopened levels), which then turns into lasting inspiration. This effect is especially strong in music composition courses. However, the same research warns that overdoing gamification can lead to "motivational burnout": when learners focus too much on collecting points, their appreciation of music itself can fade. This highlights the need to balance artistic education with these technical tools.

3.3. Social Cognition, Constructivism, and Experiential Learning in Music Education

This study draws on social cognitive theory, constructivist learning theory, and experiential learning theory to explore how smart tools and game-like features work together in music education.

Social cognitive theory explains how people learn through the give-and-take between their environment, personal traits, and actions [13]. In music education, smart feedback tools—like real-time corrections for piano fingering mistakes—provide clear, specific feedback. This helps learners see exactly where their performance falls short of their goals, boosting their confidence in improving their skills. Meanwhile, game-like features offer relatable examples through "demonstration methods" (such as videos of virtual musicians playing correctly). When learners earn rewards by following these examples, it encourages them to keep practicing—a form of indirect motivation. Together, the personalized feedback from smart tools helps refine skills, while the rewards and examples from game-like features keep motivation high—creating a cycle where thinking, doing, and wanting to learn all support each other.

Constructivist learning theory holds that knowledge is actively constructed through our engagement with the world around us [14] helps explain why this combination works. Smart tools can adapt learning activities—like chord practice that adjusts to a learner's skill level—to create what Vygotsky [15] called a "zone of proximal development." This means challenges stay doable but still stimulating. Game-like stories—such as "music adventure quests"—put abstract music theory into concrete scenarios. Learners build their understanding naturally while solving tasks like "fixing broken melodies" or "forming virtual bands." Here, smart tools provide targeted support for building knowledge, while game-like features make the context meaningful—turning learning from passive listening into active exploration.

Experiential learning theory adds another layer by focusing on the cycle of "experiencing, reflecting, making sense, and applying" [16]. In music learning, reports from smart tools—like "you're timing in 3/4 time is 20% better than last practice"—help with the "making sense" step. Game-like immersive activities—such as performing in a virtual concert hall—strengthen the "experiencing" and "applying" steps. Together, they support every part of the learning process, solving a long-standing problem in traditional music education: the gap between learning theory and putting it into practice. This combination helps develop both musical skills and a genuine connection to music. It encompasses both cognitive dimensions of skill acquisition and emotional/social dimensions of artistic expression, providing a solid theoretical basis for follow-up study.

4. Research Process

The experimental process of this study was conducted over 14 weeks, involving two distinct groups in Figure 1.

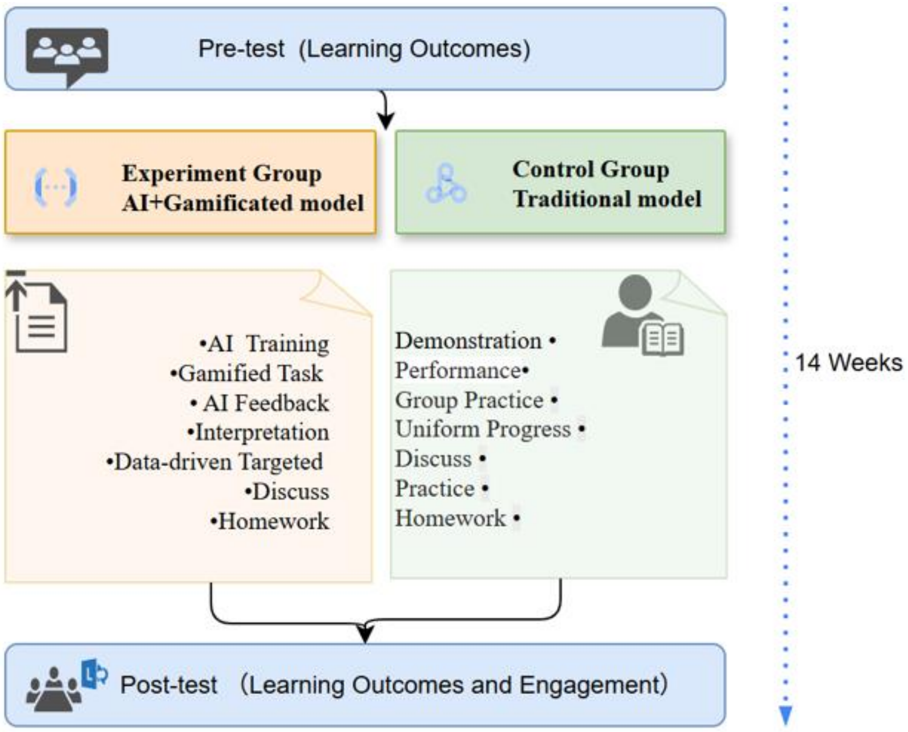

Figure 1.
The Experimental Process of AI-gamified Teaching Model.

