Journal of Contemporary Educational Research, 2026, Volume 10, Issue 7
http://ojs.bbwpublisher.com/index.php/JCER
Online ISSN: 2208-8474
Print ISSN: 2208-8466

Design and Preliminary Evaluation of a Smart Classroom Environment for Undergraduate Music Majors

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Abstract: This study reports the design and preliminary evaluation of a smart classroom environment for undergraduate music majors. A one-semester quasi-experimental pretest–posttest design was implemented at a university in Xi'an, China, in two intact classes: an experimental group receiving smart-classroom instruction ($n = 36$) and a control group receiving conventional instruction ($n = 36$). The intervention embedded digital music resources, AI-assisted creative tools, platform-based learning activities, and data-informed feedback into regular course teaching. Data were collected from student questionnaires, platform logs, teaching records, and course-product evaluations. Seven operational indicators were compared descriptively: digital resource support, participation in smart-classroom activities, teacher–student interaction timeliness, evaluation quality, learning autonomy, student output quality, and exploratory instructional cost-efficiency. Group-level results indicated improvement in both groups, with larger descriptive gains in the experimental group. The digital resource richness index increased from 42 to 81 in the experimental group and from 43 to 65 in the control group; the cost-efficiency ratio increased from 0.60 to 0.82 and from 0.61 to 0.69, respectively. Because individual-level data were unavailable, standard deviations and inferential tests were not reported. The findings offer preliminary descriptive evidence that smart-classroom design may support resource access, participation, feedback, and self-directed learning in music-major teaching.

Keywords: Technology-enhanced learning; AI-assisted teaching; Data-informed feedback; Quasi-experimental design; Descriptive comparison; Learning autonomy; Teaching evaluation; Digital resource support

Online publication: August 4, 2026

1. Introduction

Digital transformation has become an important direction in higher education, but the educational value of new technologies depends largely on how they are embedded in teaching practice. Recent reviews of artificial intelligence in higher education show that AI has been applied to assessment, learning analytics, prediction, intelligent tutoring, adaptive learning, and learner support [1–3]. These studies also point to a common problem: technological innovation often develops faster than pedagogical design. For this reason, the use of AI in education should not be understood simply as the introduction of new tools, but as part of a broader process involving curriculum design, teacher guidance, ethical use of data, and learner protection. UNESCO has similarly emphasized that AI-supported education requires human-centered governance, pedagogical validation, and attention to privacy and data security [4].

Music education offers a distinctive setting for examining smart classroom design, as smart classroom research has increasingly emphasized the integration of digital resources, interaction technologies, learning data, and pedagogical design [5]. Compared with knowledge-based courses, music learning places stronger emphasis on listening, interpretation, performance practice, creative production, and timely feedback [6,7]. These characteristics make music teaching highly dependent on resources, demonstration, repeated practice, and teacher–student interaction. Digital score libraries, audio and video resources, AI-assisted creative tools, platform-based learning records, and multimodal feedback technologies can therefore provide additional support for music-major instruction when they are connected with concrete teaching activities rather than used as isolated technologies. Recent studies have explored AI-supported music-theory learning, singing-error detection, personalized music-learning activities, and data-driven analysis of performance difficulty [8–11]. These studies indicate that AI and digital technologies have practical potential in music learning, especially in feedback, personalization, and practice support.

However, existing research still leaves several issues insufficiently addressed. First, many studies on AI in higher education classify applications by function, such as prediction, tutoring, assessment, and personalization, but pay less attention to how these functions can be organized into an integrated classroom environment for a specific discipline [1–3]. Second, music-related AI studies often focus on a single tool or task, such as music-theory support, singing-error analysis, exercise generation, or performance-difficulty estimation [8–11]. Less attention has been given to how digital resources, AI-assisted tasks, platform interaction, feedback, evaluation, and student output can be combined in one semester-long teaching process for undergraduate music majors. Third, there remains a need for classroom-based descriptive evidence showing which dimensions of teaching and learning may change after such an environment is implemented.

