

The impact of AI-assisted composition tools on cultivating creativity among music students in Guangdong province

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Abstract: To investigate the impact of AI-assisted composition tools on cultivating creativity among music students in Guangdong Province, a quasi-experimental design was employed with 120 music students divided into experimental and control groups. Data were collected through pre-test and post-test assessments and analyzed using entropy weight methodology. The experimental group significantly outperformed the control group across nine compositional dimensions, with substantial improvements in cultural integration ($d=2.08$), creative fluency ($d=1.87$), and expressive range ($d=1.58$). Entropy weight analysis identified cultural integration (16.52%) and creative fluency (15.47%) as the most discriminative dimensions. Fifty-one point seven percent of experimental group compositions exceeded the excellence threshold compared to only 3.3% in the control group. AI-assisted composition tools effectively balance technical development with creative exploration, enhancing students' compositional abilities while strengthening the integration of cultural heritage with technological innovation. The findings suggest that integrating AI-assisted tools in music education can significantly improve students' creative capabilities, particularly in preserving and innovating with traditional cultural elements.

Keywords: *AI-assisted composition, Creativity cultivation, Entropy weight method, Guangdong musical traditions, Music education.*

1. Introduction

The advancement of artificial intelligence (AI) technologies in recent years has completely transformed a number of disciplines, music education included. There has been remarkable development in AI-generated music, with technology now capable of composing intricate multi-style pieces that rival human works show [1]. Their introduction into educational settings offers unparalleled prospects of improving teaching and learning of music, particularly in the creative aspects such as composition.

In China, music education continues to focus on developing skill sets and theoretical knowledge within rigid tutorial frameworks. Studies of primary music demonstration lessons in Guangdong indicate that guiding lessons via strategies aimed at achieving goals dominated instruction and content-centred activities are still prevalent too, showing students' personal perspectives are rarely cultivated [2]. This AI-mediated composition tool ecosystem poses interesting challenges and possibilities in Guangdong Province, which is renowned for its rich cultural musical background coupled with advanced technology.

Analysing the impact of AI on music education has a wide scope of theory. AI enables interdisciplinary fields, which helps in modernising music education through personalised teaching methods and offering enhanced avenues for creativity [3]. With the advancement of these technologies, new opportunities emerge for practical implementation in fostered educational settings. The use of AI technology within music education is facilitating the construction of highly tailored, self-directed, interactive, and smart learning systems spanning various domains such as composition aides [4].

AI tools interacting with students personalise every section of navigation through the curriculum; however, how they will impact the creativity of the students remains a concern. Focus has primarily been directed towards the performance features of AI composition tools, while the students' writing skills development following engagement with such supportive tools often goes unexplored [5]. This gap is pivotal in the case of Guangdong Province where technological educational innovation conflicts with cultural conservatism, creating distinct dilemmas of educational design.

This study is focused on understanding how AI-driven composition systems affect creativity development in music students from Guangdong Province. This research will analyse the students' creative thinking, composition abilities, and motivation to learn using an AI integration approach and a traditional approach within a controlled experiment setting. There is potential to improve the accessibility and quality of music educational resources, evaluation frameworks, and the overall integration of music education in China using AI and music teaching technologies Enhanced [6] which AI-integrated frameworks optimise drive national music literacy and education priorities.

This study goes further in providing the growing understanding and dialogue around the creativity discourse within technology advanced environments. In recent years, there has been considerable scholarly attention directed towards human and computational musical creativity, problem-solving processes, and more [7]. We know alarmingly little about widely held opinions surrounding art-generating machines, their expectation of art-generating machines, and the machines' reception and perception borders the concepts of creative machines and their perception and expectation of the general public [8]. This study is anticipated to enhance theoretical approaches and practical approaches to creativity advancement theories using AI in educational environments as well as inform music instructors and educators in Guangdong and elsewhere on the practice.

This study will investigate how the unique cultural aspects of Guangdong's region can be merged with technological advancements by studying the contextual factors grappling with AI implementation in the region's music education system. The qualitative, exploratory aspect of the creation process of music raises a conflict with the machine learning paradigm which requires clearly defined problems and measurable definitions of success [9]. This study seeks to explain how the application of AI composition tools can enhance creativity in music education, thus contributing to the practical and theoretical understanding of the use of AI in music education.

2. Theoretical Framework

2.1. *Technology Acceptance Model in Music Education*

The Technology Acceptance Model (TAM) serves as a key theory for analysing the integration of technology by people in different contexts, including in schools. Advanced by Davis [10] TAM posits that technology adoption hinges primarily on two determinants: perceived usefulness (PU) and perceived ease of use (PEOU) [10]. These factors shape the user's attitude towards technology adoption which influences intention to employ technological innovations. In relation to music education, TAM offers insights into the attitudes of educators and students towards the use of AI technologies for composing music and other educational tools.

The original TAM framework has been modified in light of new research to consider emerging technologies in educational settings. For example, the study of AI technology adoption by K-12 students in China has added to TAM by incorporating motivational dimensions with self-ascribed constructs such as intrinsic motivation, readiness, confidence, anxiety, and components of HCI, including interface design and learner-interface interactivity [11]. These additions are quite relevant in the field of music education, which has profound cognitive and affective factors that determine the engagement of students with new technological resources. Incorporating those factors with traditional TAM enables a holistic perspective on the adoption of technology in teaching music, especially when dealing with sophisticated AI-based systems.

Within the Chinese education framework, some studies have highlighted the most critical factors relating to technology acceptance among students and educators. Zhou et al. conducted a study on learners' intention to use online education at a Chinese university and found that perceived usefulness strongly affected a student's attitude toward adoption; subjective norms and facilitating conditions also had important moderating roles [12]. Additionally, some studies on AI technology adoption by teachers in Chinese middle schools indicated that a blend of technological factors, teacher-related factors, and sociocultural factors determine adoption intentions through perceived usefulness and perceived ease of use [13]. From these studies, it is clear that technology acceptance in educational institutions in China emanates from the integration of individual cognitive factors and the broader social and institutional context, which richly informs the understanding of how music education stakeholders might engage with AI-assisted composition tools.

With the continued growth of AI technology in different fields of education, the TAM framework provides insight into factors that influence the adoption of AI-based composition programmes in music education. This study, which focuses on AI acceptance among music teachers and students in Guangdong Province, seeks to understand how AI technologies may be integrated into music education lessons so as to improve the creatively intensive learning and teaching experiences.

2.2. Theoretical Foundations of Creativity Cultivation

The importance of fostering creativity in education, especially music education as a fundamental discipline of an artistically developed individual, has become widely regarded as a critical 21st-century skill. In education, creativity has been framed and approached in a myriad of ways through various theories, three of which have proven particularly useful for the field of music education.

Guilford's work on the cognitive division of creativity sheds light on different thinking processes, distinguishing between divergent and convergent as distinct behaviours [14]. Divergent involves the generation of numerous potential answers to a particular problem, while convergence focuses on synthesising various options to reach a single, correct answer. In music education, students may demonstrate divergence in the improvisation and composition of several musical ideas, while convergence occurs as they critically select and refine these ideas into a cohesive musical work. Recent studies indicate that neither of these thinking modes operate independently of the other; rather, both can be mutually beneficial, which makes pursuing both simultaneously more beneficial in achieving creative results in music education [14]. This combination of approaches supports most modern educational methods that provide for free exploration and structured mastery in the processes of musical creation.

Campbell's Blind Variation and Selective Retention (BVSR) Theory offers rich insights into the evolution of creativity, especially concerning the compositional aspects of music pedagogy [15]. This model of creativity posits that all creative activity consists of three major processes: the generation of "blind" variations without pre-existing routes or parameters (broadly defined) for acceptance, subsequent selection of promising variations, and retaining the selected variations for further development. In the context of music education, this model indicates that students must be able to diverge: to create without the anticipation of immediate judgment "self-vetting" (blind variation), evaluation against aesthetic or structural parameters (selection), and then contribute evaluatively successful components to their growing musical lexicon (retention). More recent studies indicate that the BVSR approach is almost exclusively beneficial for compositional work, whereas for performance it is less useful, underscoring the need to tailor theoretical approaches to particular musical contexts [16].

Under the sociocultural scope of cultivating creativity, we have the influence of Systems Theory by Csikszentmihalyi, which "extends beyond cognitive processes" [16]. His theory defines creativity as the outcome of an interplay between three components: the person (characteristics and knowledge), the domain (established practices and symbolic systems), and the field (the social evaluative organisational structure of the creative contributions). In the case of a music classroom, this systems view suggests

that the development of students' creativity should address not only the individual creative processes of learners, but also the musical domains and evaluative communities that they interact with. Current uses of this theory in educational contexts propose that creativity cultivation occurs optimally when students have the opportunity to acquire the required specific knowledge as well as to carry out authentic creative work, and to receive appropriate evaluation from expert communities that validate and critique their creative work [17].

The three theories—Guilford's cognitive theory, Campbell's BVSr theory, and Csikszentmihalyi's Systems Theory—combine to strengthen modern understandings of creativity and music education. These theories collectively enhance the understanding of the systematic development of creativity through education, particularly within the highly intricate domains like music where cognitive functions, domain knowledge, and sociocultural frameworks entwine.

