Striking the Right Chord: How Digital Tools Amplify Student Motivation in Music Education

Qingchun Bai[1,a] and Yangrui Zhan[2,b*]

[1]Shanghai Open University, Shanghai, 200000, China
[2]Shanghai Educational Technology Development Co., Ltd., Shanghai, 200000, China

[a]qc_bai@foxmail.com,
[b*]Corresponding author: zhanyangrui1112@sina.com

Abstract. With the growing integration of intelligent digital tools in primary education, their impact on music learning and aesthetic cultivation has become increasingly evident. This study investigated how AI-assisted music learning shapes elementary students' motivation, self-efficacy, and sustained use of digital tools. In a quasi-experimental study, we worked with 83 students in S City, collecting data through child-friendly questionnaires and open-ended responses. Guided by the Technology Acceptance Model, we analyzed the roles of perceived pedagogical value, ease of use, and the social learning environment. Results show that (1) perceived pedagogical value is the primary driver of intrinsic motivation and selfefficacy; (2) teacher—student and peer interactions in a supportive learning environment significantly boost motivation; and (3) intrinsic motivation and self-efficacy mediate continuance intention to use AI tools. Findings inform the design of child-centered digital music education that promotes engagement and long-term learning.

Keywords: Learning Motivation, Learning Engagement, Artificial Intelligence, Music Education, AI Interactive Experience.

1 Introduction

The advent of generative artificial intelligence (AI) is rapidly transforming educational landscapes, particularly in creative disciplines such as music education.

AI-driven tools—including online composition platforms like AI SUNO (www.suno.com) and TianGong AI, adaptive accompaniment systems, and immersive virtual environments, are challenging and reshaping traditional pedagogical paradigms[16]. Educational institutions worldwide are increasingly embracing this digital integration, aligning with broader trends toward AI-augmented learning.

Despite their potential, such technologies emerge within a longstanding pedagogical dilemma: sustaining student motivation in compulsory music education. Conventional methods often fail to resonate with students' digital native experiences, leading to repetitive practice routines and delayed feedback—factors associated with declining engagement. Given that motivational drive is a foundational determinant of prac-

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tice habits, skill development, and long-term musical involvement [29], resolving this motivational gap is critical.

Generative AI tools can mitigate these issues by introducing novelty, interactivity, personalization, and real-time feedback—elements hypothesized to reinvigorate student motivation [28]. Empirical studies in teacher education identify factors such as performance expectancy, social influence, and perceived risk as influential in technology adoption. In music-specific settings, evidence demonstrates generative AI's positive effects on motivation, mediated by enhanced student–teacher interaction, and improved learning outcomes through AI-mediated composition or analysis [16, 13]. However, concerns persist about potential creative homogenization and overreliance on algorithmic structures, which could undermine deep artistic understanding.

Prior research has extensively emphasized the critical role of motivation in determining learning outcomes, sustained participation, and long-term artistic engagement in music education [18, 29]. However, there remains a gap regarding how students' motivation can be effectively stimulated and maintained through AI music tools. Additionally, little attention has been devoted to understanding the formation of students' attitudes toward these AI technologies, particularly how cognitive and emotional perceptions of AI-driven music tools influence their behavioral engagement. While motivation has been extensively correlated with learning outcomes, there remains a significant gap regarding the cognitive and affective mechanisms activated by AI tools in music education [18]. Specifically, little is known about how middle school students form attitudes toward these technologies—via cognitive evaluation of usability, utility, and creative threat—and how such attitudes, alongside emotional responses like excitement or anxiety, influence their intention to engage.

This study addresses this gap by adopting a cognition–affect–behavior framework. We examine how adolescents perceive generative AI tools (e.g., regarding usefulness, ease-of-use, threat to creativity) and how these perceptions elicit emotional reactions (e.g., curiosity, enthusiasm, apprehension), ultimately shaping their behavioral intention to learn with AI-supported music tools. By illuminating these psychological pathways, we aim to generate insights that inform educators, curriculum developers, and tool designers about how to integrate generative AI into music education in ways that foster intrinsic motivation, creative expression, and sustained engagement. The research questions are:

- RQ1: How do AI music tools, compared to traditional methods, affect middle school students' motivation and engagement?
- RQ2: How do cognitive appraisals and affective responses mediate the relationship between AI music tools and students' motivation and engagement?
- RQ3: How can teaching strategies be designed to enhance positive experiences, mitigate negative effects, and foster creativity through human-AI collaboration?