4.1. Research Sample

The study included 180 first-year music majors from 6 classes of the Music Department at Guilin Normal College in Guangxi. All participants had received one year of systematic music training and possessed basic music skills.

Participants were divided into two groups. Three classes with 90 students in total formed the experimental group, using the "AI + gamification" teaching system. As Table 1 shows, there were 48 boys (53.3%) and 42 girls (46.7%) in this group. The remaining three classes, also 90 students, served as the control group and received traditional multimedia instruction. This group had 40 boys (44.4%) and 50 girls (55.6%). Both groups showed comparable academic proficiency, as indicated by their passing scores in the first-year music theory exam, suggesting no significant differences in their initial music competence.

Table 1.
Socio-demographic Details of the Participants in Quantitative Studies.

	Control Group		Experimental Group	
Gender	**Number**	**Percent**	**Number**	**Percent**
Boy	40	44.4%	48	53.3%
Girl	50	55.6%	42	46.7%

4.2. Research Stages

The experiment will last for 14 weeks, with the specific details in Figure 2.

Figure 2.
The Details of Research.

4.2.1. Preparation Phase (Week 1)

All individuals taking part in the experiment were made aware of the study’s aims, steps, and related particulars. A pre-test on academic performance was administered to assess students’ baseline knowledge, establishing a reference point for subsequent experimental comparisons. During this phase, teachers in the experimental group (AI + gamification teaching mode) received specialized training on AI and gamification software. This training focused on mastering core functions such as interpreting AI-generated feedback and configuring gamified tasks, laying the groundwork for the smooth implementation of the experiment.

4.2.2. Implementation Phase (Weeks 2–13)

The experimental group adopted the “AI + gamification” teaching system for music instruction. In each class, teachers assigned learning tasks via the system—such as completing gamified challenges to earn points. While students engaged with the AI tool (Doubao), the system provided real-time feedback on their queries, answers, and progress. Teachers then offered targeted guidance based on this feedback and students’ performance, facilitating in-class discussions and assigning relevant homework.

The control group received traditional instruction, where teachers demonstrated performance techniques. After students practiced, teachers provided centralized evaluations and feedback, conducted class discussions, and assigned exercises. Both groups covered identical teaching content and maintained consistent class hours. Students in the control group also had dedicated in-class time for discussions, practice exercises, and skill development.

4.2.3. Data Collation Phase (Week 14)

Collected questionnaire data and student performance records were systematically organized and verified. Invalid questionnaires were excluded, and valid data were coded and statistically analyzed.

4.3. Research Analysis

This 14-week study involved two groups. Post-intervention, independent samples t-tests compared their music theory scores and performance skills, while MANOVA analyzed combined outcomes (including engagement data) to assess overall group differences.

Primary data included pre-test/post-test music theory scores and engagement questionnaires, with a 94.8% valid questionnaire recovery rate and 100% complete test data, ensuring robust analysis.

4.4. Introduction to Research Instruments

4.4.1. Student Achievement Assessment Scale

The music theory achievement assessment test was developed by the researchers based on Ericsson and Lehmann [17] music theory evaluation framework, with adaptations to align with the characteristics of students in Guilin, Guangxi. It includes personalized items targeting experimental content (e.g., "adjusting performance rhythm based on AI feedback" as a practical task), directly linking to intervention effect evaluation. The test covers topics such as melodic dictation (e.g., dictating C-major monophonic melodies), harmonic analysis (e.g., labeling four-part harmonic progressions), and music terminology explanation. After three rounds of review by music and education experts and pre-testing, the test demonstrated a Cronbach's α coefficient of 0.81. Its construct validity was verified through exploratory factor analysis (KMO = 0.78, cumulative variance contribution rate = 65.3%).

4.4.2. Student Engagement Scale

To assess student engagement, we used the Student Engagement Instrument (SEI), developed by Fredricks, et al. [18]. This scale has 28 items covering three dimensions: behavioral engagement, emotional engagement, and cognitive engagement. It relies on self-reports to gauge students' in-class participation (e.g., asking questions actively), emotional involvement (e.g., inclination toward learning), and cognitive effort (e.g., thinking deeply).