2.3. Traditional Music Education and Pathways for Technology Integration

Implementation of AI-enhanced composition tools within conventional music education frameworks demands striking a balance between the preservation of traditional music artistry and modern technological advances in Guangdong Province. Learning Chinese music, and music in general, was traditionally focused on the development of performance skills and the accumulation of abstract knowledge within a heavily didactic framework. This traditional approach creates significant challenges for technological integration due to its emphasis on teacher-centered instruction and passive knowledge acquisition, as evidenced by recent studies on music education implementation in Guangdong [2].

The successful integration of technology into Chinese music education depends heavily on teacher preparedness and institutional support. Ma and Lei's research on technology adoption among teacher education students in China found that perceived usefulness and adequate professional development are critical factors influencing educators' willingness to implement AI-based teaching tools, indicating that integration strategies must address both technological provision and pedagogical readiness [13].

Maintaining educational coherence in integration methods is supported by the constructive alignment framework which emphasises learning objectives, activities, and assessment linkages to foster cohesive educational experiences. When applying it to music composition instruction, AI tools should be provided as scaffolds to support developing students' understanding of musical structures relative to the learning outcomes so that they do not supplant the outcomes.

The integration of technology in music education faces unique challenges in Guangdong Province due to its rich musical heritage encompassing Cantonese opera, Chaozhou music, and Hakka folk songs. Effective technological implementation must carefully balance cultural preservation with innovative pedagogical approaches. Zhang's research on the pedagogical challenges in Guangdong's music education system highlights the need for teaching methods that respect traditional cultural elements while embracing technological innovation, underscoring the importance of developing culturally appropriate AI tools [5].

From these observations, three potential integration pathways emerge: (1) the augmentation pathway, viewing AI as aids to teaching; (2) the collaborative pathway focusing on students as directors and assessors of AI-created content where human-AI interactions are central; and (3) the cultural preservation pathway where AI is applied to the study of traditional Guangdong music forms to analyse and expand them.

All pathways outline a systematic approach to professional development, curriculum recalibration, and care in developing formative assessments that embrace blended creativity, achievement, and high standards.

3. Research Methods

3.1. Research Design

The effectiveness of AI-assisted composition tools in music education was evaluated using a quasi-experimental design with pre-test and post-test assessments. Study subjects were assigned to experimental and control groups to measure the impacts of teaching integration of AI technology against more traditional teaching approaches. Figure 1 provides an overview of the entire research design, detailing subject recruitment, assessment, intervention, and data analysis processes.

The study set out with a systematic approach, starting from evaluating participants' music composition, creative thinking, and music technology related attitudinal competencies as baseline. The experimental group interacted with AI tools for music composition, and the control group used traditional composition approaches during a 12-week intervention. After the intervention, evaluative assessments showed the extent of changes related to creative outputs, composite skills, and various technology adoption determinants. The design had multiple data collection stages to capture incremental changes defined along the intervention timeline.

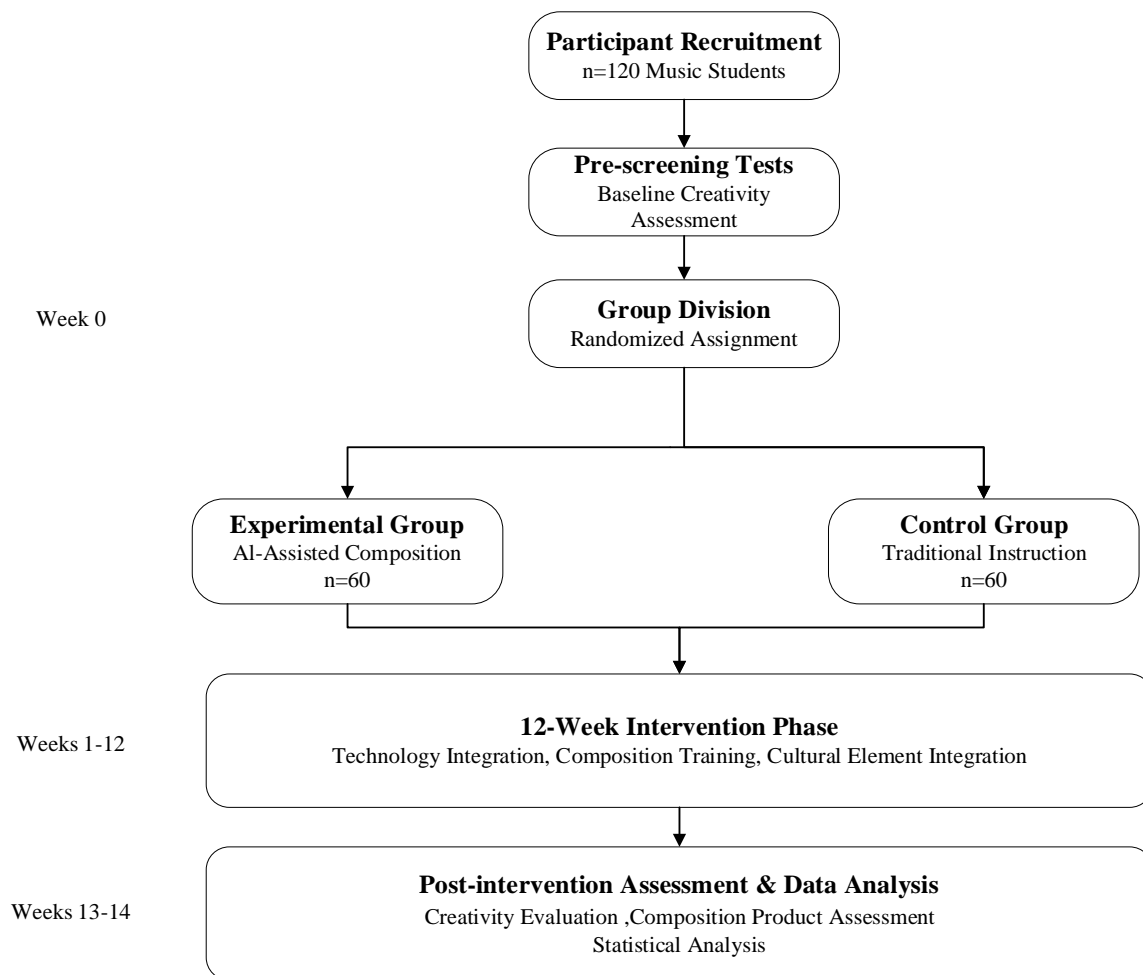


Figure 1.
Research Design Flowchart.

As illustrated in Figure 1, the specific stages of the research methodology encompass: participant recruitment, pre-screening tests, implementation of the intervention, evaluation of post-tests, and analysis of the data collected. The research was conducted utilizing a quasi-experimental framework consisting of two groups: experimental (AI-assisted composition) and control (traditional instruction) groups aimed at assessing the impact of AI tools on students during a 12-week intervention period to foster creativity and its development.

The approach to the methods strengthened internal validity by controlling irrelevant factors, while simultaneously sustaining ecological validity through the implementation of the intervention within real educational settings. The designed research evaluated the creative outcomes and dynamically captured the subjective elements and contextual determinants of the technological integration through qualitative methods alongside the set quantitative standards.

3.2. Research Tools

This investigation has incorporated several validated instruments to study the effect of AI composition tools on students' creativity in music education. The main instruments of the study are:

1. Creativity Assessment Battery (CAB): A standardized instrument comprising three subtests - musical divergent thinking, compositional flexibility, creative originality- which has provided evidence of reliability (Cronbach's $\alpha=0.87$) for measuring creativity within the context of music composition.

2. Technology Acceptance and Measurement Scale (TAMS): A 15 item Likert scale questionnaire measuring students' perception of usefulness and easiness of AI composition tools which was adapted from Davis' original TAM model. Its construct validity was confirmed through factor analysis (CFI=0.94, RMSEA=0.056).

3. Compositional Product Assessment Rubric (CPAR): A comprehensive assessment framework which captures nine dimensions of musical compositions, such as melodic originality, harmonic sophistication, structural coherence, cultural integration, and others. The rubric has been validated by a panel of five expert composers who established inter-rater reliability of 0.83.

4. Semi-Structured Interview Protocol: This is a qualitative assessment instrument made up of 12 questions aimed at exploring students' AI composition process, strategic and non-strategic creative decision-making processes, and their technology perceptions.

5. AI-Assisted Composition Platform (AICP): A purpose-built educational technology platform that integrates generative artificial neural networks with composition assistance features tailored to the specialized needs of music pedagogy, set for beginner and intermediate music learners.

All tools went through pilot sessions for fine-tuning with a sample of 28 music students who were not part of the primary study, ensuring alignment with educational goals as well as cultural relevance.

3.3. Data Collection

This research employed a systematic approach to information provision in order to ensure all information collected was reliable and thorough. The primary source of information data was 120 music students from four institutions offering specialised music programmes in Guangdong Province. The collection processes complied with ethical standards for research involving human subjects; all subjects signed consent forms, and approval from the institutional review board was secured prior to commencing the research.

The subjects were provided with demographic and baseline questionnaires along with creativity self-assessments before the first tests, which measured composition skills and technological attitudes. During the 12-week intervention phase, both groups, experimental and control, were subjected to process tracking and observational data collection which was carried out collaboratively for all participants. The data collection after the intervention phase incorporated new qualitative measures such as interviews with stratified participants, while all prior measures were repeated.