2 Literature Review

2.1 AI Interaction Experience: From Conversational to Cross-Modal

Conversational agents such as educational chatbots and intelligent tutoring systems have been shown to foster metacognitive monitoring and cognitive exploration through heuristic questioning and adaptive feedback [13, 32]. Systematic reviews confirm that chatbots in higher education provide academic and emotional support, real-time feedback, and motivational scaffolding, though challenges such as authenticity and ethical concerns remain [21, 23]. Beyond text-based interaction, cross-modal AI tools such as AI-generated painting and visualization create low-threshold channels for externalizing auditory emotions into visual symbols [26, 3]. Psychological studies show that music–color associations are mediated by emotional responses, providing a theoretical basis for visualizing music emotions [1]. Educational applications have implemented deep-learning-based music emotion recognition systems that enable real-time visual representation of musical affect, making abstract aesthetic qualities more tangible for learners [6]. Recent classroom interventions using text-to-image generation further highlight opportunities for aesthetic association, reflective discussion, and expressive creativity in arts education [30]. These cross-modal interactions extend the reach of AI pedagogy, enabling students not only to analyze but also to embody and communicate aesthetic meaning [16, 20, 22, 17].

2.2 Learning Motivation, Technology Acceptance, and Use in Music Education

Learning motivation is a key psychological driver that directs and sustains learners' engagement with music [15, 29]. Within the framework of Self-Determination Theory (SDT), autonomy, competence, and relatedness are identified as the core needs that enhance intrinsic motivation and persistence [5, 7]. In music education, these needs manifest in learners' curiosity for repertoire, confidence in performance, and the social bonds formed with peers and teachers [18, 19, 4]. Empirical evidence suggests that digital technologies can strengthen these motivational dimensions by providing autonomy-supportive environments, competence feedback, and virtual communities [31, 28].

Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) are frequently applied to explain the adoption of music learning technologies [2]. TAM emphasizes perceived usefulness and ease of use as predictors of attitudes and intentions, while UTAUT incorporates social influence and facilitating conditions. Studies show that musicians' generally positive attitudes toward technology align with TAM predictions, though traditional master-apprentice models may moderate adoption [10,11,12]. More recent interventions with augmented reality (AR) and gamified platforms indicate that perceived usefulness significantly promotes sustained engagement, but fatigue and novelty effects can temper long-term motivation.

Learning engagement functions as a behavioral, emotional, and cognitive bridge between technology use and motivation. High engagement is consistently linked to meaningful learning outcomes and persistence. In music classrooms, engagement has been shown to mediate the effects of technology integration on motivation, with emotional engagement often emerging as the strongest predictor. However, evidence also suggests that overreliance on technology may diminish intrinsic motivation, underscoring the need for balanced designs that integrate both traditional pedagogy and digital innovation [10]. Overall, the literature converges on the view that technology acceptance and engagement processes are central to sustaining motivation in contemporary music education.

3 Research Design and Methods

3.1 Research Participants and Grouping

This study adopted a quasi-experimental design (post-test control group). Participants are 83 Grade 7 students from an elementary school in City S. All of them are non-specialist music learners with no systematic training background, ensuring homogeneity in music foundation. Two parallel classes are assigned to experimental and control groups: the experimental group (n=40) engaged with the digital music learning platform, while the control group (n=43) received traditional classroom instruction without technological intervention. Baseline comparisons indicated no systematic differences in academic performance or musical aptitude between the groups. All participants joined voluntarily, with informed consent obtained from parents and school administration.

3.2 Digital Music Learning Tools Design and Development

A bespoke web-based digital music learning software was designed specifically for this study, embedding motivational arousal principles derived from Self-Determination Theory (SDT). The platform emphasized music's unique characteristics—such as auditory immediacy, rhythmic embodiment, and creative expression—to convert abstract theoretical concepts into engaging, interactive tasks as shown in fig1. The design aimed to foster students' autonomy, competence, and relatedness within musical learning, aligning with the goals of aesthetic education. The platform comprised three integrated modules.

Module One: Gamified Interactive Tutorial (Gamified Interactive Rhythm Cards). Inspired by gamification in music education, this module transformed tedious music theory (e.g., triadic chord structures) into adventure-style challenges, such as the "Chord Castle" where students drag note blocks to construct major and minor triads. Drawing on cooperative board game mechanics, clear goals, immediate feedback, and symbolic rewards (e.g., illuminated badges) stimulated achievement motivation and intrinsic interest. This process fostered a sense of musical accomplishment, similar to composing a simple melody.