4.4.3. Game and AI Software

The AI tool used was Doubao in Figure 3, an AI agent developed by China's ByteDance based on the Yunque model, featuring robust AI capabilities. It can answer students' questions on music theory knowledge (e.g., complex chord structures, musical melodies) and explain theoretical concepts. Additionally, it provides suggestions for melodic direction and lyric creation, along with generated examples, based on students' specified musical styles and emotional tones.

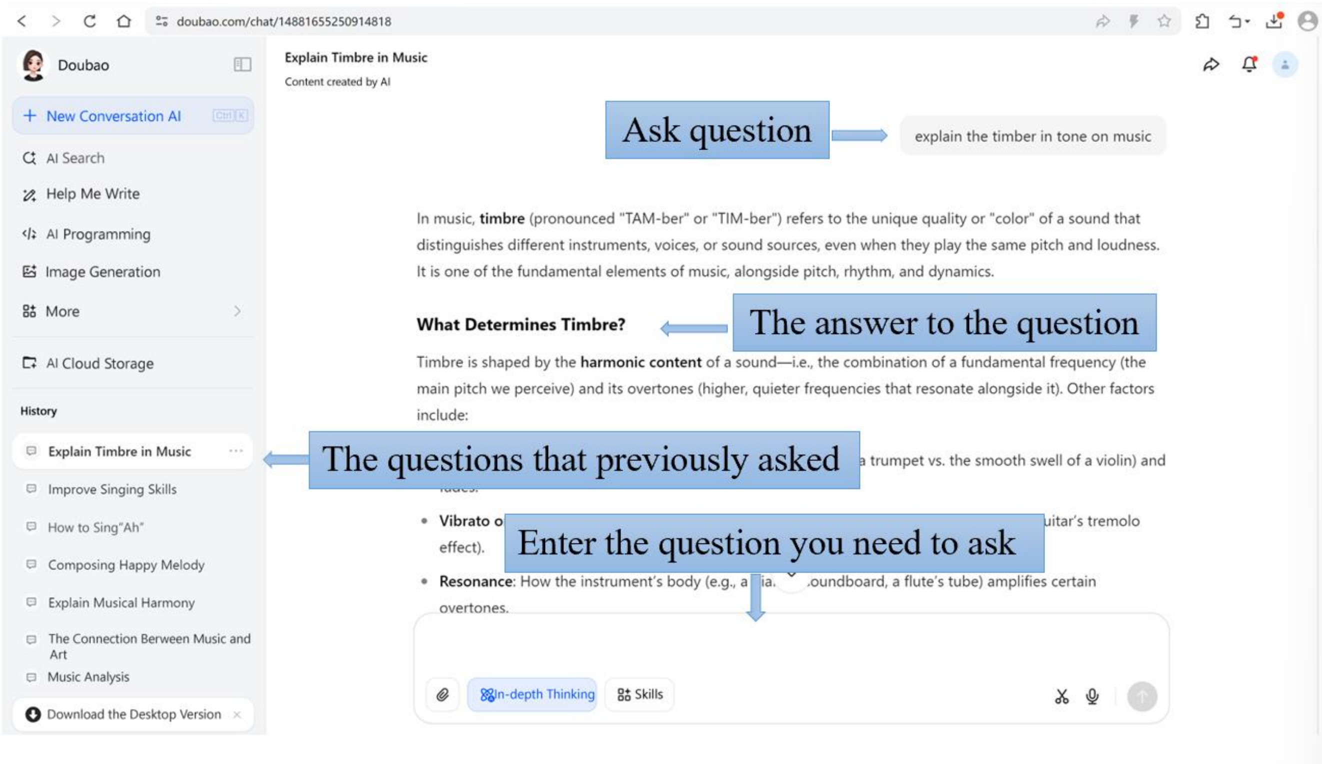

Figure 3.
AI Software Doubao Screenshot.

The rhythm game employed was Rhythm Master in Figure 4 a music rhythm software developed by China's Tencent. Players respond to heard musical rhythms by swiping the screen, with the system scoring based on the accuracy of their inputs. It includes various modes such as level challenges and multiplayer battles, enabling social interaction through game characters and point accumulation.