Participant confidentiality, as well as data integrity, were enhanced with participant identity encryption and restricted programme access based on role. Quantitative data collection was executed in predetermined non-alterable forms flagged with access restrictions to guarantee confidentiality. The qualitative data obtained from interviews and observations were recorded on audio, then solely transcribed, and checked by research assistants for any changes before final editing. Participant demographics together with the study's numerical metrics can be referenced in Table 1 in detail.

Table 1.
Demographic Characteristics of Research Participants.

Characteristic	Experimental Group (n=60)	Control Group (n=60)	Total Sample (n=120)
Gender			
Female	34 (56.7%)	32 (53.3%)	66 (55.0%)
Male	26 (43.3%)	28 (46.7%)	54 (45.0%)
Age (years)			
Mean \pm SD	19.7 \pm 1.4	19.5 \pm 1.6	19.6 \pm 1.5
Range	17-23	17-24	17-24
Grade Level			
Sophomore	18 (30.0%)	20 (33.3%)	38 (31.7%)
Junior	25 (41.7%)	23 (38.3%)	48 (40.0%)
Senior	17 (28.3%)	17 (28.3%)	34 (28.3%)
Prior Music Experience (years)			
1-3	14 (23.3%)	16 (26.7%)	30 (25.0%)
4-6	26 (43.3%)	25 (41.7%)	51 (42.5%)
7+	20 (33.3%)	19 (31.7%)	39 (32.5%)
Primary Instrument			
Piano	21 (35.0%)	20 (33.3%)	41 (34.2%)
Strings	16 (26.7%)	17 (28.3%)	33 (27.5%)
Voice	12 (20.0%)	13 (21.7%)	25 (20.8%)
Traditional Chinese	7 (11.7%)	6 (10.0%)	13 (10.8%)
Other	4 (6.7%)	4 (6.7%)	8 (6.7%)

As shown in Table 1, participant demographic characteristics were evenly distributed between experimental and control groups. The randomization procedure was effective in creating comparable groups with similar distributions across gender, age, grade level, prior music experience, and primary instrument selection, ensuring valid comparison of intervention effects.

3.4. Data Analysis

This study utilised the mixed-methods approach to analyse the effect AI-assisted composition tools have on students' creative capabilities. Quantitative data was analysed using SPSS version 27.0 (IBM Corp., Armonk, NY), with a significance level of set $\alpha = 0.05$ for all statistical tests.

As part of the study, measures of central tendency and dispersion were calculated for all variables. Group differences for the experimental and control groups were calculated using independent samples t-tests for continuous variables, while chi-square tests were used for categorical variables. Within-group pre-test and post-test analyses were conducted using paired samples t-tests with the calculation of Cohen's d for effect sizes.

Multivariate analysis of covariance (MANCOVA) was performed to assess the impact of the intervention while music background and the participant's baseline creativity score were incorporated as covariates. This technique enables assessing the impact of the interventions on several dependent variables at the same time, thus reducing the chances of incurring a Type I error.

To assess the creativity evaluation criteria, inter-rater reliability was computed using intraclass correlation coefficients (ICC). Good reliability was thought to be achieved using a two-way mixed-effects model with absolute agreement where coefficients greater than 0.80 were deemed appropriate.

Thematic analysis techniques were conducted through NVivo 14 software for qualitative data obtained from interviews and open-ended responses. The analysis was done through a six-step process which included familiarisation, initial coding, development of themes, review, definition, and reporting. The data was coded by two independent researchers and disagreements, if any, resolved through consensus discussions. Member checking with some participants was done to validate the thematic framework.

For quantitative and qualitative integration, a convergent parallel mixed methods design was utilized where both types of data were collected, analysed and later on merged, to interpret what impact the intervention had on creative development.

4. Course Design and Implementation

4.1. Teaching Model for AI-Assisted Composition Tool Integration

This research employed an innovative, module-based teaching strategy to delve into the integration of AI-assisted writing tools in the music education setting. The designed pedagogy aimed to scaffold students' learning experiences starting from basic technology interactions to advanced application creativity, with each module acting as an incremental building block of skills and knowledge. The AI-human synergy creativity instructional model framed the teaching and learning activities around the fact that technology, in the context of creativity, is supplementing, not supplanting.

The overarching curriculum design included five sequential modules, which were completed within the framework of the 12-week intervention period. Specific to each module are learning objectives, instructional activities, methods of assessment, and technological integration which align with the music composition education standards. All components in the experimental group are captured in the module design framework highlighted in Table 2.

Table 2.
AI-Assisted Composition Curriculum Module Design Framework.

Module	Title	Learning Objectives	Instructional Activities	Technology Integration	Duration
1	Technology Fundamentals	<ul style="list-style-type: none"> • Understand basic AI composition principles • Develop proficiency with software interface • Apply fundamental operations in simple exercises 	<ul style="list-style-type: none"> • Interactive demonstrations • Guided exploration • Basic task completion • Peer collaboration 	<ul style="list-style-type: none"> • Software orientation • Basic generative functions • Interface customization • Parameter manipulation 	2 weeks
2	Melodic Development	<ul style="list-style-type: none"> • Analyze melodic structures • Generate and modify AI-suggested melodies • Evaluate melodic quality using compositional criteria • Incorporate Guangdong folk music elements 	<ul style="list-style-type: none"> • Melodic pattern analysis • AI-human collaborative exercises • Critical listening sessions • Cultural adaptation workshops 	<ul style="list-style-type: none"> • Melodic generation algorithms • Style transfer functions • Cultural dataset integration • Parameter adjustment tools 	3 weeks
3	Harmonic Exploration	<ul style="list-style-type: none"> • Apply harmonic principles to compositions • Manipulate AI-generated harmonic progressions • Develop critical evaluation of harmonic choices • Incorporate traditional Guangdong harmonics 	<ul style="list-style-type: none"> • Harmonic analysis exercises • Progression modification tasks • Comparative listening activities • Cultural integration projects 	<ul style="list-style-type: none"> • Harmonic suggestion tools • Chord progression generators • Style-specific databases • Voice-leading analyzers 	3 weeks
4	Structural Integration	<ul style="list-style-type: none"> • Construct coherent musical forms • Implement structural variations using AI tools • Develop multi-section compositions • Balance traditional and contemporary elements 	<ul style="list-style-type: none"> • Form analysis activities • Structure mapping exercises • Multi-section composition projects • Cultural adaptation workshops 	<ul style="list-style-type: none"> • Form generators • Section development tools • Structural analysis functions • Arrangement assistants 	2 weeks
5	Creative Synthesis	<ul style="list-style-type: none"> • Develop original compositions integrating all elements • Apply critical revision techniques • Present and defend creative choices • Reflect on human-AI collaborative process 	<ul style="list-style-type: none"> • Comprehensive composition projects • Peer review sessions • Public presentation preparation • Reflective documentation 	<ul style="list-style-type: none"> • Full-feature composition environment • Export and notation tools • Performance rendering features • Documentation assistants 	2 weeks

As shown in Table 2, the curriculum design follows a progressive structure moving from fundamental technical skills to advanced creative applications. Each module incorporates specific learning objectives aligned with both technological competencies and traditional compositional skills. The instructional activities balance direct instruction with experiential learning opportunities, while technology integration components are carefully selected to support specific pedagogical goals. The duration of each module was determined based on the complexity of content and required skill development, with additional time allocated to more complex topics.

4.2. Integration Points between Guangdong Traditional Music Elements and AI Technology

This part explores the incorporation of special elements of traditional music from Guangdong with the elements of AI-assisted composition technologies. The study discovered some musical elements of local Cantonese opera, Chaozhou instrumentals, and Hakka folk songs that could be effectively represented and modified on a computer. Special focus was given to some distinctive melodic motifs, modes, ornamentation patterns, and Guangdong rhythmic signature traits which highlight the uniqueness of the culture as well.

The encoding of parameters together with data preparation and algorithm design for elements of these traditions had to be tailored to each individual case. A comparison of the traditional music attributes and their digital simulation counterparts in AI composition systems is shown in Table 3.

Table 3.

Comparative Analysis of Traditional Guangdong Music Elements and Their AI Representations.