Module Two: Intelligent Instant Feedback System. Based on predefined music theory algorithms, the system provided real-time, multimodal feedback during composition tasks. When students arranged notes into chords, visual cues (green checkmarks for correct chords, red crosses for errors) and auditory reinforcements (harmonious chimes vs. dissonant alerts) were displayed, supported by concise explanatory text (e.g., "This is a major triad, built on root, major third, and perfect fifth"). Such nonjudgmental, low-latency feedback reduced frustration, enhanced perceived competence, and encouraged trial-and-error exploration, which is critical for developing musical intuition.

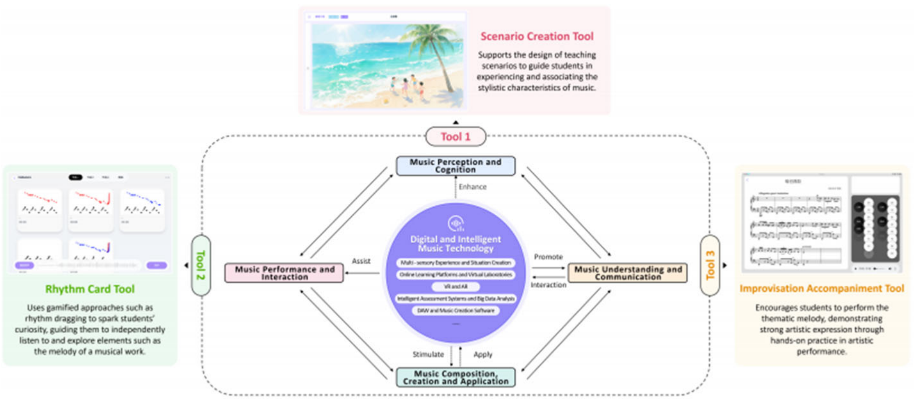

Fig. 1. Digital Music Learning Tools Design and Development.

Module Three: Low-Threshold Creation Assistant Interface. This module democratized music composition for beginners by offering a simplified piano roll interface. Students could place notes with mouse clicks,aided by a built-in metronome, diverse timbres (piano, guitar, drums), and a chord library for drag-and-drop harmonic sequencing. By lowering technical barriers, it empowered students to experiment freely with creative ideas, thereby strengthening perceived autonomy and self-efficacy while bridging theory and practice.

3.3 Questionnaire Design

To systematically assess students' perceptions and learning outcomes, a composite questionnaire was developed, combining established scales and self-developed items contextualized for digital music education. All items employed Likert-type responses, with higher scores indicating stronger endorsement of the construct. The main instrument, the Digital Music Learning Experience Questionnaire details shown as Table 1.

Table 1. Measurement Scales for the Digital Music Learning Environment

Variable	Dimension	Items	Reference / Example Item
AI Interaction Experience	Cognitive Exploration	4	Self-developed; e.g., "AI dialogue inspired me to think more deeply about music."
	Emotional Expression	4	Self-developed; e.g., "AI drawing helps me express my feelings when listening to music."

Perceived Usefulness (Pedagogical Value)	—	4	Adapted from [8]; e.g., “AI tools help me better understand music.”
Perceived Ease of Use	—	4	Adapted from [8]; e.g., “I find it easy to operate the AI tool.”
Learning Engagement	Behavioral Engagement	3	Adapted from [27]; e.g., “I actively participated in the AI music appreciation activity.”
	Emotional Engagement	4	Adapted from [27]
		4	Adapted from [27]
	Cognitive Engagement	4	Adapted from [24]
Learning Motivation	Interest / Enjoyment	4	Adapted from IMI and MSLQ
	Self-Efficacy		
Continuance Intention	—	3	Adapted from IS continuance intention models

3.4 Instructional Procedure

The experiment unfolded in three phases:**1) Phase One.** Preparation and Grouping. Students completed a demographic survey to record gender, age, and prior instrumental learning. Classes were then assigned to experimental and control conditions. 2) **Phase Two.** Instructional Intervention (45-minute lesson). Both groups undertook the same learning task: “Understand the structure of triads and compose a four-bar melody incorporating at least three different chords”. *Experimental Group.* In a computer lab, students independently used the digital music learning platform to accomplish the task, engaging with gamified tutorials, intelligent feedback, and creative composition tools. *Control Group.* In a traditional classroom, students received teacher-centered instruction using chalkboard, piano demonstration, and verbal explanation, without digital support. 3) **Phase Three.** Data Collection. Immediately after the class, all students completed the Music Learning Motivation Questionnaire, while only the experimental group also completed the Technology Acceptance Questionnaire. Student-composed melody fragments were collected as indicators of learning performance. Semi-structured interviews were conducted with a sample of students and teachers from the experimental group to gather deeper insights into their experiences, highlighting perceived benefits and limitations of the digital tools. Quantitative data were analyzed using descriptive statistics, reliability and validity testing to test hypothesized relationships among perceived pedagogical value, ease of use, social learning environment, self-efficacy, motivation, and continuance intention. Mediation effects of self-efficacy and intrinsic motivation were also tested. Qualitative data from open-ended items and interviews were analyzed thematically, focusing on dimensions of emotional resonance, collaborative interaction, and creative expression in the music classroom. Student compositions were evaluated using a rubric assessing accuracy (e.g., correct chord structures), creativity (e.g., originality of melody), and expressiveness (e.g., musical phrasing and emotional conveyance). Triangulation of quantitative and qualitative findings ensured validity and provided a holistic perspective on the impact of digital-intelligent tools in music education.