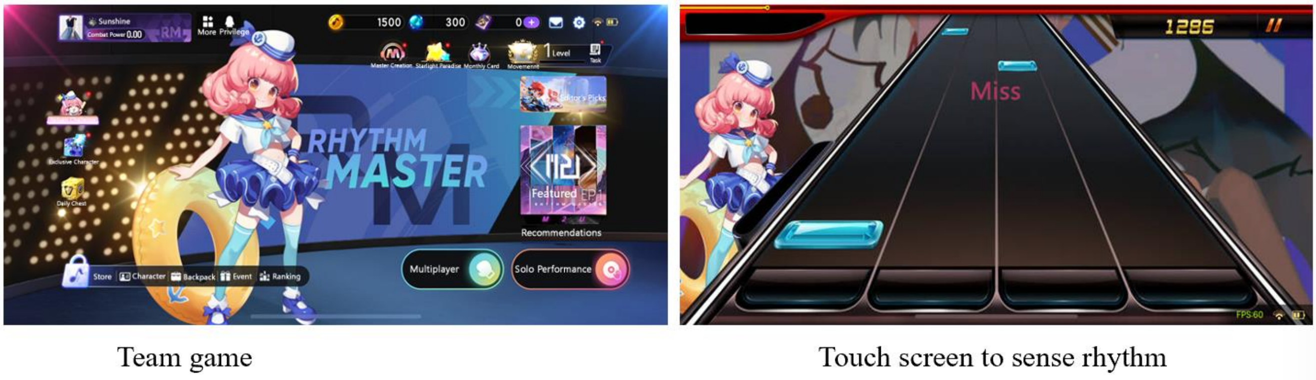

Figure 4.
Rhythm Master.

5. Result

5.1. Does AI-Gamification Teaching Mode Lead to Significantly Better Music Theory Learning Outcomes Compared to Traditional Instruction?

5.1.1. Pre-Test of Music Theory Learning Outcomes.

Table 2.
Independent Samples T-test of Pre-test for Music Theory Learning Outcomes.

DV	Group	M ± SD	Levene's Test（F,p）	t-test（t, p）	Cohen's d
Music theory learning outcomes	CG	51.75±8.62	F=0.06, p=0.805	t=0.85, p=.198	0.05
	EG	52.18±8.36			

Note: C = Control group, E = Experimental group.

Before the 14-week teaching intervention, students in both the experimental group and the control group completed a pre-test on music theory to assess their initial proficiency. It was verified that the pre-test scores of students in both groups were normally distributed, and then an independent samples t-test was conducted to analyze the data.

In terms of scores in Table 2 the initial average score of the experimental group was 52.18 (SD = 8.36), and that of the control group was 51.75 (SD = 8.62), indicating that the baseline levels of the two groups were relatively close. The result of Levene's test (F=0.06, Sig. = 0.805 > 0.05) confirmed that the data met the condition of homogeneity of variance. The independent samples t-test further showed (t = 0.85, p = 0.198 > 0.05) that there was no significant difference in the initial music theory proficiency between the two groups of students. The Cohen's d was 0.05, with a very small effect size, indicating that the two groups had good comparability before the intervention.

5.2. Post-test of Music Theory Learning Outcomes

After 14 weeks of teaching activities, students in both the experimental and control groups completed the post-test for music theory learning outcomes. The normality of the post-test scores was assessed for both groups and confirmed to be normally distributed. Subsequently, an independent samples t-test was employed to examine whether there was a significant difference between the experimental and control groups in terms of music theory learning outcomes.

Table 3 presents the results of Levene's test, which indicated homogeneity of variance for music theory learning outcomes (F=2.62, Sig. = 0.108 > 0.05). The t-test results revealed a significant difference in post-test scores (Sig. < 0.001), with the experimental group achieving a mean score of 83.42 compared to 62.31 for the control group. This indicates that the experimental group demonstrated a substantial improvement in music theory learning outcomes after the intervention, significantly outperforming the control group.

Table 3.
Independent Samples T-test of Post-test for Music Theory Learning Outcomes.

DV	Group	M ± SD	Levene's Test(F,p)	t-test (t, p)	Cohen's d
Music theory learning outcomes	CG	62.31±9.18	F=2.62, p=0.108	t=12.76 p<0.01	2.34
	EG	83.42±7.45			

Note: C = Control group (traditional instruction), E = Experimental group (AI-gamified mode); Music theory learning outcomes are measured by a 100-point scale covering basic music theory knowledge, harmony basics, skill application and practice, and comprehensive analysis and understanding.

Table 4.
The Comparison of Music Theory Learning Outcomes Between Pre-Post Test.