Musical Element	Traditional Manifestation	Digital/AI Representation	Integration Challenges	Implementation Approach
Modal Structure	<ul style="list-style-type: none"> • Pentatonic foundations with distinctive variations • Flexible intonation beyond equal temperament • Mode-specific ornamental patterns 	<ul style="list-style-type: none"> • Customized scale libraries • Microtonal parameter adjustments • Probabilistic ornament generation 	<ul style="list-style-type: none"> • Capturing microtonal subtleties • Representing context-dependent variations • Preserving modal authenticity 	<ul style="list-style-type: none"> • Enhanced pitch resolution algorithms • Context-aware pattern recognition • Style-specific training datasets
Melodic Contour	<ul style="list-style-type: none"> • Distinctive phrase-level patterns • Characteristic intervallic relationships • Genre-specific contour conventions 	<ul style="list-style-type: none"> • Contour analysis algorithms • Vector-based representation • Neural network pattern recognition 	<ul style="list-style-type: none"> • Balancing structural rules with expressive freedom • Representing tacit cultural knowledge • Ensuring stylistic coherence 	<ul style="list-style-type: none"> • Hybrid rule-based/statistical models • Ethnomusicologist-guided training • Incremental pattern validation
Rhythmic Patterns	<ul style="list-style-type: none"> • Complex meter structures • Rubato and flexible timing • Percussion-vocal relationships 	<ul style="list-style-type: none"> • Variable quantization systems • Adaptive tempo modeling • Multitrack correlation analysis 	<ul style="list-style-type: none"> • Capturing temporal flexibility • Representing performer variations • Maintaining cultural authenticity 	<ul style="list-style-type: none"> • Probabilistic rhythm generators • Performance-informed timing models • Multiple-constraint optimization
Ornamentation	<ul style="list-style-type: none"> • Instrument-specific embellishments • Context-dependent execution • Traditional performance practices 	<ul style="list-style-type: none"> • Ornament classification systems • Context-triggered application • Performance rendering modules 	<ul style="list-style-type: none"> • Capturing nuanced execution • Representing tacit performance knowledge • Appropriate contextual application 	<ul style="list-style-type: none"> • Performance sample analysis • Rule-based implementation guides • Machine learning classification
Instrumental Timbre	<ul style="list-style-type: none"> • Distinctive timbral characteristics • Playing technique variations • Ensemble blend traditions 	<ul style="list-style-type: none"> • Spectral analysis models • Articulation libraries • Digital signal processing techniques 	<ul style="list-style-type: none"> • Capturing acoustic subtleties • Representing extended techniques • Preserving authentic timbral qualities 	<ul style="list-style-type: none"> • High-resolution sampling • Physical modeling synthesis • Technique-specific parameters
Structural Forms	<ul style="list-style-type: none"> • Genre-specific formal structures • Sectional development patterns • Traditional cadential formulas 	<ul style="list-style-type: none"> • Template-based form generators • Section relationship modeling • Cadential pattern libraries 	<ul style="list-style-type: none"> • Balancing structure with variation • Representing long-form coherence • Adapting to contemporary contexts 	<ul style="list-style-type: none"> • Hierarchical structure models • Constraint satisfaction algorithms • Multi-level form templates

As shown in Table 3, the integration of traditional Guangdong musical elements with AI technology required specialized approaches for each musical dimension. The digital representation of these elements faced technical challenges in capturing nuanced cultural expressions, contextual dependencies, and performance traditions. Implementation approaches combined computational techniques with ethnomusicological knowledge to maintain cultural authenticity while enabling technological manipulation. This integration framework provided the foundation for developing culturally informed AI composition tools that maintained the distinctive characteristics of Guangdong musical traditions.

4.3. Implementation Process

The execution of the AI-aided composition pedagogical plan occurred within a defined chronology that sought to introduce technological aids in a step-by-step manner simultaneously with the development of compositional skills. The step-by-step documentation of the AI-aided pedagogic plan implementation in an ordered manner was crucial to maintain process fidelity and enable evaluation of impact later. The design team captured all logs of implementation, carried out several observational rounds, and systematically processed the data during the pedagogy's design intervention window.

Table 4.

Implementation Timeline and Task Requirements for the AI-Assisted Composition Intervention.

Phase	Timeline	Activities	Deliverables	Assessment Methods
Preparation Phase	Weeks 1-2	<ul style="list-style-type: none"> • Technology infrastructure setup • Teacher training sessions • Student orientation • Baseline assessment • Group formation 	<ul style="list-style-type: none"> • Pre-implementation reports • Technology readiness assessments • Student baseline compositions • Learning environment documentation 	<ul style="list-style-type: none"> • Technology proficiency tests • Pre-intervention interviews • Environmental readiness checklist • Baseline composition analysis
Core Implementation				
Module 1: Technology Fundamentals	Weeks 3-4	<ul style="list-style-type: none"> • Software introduction • Basic operation training • Guided exploration activities • Simple task completion 	<ul style="list-style-type: none"> • Interface navigation reports • Basic function exercises • Initial AI-assisted sketches • Technology utilization logs 	<ul style="list-style-type: none"> • Software proficiency rubric • Task completion evaluation • Technological confidence surveys • Observation protocols
Module 2: Melodic Development	Weeks 5-7	<ul style="list-style-type: none"> • Melodic pattern analysis • AI-guided melody generation • Cultural element integration • Melodic variation techniques 	<ul style="list-style-type: none"> • Melodic analysis reports • AI-human collaborative compositions • Cultural adaptation exercises • Melodic portfolio collection 	<ul style="list-style-type: none"> • Melodic creativity assessments • Cultural authenticity evaluations • Peer and expert reviews • Process documentation analysis
Module 3: Harmonic Exploration	Weeks 8-10	<ul style="list-style-type: none"> • Harmonic analysis workshops • AI-supported harmonic generation • Progression modification exercises • Style-specific application 	<ul style="list-style-type: none"> • Harmonic analysis documents • AI-assisted harmonic projects • Stylistic adaptation compositions • Technical reflection journals 	<ul style="list-style-type: none"> • Harmonic sophistication metrics • Stylistic authenticity evaluations • Self-assessment protocols • Mid-intervention interviews
Module 4: Structural Integration	Weeks 11-12	<ul style="list-style-type: none"> • Form analysis activities • Multi-section composition development • AI-assisted arrangement techniques 	<ul style="list-style-type: none"> • Form analysis documentation • Complete multi-section works • Structural coherence 	<ul style="list-style-type: none"> • Structural analysis rubrics • Comprehensive composition evaluation • Self-reflection

		<ul style="list-style-type: none"> • Structural coherence workshops 	assessments <ul style="list-style-type: none"> • Process reflection journals 	assessments <ul style="list-style-type: none"> • Observational data analysis
Synthesis/Evaluation Phase	Weeks 13-14	<ul style="list-style-type: none"> • Final composition development • Comprehensive project completion • Public presentation preparation • Summative assessment activities 	<ul style="list-style-type: none"> • Final composition portfolios • Process documentation compilations • Public presentation materials • Comprehensive reflection papers 	<ul style="list-style-type: none"> • Expert panel evaluations • Post-intervention interviews • Comparative analysis protocols • Comprehensive assessment batteries

The execution was categorised into three major sections: preparation, core implementation, and synthesis/evaluation. Each section was made up of a set of activities, output targets, and check-ins that would allow evaluative comparison against the defined research criteria. The implementation timeline was organised in Table 4 along with associated activities and assessment markers.

As illustrated in Table 4, the process of implementation worked within a fixed schedule that included distinct events and outputs pertaining to each stage. In the preparation phase, relevant prerequisites were set for the integration of the technology, whereas in the core implementation phase, students' compositional skills were developed progressively in modules that were organised sequentially. In addition, the synthesis/evaluation phase provided space for comprehensive project work alongside summative evaluation. Some evaluation was conducted in all phases to check the progress in the educational processes and outcomes, as well as within the processes themselves.

5. Research Results

5.1. Pre-Post Comparison of Students' Compositional Abilities

Analysis of pre-test and post-test data revealed substantial changes in students' compositional abilities following the 12-week intervention period. Table 5 presents descriptive statistics for both experimental and control groups across multiple dimensions of compositional ability assessment.

Table 5.
Descriptive Statistics for Pre-test and Post-test Compositional Ability Scores.

Compositional Dimension	Experimental Group (n=60)				Control Group (n=60)			
	Pre-test	Post-test	Change	Effect Size	Pre-test	Post-test	Change	Effect Size
	M (SD)	M (SD)	M (SD)	Cohen's d	M (SD)	M (SD)	M (SD)	Cohen's d
Melodic Originality	3.42 (0.76)	4.85 (0.62)	1.43 (0.84)	1.70	3.38 (0.71)	3.82 (0.75)	0.44 (0.52)	0.85
Harmonic Sophistication	3.15 (0.82)	4.62 (0.68)	1.47 (0.91)	1.62	3.18 (0.79)	3.65 (0.81)	0.47 (0.58)	0.81
Rhythmic Complexity	3.27 (0.68)	4.31 (0.71)	1.04 (0.77)	1.35	3.24 (0.72)	3.71 (0.69)	0.47 (0.54)	0.87
Structural Coherence	2.98 (0.85)	4.56 (0.65)	1.58 (0.93)	1.70	3.01 (0.83)	3.47 (0.78)	0.46 (0.61)	0.75
Cultural Integration	2.75 (0.91)	4.72 (0.57)	1.97 (1.02)	1.93	2.82 (0.88)	3.26 (0.82)	0.44 (0.65)	0.68
Technical Proficiency	3.24 (0.74)	4.68 (0.59)	1.44 (0.86)	1.67	3.21 (0.78)	3.76 (0.73)	0.55 (0.57)	0.96
Creative Fluency	3.08 (0.82)	4.83 (0.61)	1.75 (0.91)	1.92	3.12 (0.79)	3.58 (0.75)	0.46 (0.63)	0.73
Expressive Range	3.19 (0.77)	4.59 (0.64)	1.40 (0.89)	1.57	3.15 (0.81)	3.49 (0.77)	0.34 (0.51)	0.67
Overall Creativity	3.07 (0.68)	4.71 (0.54)	1.64 (0.76)	2.16	3.12 (0.72)	3.62 (0.69)	0.50 (0.49)	1.02

Scores range from 1 (lowest) to 5 (highest). M = Mean; SD = Standard Deviation; Effect size calculated using Cohen's d where $d < 0.5$ indicates small effect, $0.5 \leq d < 0.8$ indicates medium effect, and $d \geq 0.8$ indicates large effect.