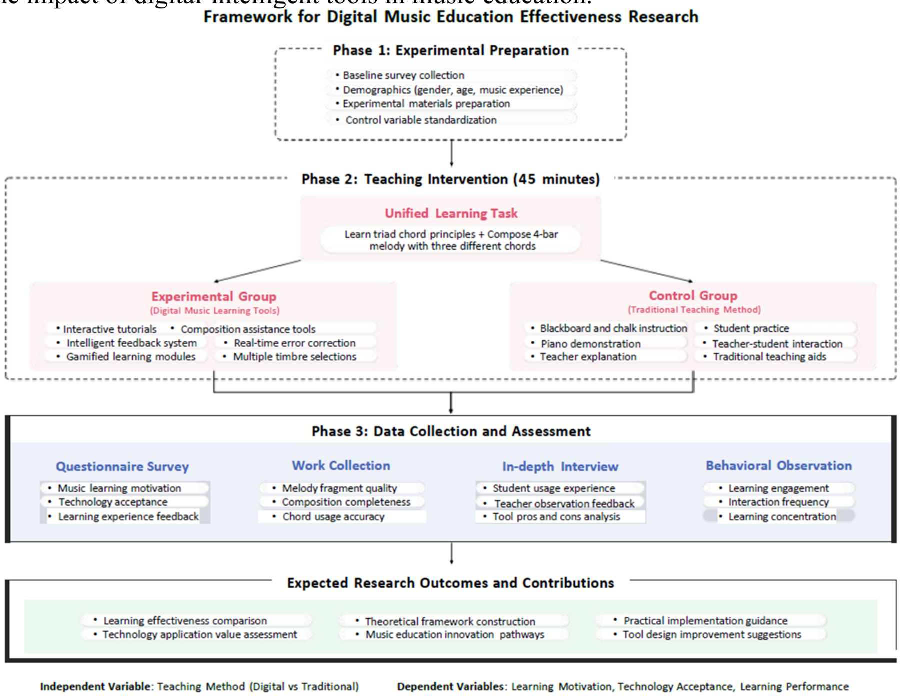

Fig. 2. Data Analysis Methods Framework

This study utilizes tools SPSS and Python for data analysis, employing statistical methods including correlation analysis and natural language processing to explore the impact of different variables on learners' acceptance and satisfaction. The framework is shown as Figure 2.

4 Results and Discussion

This study aimed to examine the effects of a digital music learning tool on elementary school students' learning motivation, user experience, and continuance intention. The analysis was conducted in three steps: (1) descriptive statistics of participants' demographic information and music learning background, (2) correlation analysis of the core research variables, and (3) interpretation of findings in light of motivational and technology acceptance theories.

4.1 Descriptive Statistics and Frequency Analysis

A total of 83 valid questionnaires were collected. The sample presented a balanced gender distribution: 41 boys (49.40%) and 42 girls (50.60%), suggesting representativeness in terms of gender. Regarding the frequency of digital tool use in music learning, more than half of the students (56.63%) reported using such tools 1–2 times per week, while 14.46% used them less than once per week and 28.92% reported higher frequencies (3 or more times weekly). Table 2 presents the frequency analysis of core demographic variables and tool-use behaviors.

Table 2. Frequency Analysis of Demographics and Tool-Use Behaviors

Item	Option	Frequency	Percentage (%)
Gender	Male	41	49.40
	Female	42	50.60
	<1 time	12	14.46
Weekly tool use	1—2 times 3 times	47	56.63
	>3 times	12	14.46
		12	14.46
	Music creation app	47	56.63
Preferred tool type	Online tutorial platform	11	13.25
	Intelligent feedback system Gam-	10	12.05
	ified learning software Other	12	14.46
		3	3.61

4.2 Correlation Analysis of Core Variables

Subsequent correlation analyses were conducted among the main constructs: perceived pedagogical value, perceived ease of use, social learning environment, intrinsic/extrinsic motivation, self-efficacy, and continuance intention. Preliminary results revealed positive associations among these constructs, indicating that higher perceived pedagogical value was significantly related to stronger intrinsic motivation and self-efficacy. Similarly, a supportive social learning environment (including teacher and peer interactions) showed significant correlations with both emotional engagement and continuance intention.