Group	Pre-test Score	Post-test Score	Score Change	Improvement Rate	Statistical Comparison	Effect Size
(CG)	51.75±8.62	62.31±9.18	+10.56	+20.4%	Pre-test vs CG: t=0.85, p=.198 (NS)	d=0.05
(EG)	52.18±8.36	83.42±7.45	+31.24	+59.9%	Post-test: t=-12.76, p<0.001 (***)	d=2.34

Note: 1. All scores represent Mean ± SD on 100-point scale (assessing: basic theory=30pts, harmony=25pts, application=25pts, analysis=20pts 2.Variance homogeneity confirmed (Levene's test: pre p=0.805; post p=.108) 3.NS=Not Significant; ***p<0.0013.Improvement Rate = [(Post-Pre)/Pre]×100% 4.Cohen's d interpretation: 0.2=small, 0.5=medium, 0.8=large effect.

Looking at the combined data from pre-test and post-test, the experimental group (EG) and control group (CG) showed distinct patterns in their music theory learning outcomes, with key differences emerging after the intervention.

Both groups started on nearly equal footing. In the pre-test, EG scored an average of 52.18 (SD = 8.36) and CG 51.75 (SD = 8.62). An independent samples t-test confirmed no significant difference between them (t = 0.85, p = 0.198), with a tiny effect size (d = 0.05) reinforcing that their initial music theory foundations were comparable—critical for validating the intervention's impact later.

The gap widened sharply after the intervention. Post-test results revealed EG's average score surged to 83.42, while CG reached 62.31. Statistical analysis (t = -12.76, p < 0.001) underscored the significance of this difference, backed by a large effect size (d = 2.34) that highlights the practical relevance of the gap.

Improvement rates told a similar story. EG's scores jumped by 31.24 points, a 59.9% increase from their pre-test, whereas CG gained 10.56 points, a 20.4% rise. This stark contrast—with EG improving nearly three times as much as CG—suggests the experimental teaching approach (AI-integrated gamified instruction) not only drove meaningful progress but also outperformed traditional methods by a substantial margin.

5.2. Does AI-gamification teaching mode enhance student engagement in music theory learning compared to traditional instruction across multiple dimensions?

After the intervention, both groups took a post-test to measure engagement across the same four dimensions. Tests confirmed the data was normally distributed, so we used independent samples t-tests to check for group differences.

The experimental group scored significantly higher in overall engagement in Table 5. with an average of 52.38 (SD = 5.76) compared to 39.72 (SD = 6.93) in the control group. Breaking it down by dimension, the same pattern held:

Behavioral engagement (which looks at class participation and task completion) was stronger in the experimental group (14.26 ± 1.85) than the control group (10.35 ± 2.24);

Emotional engagement, reflecting interest and enjoyment, averaged 13.85 ± 1.72 for the experimental group versus 9.87 ± 2.11 for the control group;

In cognitive engagement—measuring deep questioning and self-regulation—the experimental group scored 13.52 ± 1.96, well above the control group's 9.63 ± 2.08;

Social engagement, which includes peer collaboration and discussion, was also higher in the experimental group (12.75 ± 1.68) than the control group (9.01 ± 1.95).

Levene's test showed variance was homogeneous across all dimensions (Sig. > 0.05), and t-test results (t = -8.632 to -10.543, all p < 0.001) made it clear: the experimental group had significantly higher engagement than the control group in every area.

Table 5.
Independent Samples T-test of Post-test for Student Engagement.

DV	Dimension	IV	M ± SD	Levene's Test		t-test		Compare results
				F	p	t	p	(EG vs. CG)
Student Engagement	Overall	C	39.72±6.93	0.105	0.746	-8.632	<.001	EG > CG
		E	52.38±5.76					
	Behavioral	C	10.35±2.24	0.087	0.769	-9.217	<.001	EG > CG
		E	14.26±1.85					
	Emotional	C	9.87±2.11	0.063	0.802	-10.543	<.001	EG > CG
		E	13.85±1.72					
	Cognitive	C	9.63±2.08	0.092	0.762	-8.976	<.001	EG > CG
		E	13.52±1.96					
	Social	C	9.01±1.95	0.075	0.785	-9.824	<.001	EG > CG
		E	12.75±1.68					

Notes: 1.C= Control group (traditional model), E= Experimental group (AI-gamified model).2. Engagement dimensions: Behavioral: Class participation, task completion; Emotional: Interest, enjoyment; Cognitive: Deep questioning, self-regulation; Social: Peer collaboration, discussion. 3.All t -tests assume equal variances (Levene's p> .05). Negative*t*values indicate higher means for EG. 4. p< .001denotes highly significant differences favoring EG.