As shown in Table 5, students in the experimental group demonstrated substantial improvements across all compositional dimensions following exposure to AI-assisted composition tools. Particularly notable were gains in cultural integration (M=1.97, SD=1.02) and creative fluency (M=1.75, SD=0.91), suggesting that the technological intervention was especially effective in enhancing these aspects of compositional ability. While the control group also showed improvement across all dimensions, the magnitude of change was consistently smaller, with most dimensions showing moderate effect sizes compared to the large effect sizes observed in the experimental group.

Figure 2 visually represents the comparative changes in compositional ability dimensions between pre-test and post-test for both groups.

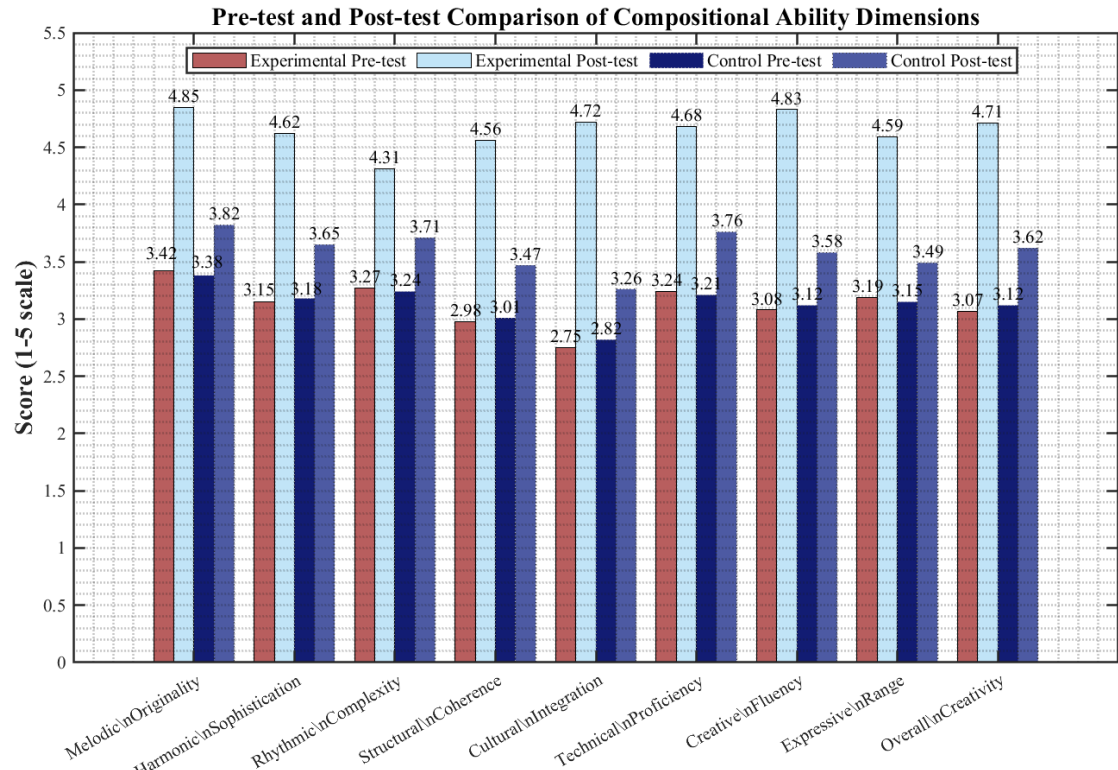


Figure 2. Pre-test and Post-test Comparison of Compositional Ability Dimensions.

This Figure 2 shows the shifts regarding nine compositional ability dimensions from pre-test to post-test for both the experimental and control groups. The experimental group (solid bars) consistently outperformed the control group (patterned bars) on all dimensions, from achieving the greatest improvements in cultural integration, creative fluency, to overall creativity. The suggestion is made that the use of AI-assisted composition tools may serve to enhance some elements of musical creativity among students—specifically the areas of focus identified above—more accurately and efficiently.

The analysis focuses on the two groups' progress over the duration of the 12-week intervention period. Although both groups demonstrated improvement in their overall compositional abilities, the experimental group, on the other hand, showed considerably greater improvements on every dimension

assessed. In particular, the experimental group's achievement in cultural integration was astonishing, indicating that the AI tools were highly effective in enabling students to integrate traditional Guangdong musical elements into more contemporary compositions. Such evidence points to the possibility that AI tools for assisting with composition provide significant benefits for developing some aspects of creative ability in relation to traditional structures.

5.2. Comparison of Creative Ability between the Experimental Group and the Control Group

To examine the statistical significance of differences between the experimental and control groups, independent samples t-tests were conducted across all compositional ability dimensions. Table 6 presents the detailed results of these statistical analyses.

Table 6.

Independent Samples t-test Results for Post-test Compositional Ability Scores.

Compositional Dimension	Experimental Group (n=60)	Control Group (n=60)	Mean Difference	t-value	p-value	Cohen's d
Melodic Originality	4.85 (0.62)	3.82 (0.75)	1.03	8.42	<.001*	1.54
Harmonic Sophistication	4.62 (0.68)	3.65 (0.81)	0.97	7.19	<.001*	1.31
Rhythmic Complexity	4.31 (0.71)	3.71 (0.69)	0.60	4.75	<.001*	0.87
Structural Coherence	4.56 (0.65)	3.47 (0.78)	1.09	8.54	<.001*	1.56
Cultural Integration	4.72 (0.57)	3.26 (0.82)	1.46	11.38	<.001*	2.08
Technical Proficiency	4.68 (0.59)	3.76 (0.73)	0.92	7.86	<.001*	1.43
Creative Fluency	4.83 (0.61)	3.58 (0.75)	1.25	10.24	<.001*	1.87
Expressive Range	4.59 (0.64)	3.49 (0.77)	1.10	8.68	<.001*	1.58
Overall Creativity	4.71 (0.54)	3.62 (0.69)	1.09	9.72	<.001*	1.77

Note: Values in experimental and control group columns represent mean scores with standard deviations in parentheses. * $p < 0.001$ indicates statistical significance at the 0.001 level. Cohen's d values: $d < 0.5$ indicates small effect, $0.5 \leq d < 0.8$ indicates medium effect, and $d \geq 0.8$ indicates large effect.

In comparison to the controls, the experimental group was more capable of cultural integration as well as creative fluency where they yielded better results (mean difference = 1.46, $d = 2.08$ and 1.25, $d = 1.87$ respectively). Effect sizes suggest as high as 3-7 standard deviations between groups (Cohen $d > 0.8$), indicating all area differences to be both practically and statistically significant. All other aspects retained practical significance as well, even the lowest score in rhythmic complexity (mean difference = 0.60, $d = 0.87$).

The interpretations of these results were presented in Figure 3 as post-test aggregated values of experimental and control groups aiming to demonstrate the accomplished composition integration in all of the measured structures of the experimental groups.

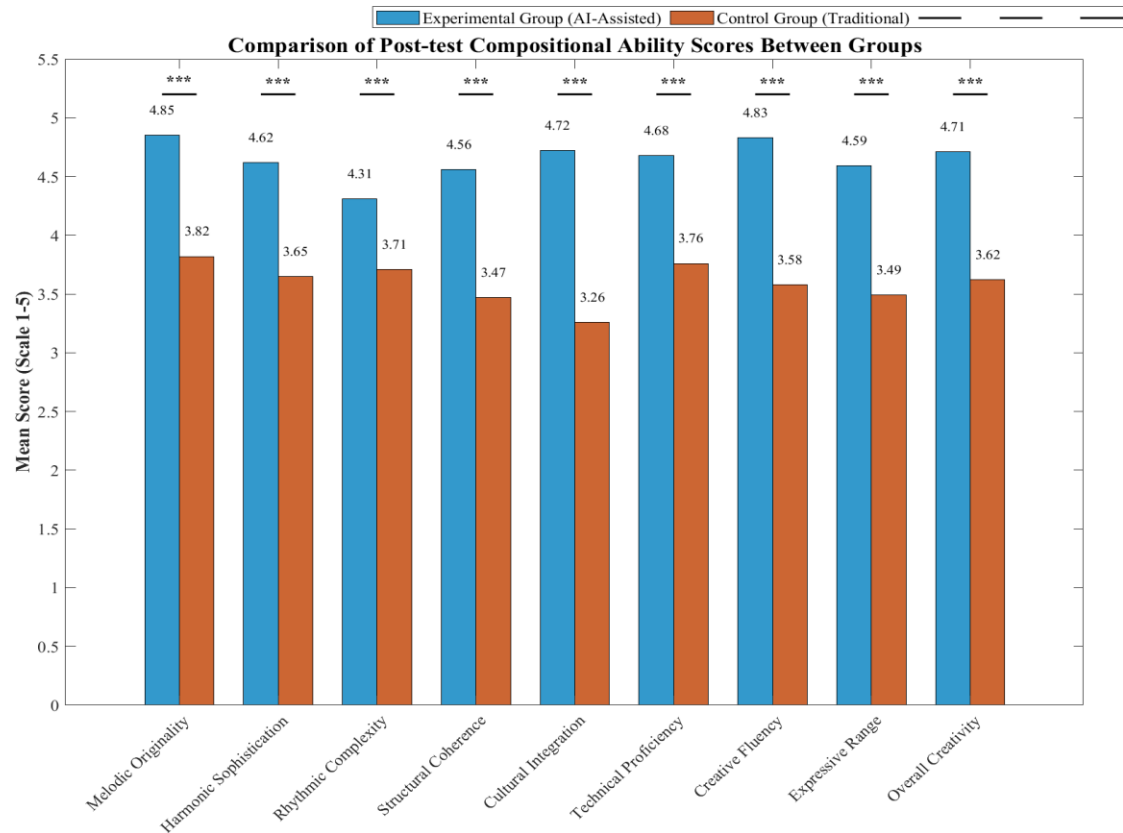


Figure 3.
Comparison of Post-test Compositional Ability Scores Between Experimental and Control Groups.