The descriptive and correlational evidence points to three central insights. First, perceived pedagogical value emerged as the most critical factor in stimulating intrinsic motivation and enhancing self-efficacy. Students were more motivated when the tool not only simplified theory learning but also allowed for creative expression, such as composing short melodies. Second, the social learning environment, manifested through teacher guidance and peer collaboration, positively influenced motivation and engagement. This suggests that digital tools, when embedded in collaborative classroom contexts, can extend beyond individual use to foster relatedness, a core SDT component. Third, self-efficacy and intrinsic motivation were identified as mediating factors for continuance intention, indicating that students' sustained willingness to use digital tools depends not solely on usability but also on their sense of competence and enjoyment.

4.3 Reliability and Validity Analysis

Validity Analysis. To examine the construct validity of the questionnaire, exploratory factor analysis (EFA) was performed. The Kaiser-Meyer-Olkin (KMO) shown as Table 3, the value was 0.871, exceeding the recommended threshold of 0.80 [14], indicating sampling adequacy. Bartlett's Test of Sphericity yielded a significant result, $\chi 2$ (210) = 2126.785, $p < 0.001$, rejecting the null hypothesis that the correlation matrix is an identity matrix. Together, these results demonstrate that the dataset was highly suitable for factor analysis.

Using principal component analysis (PCA) with Varimax rotation, five common factors were extracted according to the eigenvalue-greater-than-one criterion. These five factors jointly explained 83.322% of the total variance, far exceeding the conventional 50% threshold, suggesting that the instrument captured the majority of the information contained in the observed variables. Communalities of all items ranged from 0.644 to 0.920, surpassing the 0.40 benchmark, with no low-loading or cross-loading items observed. Factor loadings for each item exceeded 0.60 on their respective dimensions, confirming strong item–construct alignment.

The factor structure was consistent with theoretical expectations, corresponding to five latent constructs: (1) Technology Perception & Social Motivation, (2) Intrinsic Motivation, (3) Perceived Pedagogical Value, (4) Learning Self-Efficacy, and (5) Extrinsic Motivation. The first factor explained the largest proportion of variance (43.152%), reflecting students' perceptions of tool usefulness, ease of use, and the presence of social support. Intrinsic motivation (16.35%) captured enjoyment and immersion in music activities, while the feedback dimension of pedagogical value (10.389%) highlighted the salience of external recognition and system-generated encouragement. Learning self-efficacy (7.652%) emerged as a distinct but interrelated dimension, and extrinsic motivation (5.775%) was uniquely represented by goal-oriented items such as exam preparation and competitions.

Reliability Analysis. Internal consistency reliability was assessed using Cronbach's alpha coefficients. The reliability of the scales was examined using Cronbach's α . As shown in Table 4, all dimensions demonstrated high internal consistency. Specifically, the Technology Perception dimension reached an excellent reliability level ($\alpha = 0.905$), while Social Motivation ($\alpha = 0.870$) and Self-Efficacy ($\alpha = 0.856$) also exhibited strong consistency. Extrinsic Motivation ($\alpha = 0.897$) and Intrinsic Motivation ($\alpha = 0.924$) further confirmed the robustness of the measurement instruments.

Table 3. KMO and Bartlett's Test Results

KMO and Bartlett's Test	Value	
KMO Measure of Sampling Adequacy		0.871
Bartlett's Test of Sphericity	Approx. Chi-Square	2126.785

df	210
p-value	0.000

Note. Bartlett's test of sphericity was significant ($p < .001$).

Table 4. Cronbach's Reliability Analysis

Dimension	CITC	Alpha if Item Deleted	Cronbach's α
Technology Perception	0.838	0.869	0.905
Social Motivation	0.830	0.870	—
Self-Efficacy	0.887	0.856	—
Extrinsic Motivation	0.705	0.897	—
Intrinsic Motivation	0.579	0.924	—

Note. KMO = Kaiser-Meyer-Olkin. Bartlett's Test of Sphericity was significant at $p < .001$.

Reliability Analysis. Correlation Analysis. Pearson correlation analysis was conducted to examine the relationships among the key variables in the digital music learning environment. Descriptive statistics indicated that the mean scores of all dimensions exceeded 4.0 on a five-point scale, with Technology Perception ($M = 4.359$) being the highest, suggesting that students generally held positive evaluations of the pedagogical value and ease of use of the digital tools.