Table 6.
Post-test Comparison of Music Theory Learning Outcomes and Overall Student Engagement.

Indicator	Control Group (CG, Traditional Instruction) Mean ± SD	Experimental Group (EG, AI-Gamification Teaching) Mean ± SD	t-test Significance (Sig.)
Music Theory Learning Outcomes (Total Score)	62.31 ± 9.18	83.42 ± 7.45	< 0.001
Overall Student Engagement	39.72 ± 6.93	52.38 ± 5.76	< 0.001

Note: 1. Music theory scores are measured on a 100-point scale, encompassing basic music theory knowledge, harmony basics, skill application, and comprehensive analysis. 2. Overall student engagement is a composite measure integrating behavioral, emotional, cognitive, and social dimensions of involvement. 3. Notable statistically significant disparities (with a significance level of less than 0.001) emerged across both metrics, indicating that the experimental cohort surpassed the control cohort in terms of both music theory learning achievements and general engagement levels.

An examination of the post-assessment data reveals a distinct divergence between the control group (CG) and the experimental group (EG) in two key areas: music theory learning results and overall student involvement.

When considering music theory learning outcomes, the experimental group, which received AI-gamified instruction, attained a substantially higher average score of 83.42 ± 7.45. In contrast, the control group, which was taught using traditional methods, scored an average of 62.31 ± 9.18. This difference was found to be statistically significant (Sig. < 0.001).

Likewise, in the aspect of overall student engagement, the experimental group obtained a markedly higher score of 52.38 ± 5.76 compared to the control group's 39.72 ± 6.93. This discrepancy also reached a statistically significant level (Sig. < 0.001).

Taken together, these findings suggest that the AI-gamified teaching approach is more efficacious than conventional teaching methods in both boosting students' music theory learning results and elevating their overall engagement.

6. Discussion

6.1. AI+Gamified Model Effectively Enhances Music Theory Learning Outcomes

This study makes it clear that combining AI with gamified teaching works far better than traditional methods when it comes to improving students' music theory skills. The findings show how AI tools, game elements, and music education can come together to great effect.

6.1.1. The New Approach's Effectiveness Starts with a Solid Baseline

Before the intervention, the experimental group (using AI+ gamified) and control group (using traditional methods) had almost identical music theory skills. The experimental group scored 52.18 on average (with a standard deviation of 8.36), while the control group scored 51.75 (SD=8.62). Statistical tests confirmed there was no meaningful difference between them (t=0.85, p=0.198), and other checks (like Levene's test for variance homogeneity, p=0.805) backed this up. The tiny effect size (Cohen's d=0.05) reinforces that both groups started on equal footing—this is crucial because it means any differences after the intervention can be credited to the teaching method itself, not pre-existing gaps.

After the intervention, the results were striking. The experimental group's average score jumped to 83.42 (SD=7.45), while the control group only reached 62.31 (SD=9.18). The gap was statistically significant (t=-12.76, p<0.001) and practically meaningful, with a large effect size (Cohen's d=2.34). The progress rates tell an even clearer story: the experimental group improved by 59.9% (31.24 points), nearly triple the control group's 20.4% (10.56 points) gain. This 21.11-point difference in final scores isn't just a number—it reflects real mastery of core music theory: the 30-point foundational knowledge section, 25-point harmony section, 25-point skill application, and 20-point comprehensive analysis.

6.1.2. Underlying Mechanisms of the AI-Gamified Model's Superiority

The success of the AI-gamified model ties back to well-established educational theories. First, gamified features like feedback loops and achievement systems align with self-determination theory [19] which says people are motivated when their needs for autonomy, competence, and connection are met. This built-in motivation kept students engaged throughout the intervention, unlike traditional teaching, which often relies on external pressures like grades—something that can sap long-term interest.

Second, AI makes gamification smarter by tailoring lessons to each student. Algorithms adjusted difficulty, pace, and content based on how well each student was doing, fixing the "one-size-fits-all" problem in traditional classes [20]. For example, if a student struggled with basic harmony, they'd get targeted gamified exercises; advanced students could dive into complex analysis challenges. This fits with Vygotsky [15] idea of the "zone of proximal development"—stretching students just enough to keep them growing without overwhelming them. It's why the experimental group progressed so quickly, and their smaller post-test standard deviation (7.45 vs. 9.18 in the control group) shows this personalized approach helped more students succeed consistently.
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6.1.3. Link to Existing Literature and Research Contributions

These findings line up with earlier studies showing gamification works in STEM and language classes, but they add something new by focusing on music theory—a subject where technical rules (like sheet music symbols or chord patterns) meet creative understanding. This mix makes engagement both critical and tricky.