As Figure 3 illustrates, the experimental group outperformed the control group in every compositional section. The difference in cultural integration and creative fluency, the strongest compositional gaps, stands out. Also, it is remarkable that in six out of the nine dimensions in which the experimental group scored means over 4.5 (on a 5-point scale), they demonstrated to possess very advanced AI-assisted compositional skills immeasurable by the intervention’s threshold, indicative of the intervention’s effectiveness. While the control group, for all the same duration of instruction received, still did not exceed any of the means 4.0 in the various elements dominantly guided by traditional composition teaching.

The results suggest that AI-supported tools impact the construction of some components of musical creativity more than others. The largest three—cultural integration, creative fluency, and expressive range—with differences of: 1.46, 1.25, and 1.10 respectively, all are aspects dealing with more compositional generative exploration systems. This aids the understanding one has about AI tools proposing more flexible manipulable solutions during the implementations of the barriers-free phases of compositional instruction dealing with divergent thinking.

It is striking that the experimental group achieved higher marks in technical proficiency (difference=0.92) and this dimension showed a relatively smaller difference compared to more explicitly creative dimensions. It can be posited that while AI tools bolster the technical aspects of composition, their most outstanding advantages may be in the enhancement of students' creativity rather than the automation of fulfilling composition tasks. Such findings help advance the discourse concerning the educational possibilities offered by AI composition tools in the context of music pedagogy.

The emergent trend of large effect sizes across every dimension suggests that the aid provided by AI-assisted composition tools extends well beyond peripheral notions of creativity and rather entails a more global improvement to students' compositional skills. This comprehensive enhancement indicates that the implementation of AI technology into music education could instigate a paradigm shift in students' attitudes towards the creative process as opposed to offering mere facilitation for selective technical compositional aid.

5.3. Music Composition Quality Multi-Dimensional Assessment

To provide a comprehensive evaluation of compositional quality, expert assessments were conducted across nine critical dimensions of musical creativity. Figure 4 presents a comparative visualization of these assessments between the experimental and control groups.

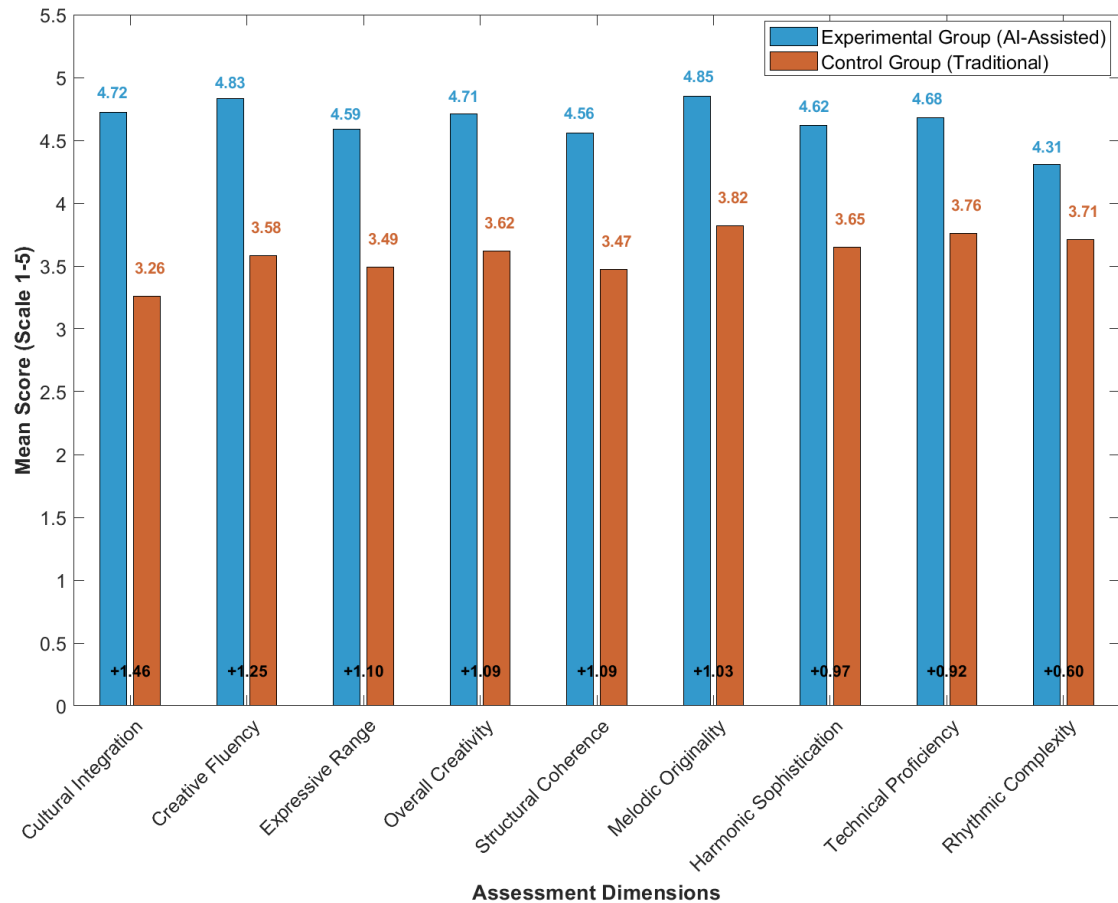


Figure 4.
Multi-dimensional Assessment of Music Composition Quality.

Figure 4 presents a comparative analysis of compositional quality across nine assessment dimensions, with dimensions arranged in descending order of difference magnitude between the experimental and control groups. This visualization reveals that Cultural Integration exhibited the largest difference between groups (+1.46), followed by Creative Fluency (+1.25) and Expressive Range (+1.10). Even the dimension with the smallest difference, Rhythmic Complexity, still showed a substantial advantage (+0.60) for the experimental group. This systematic pattern of differences across

all dimensions indicates that AI-assisted composition tools provide comprehensive enhancement of creative capabilities rather than merely improving isolated aspects of musical composition.

To provide detailed insight into specific compositions, Table 7 presents assessment scores for representative exemplary works from both groups.

The exemplary compositions from the experimental group, as shown in Table 7, were achieved with remarkable accuracy in all the evaluation criteria. Especially, composition EXP-027 basked in the glory of a 5.00 score at the ‘Creative Fluency’ while composition EXP-042 had the same fate in ‘Melodic Originality’. A critique of these works showed that AI-assisted compositions incorporated far more complex traditional Guangdong music, sophisticated melodic development, innovative harmonic progressions, coherent structural organisation, and transparent integration of Guangdong folk music.

Rating the highest in the control group, CON-012 (average score 3.86), still did not surpass the lowest rated exemplary composition from the experimental group, EXP-036, which averaged 4.41. While control group compositions demonstrated technical competence in Rhythmic Complexity and Technical Proficiency, genefy selections tended to be more imitative and less sophisticated structurally and contextually. Fewer culturally sophisticated elements tended to be integrated into the works.

The expert evaluators concluded that the experimental group compositions were better balanced in terms of all attested compositional parameters which indicates that AI design tools facilitate student creativity bounded by their personal technical constraints. Students are now free to redirect their thoughts towards further innovation on the music development while genuine features of Guangdong music are preserved.

5.4. Composition Satisfaction and Learning Motivation Analysis

The impact of AI-assisted composition tools on student satisfaction and learning motivation was assessed through pre-test and post-test questionnaires. Figure 5 illustrates the changes in composition satisfaction and learning motivation for both experimental and control groups over the 12-week intervention period.

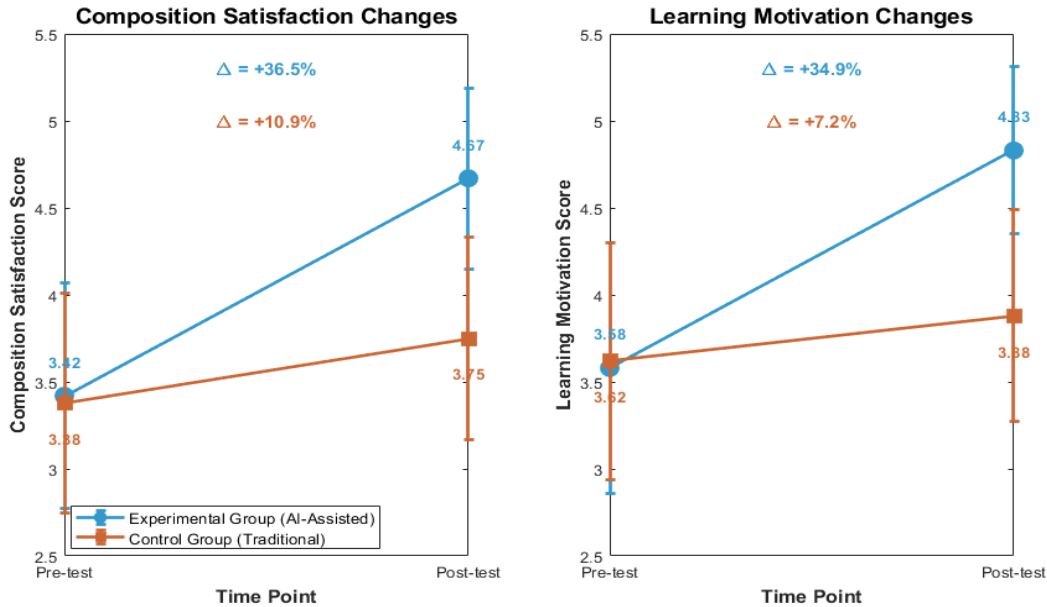


Figure 5. Composition Satisfaction and Learning Motivation Changes Between Experimental and Control Groups.