As shown in Table 5, all study variables were positively and significantly correlated at the $p < .01$ level, lending preliminary support to the theoretical model of this study. Several notable patterns emerged. First, Technology Perception was strongly associated with both Social Motivation ($r = .886$) and Self-Efficacy ($r = .865$), underscoring its central role in shaping students' learning experience. When students perceived the tools as useful and user-friendly, they not only engaged more actively in collaborative and social learning activities but also reported greater confidence in their own musical abilities.

Second, Self-Efficacy exhibited a strong positive correlation with Social Motivation ($r = .832$), highlighting the social basis of students' confidence in learning. This finding suggests that encouragement and peer interaction serve as fertile ground for cultivating self-belief. Moreover, Self-Efficacy was moderately to strongly correlated with both Extrinsic Motivation ($r = .676$) and Intrinsic Motivation ($r = .599$), indicating that students with stronger confidence are more likely to pursue both external achievements and internal enjoyment in music learning.

Finally, the associations of Intrinsic Motivation with Technology Perception ($r = .466$) and Social Motivation ($r = .475$), though significant, were comparatively weaker than other relationships. This pattern implies that intrinsic interest and enjoyment, while influenced by high-quality tools and supportive social contexts, are more individualized and less dependent on external reinforcement. In contrast, Extrinsic Motivation demonstrated stronger correlations with Technology Perception ($r = .615$) and Social Motivation ($r = .624$), suggesting that external goal-oriented behaviors, such as striving for recognition or achievement, are more directly shaped by functional tools and socially stimulating environments.

Table 5. Descriptive Statistics and Pearson Correlations Among Key Variables

Variable	M	SD	1	2	3	4	5
Technology Perception	4.359	0.822	1				
Social Motivation	4.295	0.856	.886**	1			
Self-Efficacy	4.259	0.925	.865**	.832**	1		
Extrinsic Motivation	4.066	0.750	.615**	.624**	.676**	1	
Intrinsic Motivation	4.166	0.884	.466**	.475**	.599**	.549**	1

Note. N = 83. *p < .05, **p < .01.

4.4 Independent Samples T-Test on Gender Differences

To explore whether gender differences influenced students' motivational and perceptual experiences in the digital music learning environment, independent samples t-tests were conducted across five core dimensions. The sample was balanced by gender (41 males, 49.4%; 42 females, 50.6%), ensuring comparability between groups. As presented in Table 6, no significant gender differences were found on any of the measured dimensions (p > .05). For instance, intrinsic motivation was slightly higher among males (M = 4.23, SD = 0.76) than females (M = 4.11, SD = 1.00), but this difference was not statistically significant (t = 0.608, p = .545). Similarly, extrinsic motivation (t = 1.258, p = .212), self-efficacy (t = 0.444, p = .658), social motivation (t = -0.154, p = .878), and technology perception (t = 0.021, p = .983) all showed no meaningful differences.

Table 6. Independent Samples t-Test on Gender Differences

Dimension	Male (n=41)	Female (n=42)	t	p
Intrinsic Motivation	4.23 ± 0.76	4.11 ± 1.00	0.608	0.545
Extrinsic Motivation	4.17 ± 0.73	3.96 ± 0.76	1.258	0.212
Self-Efficacy	4.30 ± 0.98	4.21 ± 0.88	0.444	0.658
Social Motivation	4.28 ± 0.94	4.31 ± 0.78	-0.154	0.878
Technology Perception	4.36 ± 0.88	4.36 ± 0.77	0.021	0.983

Note. All tests were two-tailed; no significant gender differences were observed (p > .05).

To complement the t-test findings, pooled variance estimates and Cohen's d values were calculated to assess the effect sizes of gender differences. As shown in Table 7, all dimensions exhibited negligible to small effects. Intrinsic motivation (d = 0.134), self-efficacy (d = 0.097), social motivation (d = 0.034), and technology perception (d = 0.005) reflected trivial differences, while extrinsic motivation showed the largest effect size (d = 0.276), still below the conventional threshold for a small effect (d = 0.20; Cohen, 1988).

These results reaffirm the absence of practically meaningful gender differences, indicating that both boys and girls responded similarly to the pedagogical value, social affordances, and usability of the digital tools. The motivational model underpinning this study thus appears robust and gender-neutral, supporting the universality of AI-assisted music learning across diverse student groups.

Table 7. Effect Size Analysis of Gender Differences

Dimension	S^2_{pooled}	Cohen's d
Intrinsic Motivation	0.787	0.134
Extrinsic Motivation	0.559	0.276
Self-Efficacy	0.864	0.097
Social Motivation	0.742	0.034
Technology Perception	0.683	0.005

Note. Effect size benchmarks follow Cohen (1988), where d = 0.20 (small), d = 0.50 (medium), and d = 0.80 (large).