Traditional music theory often leans on repetitive memorization, which can make students tune out. But this study shows that AI-gamified teaching can change that, blending the need for technical accuracy with interactive, motivating elements. What's especially strong is that the pre-test scores were so similar—this avoids a common criticism of education research, where pre-existing group differences can muddle results. Here, we can be confident the improvements came from the teaching model itself, making it more likely these effects can be repeated elsewhere.

6.1.4. Implications for Practice and Future Research

For teachers, these findings suggest AI-gamified tools are worth using in music theory, especially when the goal is both engagement and technical skill. Professional development should focus on training teachers to use AI-driven gamified elements—like adaptive quizzes or collaborative music challenges—in their lessons.

6.2. AI+Gamified Model Effectively Enhances Student Engagement

This study clearly shows that the AI-gamified teaching method boosts student engagement in music theory across the board—how they participate, how they feel, how they think, and how they interact—far more than traditional instruction. This multi-dimensional improvement isn't just what theory would predict for gamification and tech-enhanced learning; it also shows this model could redefine how students connect with music education.

6.2.1. Uniform Superiority Across Engagement Dimensions

Post-intervention data (Table 5) shows the experimental group (EG) outperformed the control group (CG) in every measure of engagement, with differences that matter both statistically and in real classrooms.

Overall engagement tells the biggest story: EG scored an average of 52.38 (SD=5.76), way higher than CG's 39.72 (SD=6.93). Statistical tests confirmed this gap was real ($t=-8.632$, $p<0.001$), and Levene's test ($p=0.746$) ensured the data was consistent enough to trust.

Breaking it down by dimension, the pattern stays the same:

Behavioral engagement: EG scored 14.26 (SD=1.85) versus CG's 10.35 (SD=2.24) ($t=-9.217$, $p<0.001$), meaning they participated more in class and got tasks done more reliably.

Emotional engagement: EG's 13.85 (SD=1.72) beat CG's 9.87 (SD=2.11) ($t=-10.543$, $p<0.001$), showing they were more interested and enjoyed the lessons more.

Cognitive engagement: EG scored 13.52 (SD=1.96) compared to CG's 9.63 (SD=2.08) ($t=-8.976$, $p<0.001$), reflecting deeper questions and better focus.

Social engagement: EG's 12.75 (SD=1.68) topped CG's 9.01 (SD=1.95) ($t=-9.824$, $p<0.001$), meaning they collaborated and discussed more with peers.

In every case, Levene's test confirmed the data was consistent ($p>0.05$), and the size of the differences—shown in both the scores and statistical values—proves these aren't just small, random blips but meaningful changes for the classroom.

6.2.2. Mechanisms Driving Enhanced Engagement

The across-the-board improvement in engagement comes from how AI and gamification work together, fixing key problems in traditional music theory classes:

Gamification as a motivational engine: Features like progress badges, real-time feedback, and interactive challenges fit with self-determination theory [13]. They make students feel capable (by hitting achievable milestones), in control (by choosing their learning path), and connected (through team goals). This turn learning from something you do for a grade into something you want to do—explaining why EG students cared more emotionally and kept participating consistently.

AI-powered personalization: AI adjusts lesson difficulty and speed to match each student's level, so no one gets stuck or bored. A student struggling with chord progressions might get simple, gamified drills; advanced students could tackle tough harmony puzzles. This lines up with Vygotsky [15]"zone of proximal development," keeping students challenged but not frustrated. It's why EG showed better focus and deeper thinking.

Social learning amplified by technology: Traditional music theory often focuses on solo practice, limiting how much students interact. But the AI-gamified model includes team-based puzzles and peer feedback, building on social learning theory [11]. This doesn't just get students working together—it helps them learn by explaining things to each other, which is why EG's social engagement scores were so much higher.

6.2.3. Alignment with Literature and Unique Contributions

These findings build on past research that gamification works in subjects like science or language, but they're unique because they focus on music theory—a field where you need both technical precision (like reading notation or following harmony rules) and creative interpretation. Traditional music classes often rely on memorization, which can make students disengage, but this study shows AI-gamification can make technical learning interactive and social.