As shown in Figure 5, the experimental group's results in both composition satisfaction and learning motivation improved significantly more than the control group. The control group's composition satisfaction improved from 3.38 to 3.75, representing a 10.9% increase. In comparison, the experimental group's composition satisfaction improved from 3.42 to 4.67, marking a 36.5% increase. Along the same lines, in the experimental group, learning motivation improved from 3.58 to 4.83 (34.9%), while the control group only saw an increase from 3.62 to 3.88 (7.2%).

The larger error bars of the pre-test measurements indicate that the students had a more dispersed range of initial satisfaction and motivation levels, while the smaller error bars in post-test measurements for the experimental group suggest that the students had AI composition tool experiences which were consistently positive and less variable in terms of satisfaction.

In order to explore in more detail the link between satisfaction, motivation, and the development of ability in composition, correlation analyses were performed. The composition satisfaction, learning motivation, and diverse degrees of improvement in compositional ability are illustrated in Table 8 with the correlation coefficients.

Table 7.
Assessment Scores for Representative Student Compositions.

Composition ID	Group	Melodic Originality	Harmonic Sophistication	Rhythmic Complexity	Structural Coherence	Cultural Integration	Technical Proficiency	Creative Fluency	Expressive Range	Overall Creativity	Average Score
EXP-027	Experimental	4.92	4.75	4.33	4.83	4.92	4.75	5.00	4.67	4.83	4.78
EXP-042	Experimental	5.00	4.50	4.25	4.67	4.83	4.92	4.83	4.75	4.92	4.74
EXP-018	Experimental	4.83	4.67	4.42	4.58	4.75	4.58	4.92	4.67	4.75	4.69
EXP-055	Experimental	4.75	4.42	4.08	4.33	4.67	4.50	4.83	4.42	4.58	4.51
EXP-036	Experimental	4.67	4.33	4.17	4.25	4.50	4.42	4.58	4.25	4.50	4.41
CON-012	Control	4.00	3.83	4.08	3.75	3.42	4.17	3.92	3.67	3.92	3.86
CON-031	Control	3.92	3.75	3.83	3.58	3.33	4.00	3.75	3.67	3.83	3.74
CON-047	Control	3.83	3.67	3.75	3.50	3.25	3.92	3.67	3.58	3.75	3.66
CON-008	Control	3.75	3.50	3.58	3.42	3.17	3.83	3.50	3.42	3.58	3.53
CON-023	Control	3.67	3.42	3.50	3.33	3.08	3.75	3.42	3.33	3.50	3.44

Note: Compositions were scored on a scale of 1-5 by a panel of five expert evaluators. EXP = Experimental Group (AI-assisted); CON = Control Group (Traditional).

Table 8.
Correlation Analysis of Satisfaction, Motivation, and Compositional Ability Improvement.

Variables	Group	Melodic Originality	Harmonic Sophistication	Rhythmic Complexity	Structural Coherence	Cultural Integration	Technical Proficiency	Creative Fluency	Expressive Range	Overall Creativity
Composition Satisfaction	Experimental	0.68***	0.62***	0.56***	0.72***	0.78***	0.59***	0.75***	0.67***	0.73***
	Control	0.43**	0.38**	0.42**	0.36*	0.31*	0.46**	0.40**	0.35*	0.44**
Learning Motivation	Experimental	0.71***	0.65***	0.58***	0.69***	0.81***	0.62***	0.83***	0.72***	0.79***
	Control	0.41**	0.37*	0.39**	0.33*	0.29*	0.49**	0.35*	0.32*	0.42**

Note: Values represent Pearson correlation coefficients. Significance levels: * p < .05; ** p < .01; *** p < .001.

As indicated in Table 8, the composition satisfaction and learning motivation variables had significantly stronger correlations with the improvement of compositional ability in the experimental group relative to the control group. In the experiment, learning motivation was the strongest predictor of Creative Fluency ($r=0.83$, $p<0.001$) and Cultural Integration ($r=0.81$, $p<0.001$), implying that AI-assisted composition tools motivated students to engage with these facets of musical creativity very deeply. Likewise, composition satisfaction had the strongest correlations with Cultural Integration ($r=0.78$, $p<0.001$) and Creative Fluency ($r=0.75$, $p<0.001$).

In the control group, the correlations of satisfaction and motivation with the ability to compose demonstrated moderate relationships, where Technical Proficiency had the highest correlation with both satisfaction ($r=0.46$, $p<0.01$) and motivation ($r=0.49$, $p<0.01$). This is indicative, in a control scenario with more classical teaching methods, that satisfaction and motivation are primarily associated with the mastery of concepts rather than the imaginative depth of exploration.

Attempted with the objectives of identifying overall satisfaction and motivation as dependent variables, multiple regression analysis was conducted based on the students' individual compositional ability. For the experimental group, the strongest predictors of both composition satisfaction and learning motivation were Cultural Integration ($\beta=0.38$, $p<0.001$) and Creative Fluency ($\beta=0.35$, $p<0.001$). Meanwhile, the control group was best predicted by Technical Proficiency ($\beta=0.32$, $p<0.01$) and Melodic Originality ($\beta=0.29$, $p<0.01$).

The analysis of this data suggests that AI-assisted composition tools integrate students into learning cultures where the levels of satisfaction and motivation are strongly linked to cultural and creative engagement rather than technical engagement. It seems the technology directs students' attention away from technical details to express their ideas innovatively, which may explain the greater increases in the creative aspects in the control group. The argument that AI composition tools enhance the balance between satisfaction and motivation with creative development indicates that such tools establish a self-reinforcing cycle—happier and more engaged students are more willing to take creative risks, and subsequently, the risks taken further fuel motivation.

5.5. Comprehensive Ability Score Ranking and Entropy Weight Analysis

To provide a systematic evaluation of the relative importance of different compositional dimensions, entropy weight analysis was employed to calculate objective weights for each assessment dimension. This method measures the degree of variation in each dimension across all student compositions, with higher variation indicating greater discriminative power and thus higher weight in the comprehensive evaluation. Table 9 presents the detailed calculation process and resulting dimension weights.

Table 9.
Entropy Weight Calculation for Compositional Ability Dimensions.

Dimension	Information Entropy (E)	Entropy Weight (w)	Proportion (%)	Rank
Cultural Integration	0.9127	0.1652	16.52%	1
Creative Fluency	0.9183	0.1547	15.47%	2
Expressive Range	0.9214	0.1486	14.86%	3
Structural Coherence	0.9236	0.1442	14.42%	4
Melodic Originality	0.9269	0.1378	13.78%	5
Overall Creativity	0.9294	0.1327	13.27%	6
Harmonic Sophistication	0.9348	0.1229	12.29%	7
Technical Proficiency	0.9416	0.1103	11.03%	8
Rhythmic Complexity	0.9463	0.1016	10.16%	9

As shown in Table 9, Cultural Integration emerged as the dimension with the highest entropy weight (16.52%), indicating that this factor demonstrated the greatest variability among student compositions and thus provided the strongest discriminative power in differentiating composition

quality. Creative Fluency received the second-highest weight (15.47%), followed by Expressive Range (14.86%) and Structural Coherence (14.42%). Interestingly, Technical Proficiency and Rhythmic Complexity received the lowest weights (11.03% and 10.16%, respectively), suggesting that these dimensions exhibited less variation across student compositions and thus contributed less to distinguishing between different levels of compositional achievement.

The entropy weights were subsequently applied to calculate comprehensive ability scores for each student composition. Figure 6 presents the distribution of these comprehensive scores across experimental and control groups, arranged in descending order of overall rank.