4.5 Independent Samples t-Test Results

To evaluate the impact of AI-assisted music learning tools on students' motivation, perceptions, and self-efficacy, independent samples t-tests were conducted between the experimental group (n = 40, blended instruction with AI tools) and the control group (n = 43, traditional instruction). Seven key constructs were examined: intrinsic motivation, extrinsic motivation, perceived ease of use, perceived usefulness, technology perception, social motivation, and self-efficacy.

4.6 Overall Effects of the Intervention

As shown in Table 8, the experimental group scored significantly higher than the control group across all dimensions. Mean differences ranged from 0.42 to 0.54, demonstrating that the AI-assisted blended learning intervention produced consistent and broad improvements in students' motivational and perceptual outcomes.

4.7 Dimension-Specific Findings

First, in the domain of motivation enhancement, both intrinsic and extrinsic motivation were significantly improved. Intrinsic motivation increased moderately (t = 2.193, p = .031, d = 0.482), suggesting that gamified activities and creative tasks effectively stimulated students' interest and enjoyment. Extrinsic motivation showed the strongest effect (t = 3.144, p = .002, d = 0.683), indicating that goal-setting and achievement feedback mechanisms strengthened students' pursuit of external rewards. Self-efficacy also improved substantially (t = 2.766, p = .007, d = 0.604), suggesting that real-time feedback and lowthreshold creation tools fostered students' confidence in mastering music tasks.

Second, in terms of technology perception and usability, the experimental group reported significantly higher scores on perceived ease of use (t = 2.406, p = .018, d = 0.524), perceived usefulness (t = 2.429, p = .017, d = 0.531), and overall technology perception (t = 2.509, p = .014, d = 0.548). These results indicate that the intervention not only enhanced the pedagogical relevance of the tools but also improved students' technical comfort and usability experiences.

Third, with respect to social motivation, students in the experimental group reported significantly greater motivation to engage in collaborative and interactive learning ($t = 2.357$, $p = .021$, $d = 0.518$). This suggests that the AIenhanced environment, rather than isolating learners, effectively facilitated peer interaction and community-based engagement.

Effect Size Analysis and Educational Implications. Cohen's d values ranged from 0.482 to 0.683, falling within the medium-to-large range. The largest effects were observed for extrinsic motivation ($d = 0.683$) and self-efficacy ($d = 0.604$), highlighting that the intervention most powerfully strengthened students' confidence and their drive for external achievements. Other constructs, including intrinsic motivation, technology perception, perceived ease of use, perceived usefulness, and social motivation, all demonstrated medium effect sizes ($d = 0.482 – 0.548$). These results confirm that the group differences are not only statistically significant but also educationally meaningful, with tangible benefits that can be readily perceived in real classroom contexts.

Table 8. Independent Samples t-Test Results for Experimental and Control Groups

Dimension	Experimental (n = 40)	Control (n = 43)	t	p
Intrinsic Motivation	4.38 ± 0.77	3.97 ± 0.94	2.193	.031*
Extrinsic Motivation	4.32 ± 0.59	3.83 ± 0.81	3.144	.002**
Perceived Ease of Use	4.58 ± 0.75	4.12 ± 0.98	2.406	.018*
Perceived Usefulness	4.59 ± 0.75	4.17 ± 0.83	2.429	.017*
Technology Perception	4.59 ± 0.72	4.15 ± 0.86	2.509	.014*
Social Motivation	4.52 ± 0.81	4.09 ± 0.85	2.357	.021*
Self-Efficacy	4.54 ± 0.81	4.00 ± 0.96	2.766	.007**

Note. N = 83. Values are presented as mean ± standard deviation. * $p < .05$, ** $p < .01$. Cohen's d ranged from 0.482 to 0.683, indicating medium-to-large effect sizes.

5 Discussion

This study employed a quasi-experimental design to systematically compare the effects of an AI-assisted blended music education model with those of traditional instruction on elementary students' learning experiences and motivation. The findings provide convergent evidence that the integration of AI tools significantly outperformed traditional approaches across all examined dimensions, including technology perception, social motivation, self-efficacy, and both intrinsic and extrinsic motivation. These results not only reached statistical significance but also yielded medium-to-large effect sizes, confirming their practical educational relevance. The study revealed three central outcomes. First, AI-assisted tools substantially optimized learning experiences: students in the experimental group reported higher perceptions of pedagogical value, usability, and social engagement than their peers in the control group. Second, AI tools effectively enhanced students' confidence, with self-efficacy showing one of the strongest effects (d = 0.604), indicating that the tools served as scaffolds for skill mastery and as amplifiers of students' creative capacity. Third, AI-assisted instruction broadly stimulated both intrinsic motivation (enjoyment and curiosity) and extrinsic motivation (achievement and recognition), demonstrating that well-designed digital interventions can simultaneously foster engagement with the learning process and pursuit of external goals.