What's special here is that engagement improved in every dimension. Some studies only see gains in one area—like more participation but not deeper thinking—but here, emotional investment fed into better focus, and working with peers encouraged more participation. It's a cycle where each part of engagement boosts the others, showing technology can improve not just one part of learning but the whole experience.

6.2.4. Implications for Practice and Future Research

For teachers, these results mean AI-gamified tools are worth adding to music theory classes—with a focus on elements that hit all types of engagement:

Behavioral: Use gamified trackers to encourage participation.

Emotional: Try story-based challenges to make lessons more fun.

Cognitive: Use adaptive AI quizzes to get students asking deeper questions.

Social: Add team game modes to get peers working together.

Future research could dig into which gamified features matter most for music—like whether rewards work better than stories. Long-term studies would also show if this engagement leads to better long-term memory of music theory. And talking to students about their experience could add more depth to the numbers.

7. Conclusion

This study set out to explore whether using an AI-gamified approach in music theory classes could boost student engagement more effectively than traditional teaching methods—looking at how students participate, feel, think, and interact with others. The results paint a clear picture:

For starters, the AI-gamified method significantly upped student engagement across the board. After the intervention, the group using this new approach scored much higher than the traditional group in overall engagement—52.38 versus 39.72. Break it down, and the same pattern holds: they participated more in class and got tasks done more reliably (14.26 vs. 10.35), seemed more interested and enjoyed the lessons more (13.85 vs. 9.87), asked deeper questions and stayed more focused (13.52 vs. 9.63), and worked better with classmates (12.75 vs. 9.01). All these gaps were statistically meaningful, with big enough differences to matter in real classrooms.

What makes this work? It's the mix of gamification and AI. Gamified features like tracking progress and earning rewards tap into what motivates students naturally. AI steps in by tailoring lessons to each student's level, so no one gets too frustrated or bored. And the tech makes it easier for students to work together—something traditional music theory classes often miss. Together, these pieces fix old problems, like lessons feeling one-size-fits-all or students just going through the motions. Instead, they create a cycle that joining in, caring about the material, thinking hard, and working with peers all feed into each other.

These findings add something new to what we know about teaching. While gamification has worked in subjects like science or language, this study shows it works in music theory too—a field where you need both technical skill and creativity. Unlike some studies that only see improvements in one area, here every part of engagement got better. That's a big deal because keeping students involved in learning music theory has always been tough.

For teachers, this means AI-gamified tools are worth trying in music classes. It's good to design lessons that hit all parts of engagement—getting students to participate, keeping them interested, making them think deeply, and encouraging them to work together. For future research, it would help to figure out which parts of the AI-gamified model matter most, see if the effects last over time, and check if it works in different types of music classes.

All in all, the AI-gamified teaching mode is a promising way to make music theory class more live. It makes learning technical stuff feel more engaging, fits each student's needs, and gets everyone working together—helping students get more out of learning music.

8. Limitation

Although the present research successfully illustrates the favorable influence of the AI-integrated gamified instructional approach on students' involvement in music theory education, it is not without limitations that necessitate further refinement in subsequent studies. First, constraints exist in the sample and intervention duration. The study was conducted with a single cohort over a 14-week intervention period. Despite significant short-term effects, the sample lacks diversity (e.g., excluding groups with different ages, musical backgrounds, or educational experiences). Additionally, there is a lack of follow-up data (such as 3–6 months after the intervention) to verify the model's long-term sustainability in maintaining engagement, which may limit the generalizability of the conclusions.

Second, the moderating role of individual differences has not been thoroughly explored. Students vary in their acceptance of gamified elements (e.g., prior gaming experience) and adaptability to AI technology, yet the study did not analyze how these variables influence engagement outcomes. This oversight may hinder nuanced judgments about whether the model is suitable for all students.

Third, the measurement of engagement lacks depth. Current assessments rely primarily on quantitative data (e.g., scale scores) and lack qualitative evidence (e.g., student interviews, classroom observation records) to explain why AI-gamification enhances engagement. This makes it difficult to capture the dynamic processes of deeper changes, such as emotional investment and cognitive strategy adjustments.

These limitations point to directions for future research: expanding sample diversity, extending follow-up periods, isolating the independent effects of technology and gamification, and adopting mixed-methods approaches (quantitative + qualitative) to more comprehensively unravel the mechanisms through which the AI-gamified teaching model influences engagement.

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