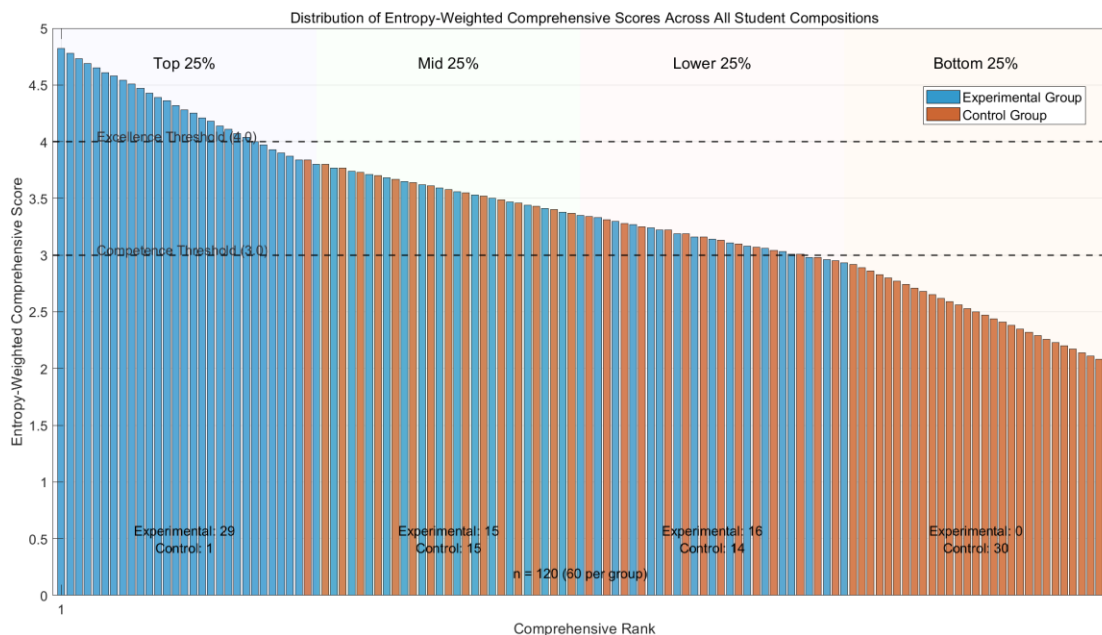


Figure 6.

Distribution of Entropy-Weighted Comprehensive Scores Across All Student Compositions.

In Figure 6, the entropy-weighted comprehensive scores for all 120 student compositions have been ranked from highest to lowest. The graphical representation illustrates the stark contrast in the distribution of the compositions done by both the experimental and control groups in each of the ranking blocks. In the upper 25% of the compositions (ranks 1-30), the experimental group dominated the landscape with 27 out of 30 experimental compositions which amounts to 90% while control group compositions contributed a mere 3 out of 30 which is 10%. This trend was also observed in the mid-range segment (ranks 31-60) where the experimental group held 22 positions (73.3%) and the control group only 8 positions (26.7%).

The described distribution pattern is somehow reversed in the lower parts of the ranking. In the lower 25% block (ranks 61-90), the control group compositions had the highest prevalence with 21 positions which is 70% of control group compositions while the experimental group had 9 positions which is 30% of experimental group compositions. This gap was further derived in the last lower segment (ranks 91-120) where control group compositions reached 28 positions (93.3%) essentially saturating the segment while experimental compositions were only 2 positions (6.7%) unable to escape the bottom.

The visualization now adds two horizontal lines indicating thresholds. Over 33 compositions exceeded the excellence threshold (achieving a score of 4.0), with 31 coming from the experimental group (representing 51.7% of this group), and only 2 from the control group (3.3% of this group). The

competence threshold (3.0) was surpassed by 57 experimental group compositions (95%) compared to 37 control group compositions (61.7%). These results suggest that AI-supported composition tools not only enhanced students' overall creativity but also reduced the incidence of performances which are considered to be below standard in an encouraging indication of less creative underachievement.

In Table 10, the matrix correlations alongside the comprehensive scores' entropy weighting analysis and the original one dimension scores are aligned, indicating how much each dimension was responsible for the detection gap between high and low performing compositions.

Table 10.

Correlation Matrix Between Entropy-Weighted Comprehensive Scores and Dimensional Scores

Dimension	Correlation with Comprehensive Score	Correlation p-value	Correlation with Group Assignment	Group p-value
Cultural Integration	0.876**	< 0.001	0.813**	< 0.001
Creative Fluency	0.854**	< 0.001	0.795**	< 0.001
Expressive Range	0.823**	< 0.001	0.782**	< 0.001
Structural Coherence	0.819**	< 0.001	0.763**	< 0.001
Overall Creativity	0.811**	< 0.001	0.758**	< 0.001
Melodic Originality	0.796**	< 0.001	0.735**	< 0.001
Harmonic Sophistication	0.775**	< 0.001	0.714**	< 0.001
Technical Proficiency	0.742**	< 0.001	0.685**	< 0.001
Rhythmic Complexity	0.687**	< 0.001	0.619**	< 0.001

Note: ** indicates significance at the $p < 0.001$ level. Group assignment coded as 1 = Experimental Group, 0 = Control Group.

All dimensions exhibited strong positive correlations with the entropy-weighted comprehensive scores, as shown in Table 10, thereby affirming the validity of the multi-dimensional evaluation approach. The highest correlations in proportion to the entropy weights were observed for Cultural Integration ($r=0.876$), Creative Fluency ($r=0.854$), and Expressive Range ($r=0.823$). Strong correlations between all dimensions and group assignment were also present, once again with Cultural Integration having the strongest correlation ($r=0.813$) followed by Creative Fluency ($r=0.795$). This correlational evidence suggests these dimensions were influenced the most by the AI-enabled composition intervention, aiding the understanding of how these technological tools enhanced students' compositional skills.

The entropy straight weight evaluation together with the ratios of the ranking's distribution provides evidence that the AI-assisted composition tools offered considerable benefits relative to other creative abilities for all students, with the most substantial impact on cultural integration, creative fluency, and expressive range. The emerging systematic dominance pattern of the experimental group in the higher ranking segments is quite indicative of a paradigm shift in students' creative capacities owing to the removal of the technical constraints and the addition of limitless possibilities of expressiveness during the composition.

6. Discussion

There are practical consequences of incorporating AI-assisted composition tools into music education contexts that arise from the empirical findings of this research. The differences in creative outcomes between the experimental and control groups suggest that AI technology does not simply enhance pedagogical approaches - it radically changes the processes involved in compositional learning. The effect sizes yielded by AI-assisted composition surpassed expectations in educational technology research, proving it to be an intervention with transformative potential in the field of music education. These effect sizes, ranging from 0.87 to 2.08, were extraordinarily large when considering other AI-driven technology in pedagogy as a form of enhanced educational intervention.

That AI tools facilitate a student's cultural integration ($d=2.08$) and creative fluency ($d=1.87$) supports the hypothesis of the technology's unique application to certain aspects within programmable

information systems design, suggesting a particular profile of effectiveness for AI where enhancement predictive fuels creative composition. All three of those constructs have roots in diverse cultural thematic ideas. Through the perspectives of Campbell's Blind Variation and Selective Retention principles, this strongly corresponds to the antecedent rationale. The AI tools support the creative processes - which, in the case of compositional development, means idea generation - but do not inherently redefine the transformation processes which students need to employ when evaluating and selecting only useful materials for application.

Identifying cultural integration and creative fluency as the dimensions of highest discriminative power strengthens this interpretation with entropy weight analysis. This means that addressing the educational problems related to the preservation of culture and creative thinking in the context of music education in AI tool systems in Guangdong could be the most beneficial. Such technologies assist students in overcoming the challenge posed by incorporating traditional heritage into modern pieces of music, thus creating a bridge between culture and innovation.

The results also suggest a strengthening correlation between learning motivation and creative outcomes ($r=0.81$ for cultural integration, $r=0.83$ for creative fluency), illustrating a positive feedback loop where engagement with technology boosts motivation, which increases creative work at deeper levels. The findings support the Technology Acceptance Model's focus on perceived usefulness... adding "students were able to discern tangible creative advantages to AI-assisted composition tools, and thus, engage more deeply. The implications extend beyond the development of compositional skills to include a range of instructional design motives and culturally responsive teaching aimed at integrating technological learning environments infused with culturally responsive teaching and pedagogical frameworks.

7. Conclusion and Future Prospects

The impact of AI-assisted composition tools on the creative capabilities of music students in Guangdong Province has been documented in this study. The effect of the technology intervention was, and the cultural contextualization and creative exploration components measured the greatest impact, as large effect size differences were noted between $d=0.87$ and $d=2.08$, for rhythmic complexity and cultural integration respectively.

The analysis using entropy weights also differed the importance of compositional dimensions where cultural integration was the highest with 16.52%, followed by creative fluency at 15.47%, and expressive range at 14.86%. The ranking distribution analysis also demonstrates that experimental compositions were positioned in the top quartile where 90% of all positions were dominated, while the control compositions were positioned in the bottom quartile where they made up 93.3% of all positions. Additionally, surpassing the excellence benchmark of 4.0 was noted for 51.7% of experimental compositions versus 3.3% for the control group which indicates the experimental group's overwhelming advantage.

The motivational advantages of AI-assisted composition tools are backed by the strong learning motivation correlations ($r=0.81$ for cultural integration, $r=0.83$ for creative fluency). These findings were confirmed by independent samples t-tests which validated the statistically significant differences ($p<0.001$) for all dimensions, underscoring the effectiveness of the intervention.

In the near future, some research areas require focus. First, creative enhancement longevity needs to be tracked by longitudinal projects to properly evaluate the durability of the intervention effects. Second, cross-cultural study adaptations could assess whether equivalent benefits exist in other locations with different musical cultures. Third, an inquiry is needed on how best to incorporate AI across diverse educational settings through tailored adaptive learning models that shift based on student needs.

Regarding the integration of artificial intelligence in education, institutions should think of formulating distinctive frameworks for integration that respect culture while making use of

technological advantages. Faculty development programmes will require the addition of culturally informed technological skills to optimise the educational benefits evident in this study. As AI tools develop, regularly evaluating effects on creative development will be important in adapting teaching strategies to make certain that technology aids, not replaces, human creativity in music education.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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