5.1 Why Does AI Effectively Foster Motivation and Confidence?

The advantages of AI-based instruction can be explained by its ability to restructure learning interactions in ways that meet core psychological needs. First, the comprehensive improvement in motivation can be attributed to the dual satisfaction of autonomy and competence. Traditional instruction often limits students' pace of learning and access to timely feedback. By contrast, the digital platform provided (a) a low-threshold creation interface that enabled perceived autonomy and exploratory freedom, and (b) gamified tutorials and intelligent real-time feedback that offered non-judgmental, immediate reinforcement. According to self-determination theory, these conditions fostered both intrinsic enjoyment and the internalization of extrinsic goals. Second, the notable gains in self-efficacy highlight the dual role of AI as both a "cognitive scaffold" and a "capability amplifier." On the one hand, the gamified tutorials made abstract music theory concepts (e.g., triadic harmony) concrete and approachable. On the other hand, intelligent feedback and error-prevention mechanisms allowed students to focus on creativity rather than technical correctness. The resulting success experiences contributed to stronger confidence in musical abilities and reinforced persistence.

5.2 Implications for Music Education in the Digital Age

The findings of this study hold several implications for practice and future directions. For educators, the results suggest a shift in role from knowledge transmitters to designers and facilitators of learning experiences. Teachers should leverage AI tools to create low-pressure, feedback-rich, and engaging environments. Importantly, students must also be guided to critically view AI support, ensuring that they contribute unique emotional and aesthetic perspectives rather than over-relying on automated suggestions. For developers, the evidence underscores the need for tool design that deeply integrates educational and psychological principles. Beyond algorithmic power, successful tools should address learners' needs for autonomy, competence, and relatedness. Future systems could incorporate "micro-models" tailored to specific challenges in music pedagogy (e.g., Bach-style fugue composition or jazz improvisation), allowing more targeted and pedagogically meaningful support. For future research, the findings call for exploring hybrid-intelligence paradigms in music education. Such models could assign complementary roles: human learners contributing creativity, emotional expression, and aesthetic judgment, while AI systems handle technical execution, structural analysis, and provision of diverse musical materials. Investigating how students' creativity, critical thinking, and comprehensive musicianship evolve under this human-AI collaboration presents an exciting and valuable research agenda.

5.3 Limitations and Future Directions

Despite its promising findings, this study is not without limitations. First, the relatively small sample size (N = 83) and its restriction to a single elementary school in one city may limit the generalizability of the results. Larger-scale studies involving diverse cultural and educational contexts are needed to confirm the robustness of the observed effects. Second, the quasi-experimental design relied on post-test comparisons and thus cannot fully establish causal pathways or account for long-term retention. Future research should adopt longitudinal designs, repeated-measures ANOVA, or randomized controlled trials to explore the sustainability of motivational and perceptual gains over time.

Third, the study primarily focused on self-reported measures such as motivation, self-efficacy, and technology perceptions. While these indicators are valuable for understanding psychological mechanisms, they may be subject to social desirability bias or limitations of self-awareness. Complementary objective data, such as log-file analyses of student interactions, performance assessments of music compositions, or physiological measures of engagement, could provide more nuanced insights.

Finally, although the intervention successfully integrated AI tools into music appreciation and theory tasks, the scope of musical activities (e.g., performance, improvisation, composition in diverse styles) was relatively limited. Future research should investigate how AI can support broader aspects of musicianship, including creativity, emotional expression, and collaborative performance, within both classroom and online environments.

Overall, addressing these limitations will advance the development of a hybrid-intelligence paradigm in music education, enabling a more holistic understanding of how human creativity and AI-driven assistance can complement each other in fostering deep and sustainable learning.

6 Conclusion

This study demonstrated that integrating AI-assisted tools into elementary music education significantly enhanced students' motivation, self-efficacy, social engagement, and perceptions of technology compared to traditional instruction. The intervention produced medium-to-large effect sizes, indicating not only statistical but also practical educational value. These findings suggest that AI can serve as an effective enhancer of music learning by fostering autonomy, competence, and relatedness. Future research should further validate these results through larger samples, longitudinal designs, and diverse contexts to advance the development of hybrid-intelligence models in music education.

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