In response to these gaps, this study reports the design and preliminary evaluation of a smart classroom environment for undergraduate music majors. The smart-classroom intervention was treated as an instructional system that linked digital music resources, AI-assisted creative activities, platform-based learning tasks, teacher feedback, process-oriented evaluation, and course-product assessment. Rather than claiming to establish definitive causal effects, the study provides a group-level descriptive comparison between a smart-classroom condition and conventional instruction over one academic semester. Seven operational indicators were examined: digital resource support, participation in smart-classroom activities, teacher–student interaction timeliness, evaluation quality, learning autonomy, student output quality, and exploratory instructional cost-efficiency.

The study was guided by the following research questions:

RQ1. How did the smart-classroom condition and the conventional teaching condition change across the seven operational indicators after one semester of instruction?

RQ2. Which dimensions showed the largest descriptive changes in the smart-classroom condition?

RQ3. What practical implications and methodological limitations can be identified from implementing an integrated smart classroom for undergraduate music majors?

2. Materials and methods

2.1. Study design and participants

This study used a quasi-experimental pretest–posttest design with a nonequivalent control group [12,13]. It was conducted over one academic semester at a university in Xi'an, China. Two intact classes of undergraduate music majors from the same cohort were selected because they followed the same course syllabus and had comparable learning schedules. One class was assigned to the smart-classroom condition, and the other continued with conventional instruction.

A total of 72 students participated in the study, with 36 students in the experimental group and 36 in the control group. As random assignment was not feasible in the regular teaching context, the study should be understood as a classroom-based quasi-experimental evaluation rather than a randomized controlled trial. Before the intervention, the two classes were reviewed using available pretest scores, prior music-related academic performance, and basic demographic information to check whether the groups were broadly comparable at baseline. To reduce instructional variation, both groups were taught by the same instructor, used the same course syllabus, completed the same number of weekly teaching hours, and were assessed according to the same final course requirements.

The study focused on group-level changes in seven operational indicators related to resource support, technology-supported participation, interaction timeliness, evaluation quality, learning autonomy, student output quality, and instructional cost-efficiency. No interview data were included in the present analysis. Because the available dataset consisted of group-level pretest and posttest values, the study was positioned as a preliminary descriptive evaluation.

2.2. Instructional environment and materials

The control group received conventional classroom instruction. Teaching mainly included teacher explanation, live demonstration, guided practice, classroom discussion, and manually graded written or performance-based assignments. In music theory and music history sessions, students learned through teacher-led explanation, score reading, listening examples, and classroom questioning. In vocal and instrumental practice, the teacher demonstrated techniques, corrected errors during class, and provided feedback on students' practice and submitted assignments. Students mainly relied on printed scores, classroom notes, teacher demonstrations, and after-class rehearsal.

The experimental group received the same course content and formal assessment requirements, but the teaching process was reorganized through a smart classroom environment. The intervention was not designed to replace conventional music training. Instead, it added digital resources, platform-based learning tasks, AI-assisted creative activities, and data-informed feedback to regular music-major teaching. Four components were used in the smart-classroom condition.

First, a digital music teaching platform was used to organize course materials, assignment submission, feedback, and learning records. The platform included digitized scores, audio and video examples, course slides, music-theory resources, and extended listening materials. These resources were arranged by teaching module so that students could review class content and complete extension tasks outside scheduled class time.

Second, AI-assisted composition tools, including AIVA and Amper Music, were used in creative learning tasks. Students used these tools to explore melodic ideas, harmonic patterns, rhythmic materials, and stylistic possibilities. The generated materials were not treated as final works. They were used as starting points for discussion, revision, and teacher-guided reflection on musical structure and creative intention.

Third, motion-capture and audio-analysis tools were used selectively in vocal and instrumental practice. The equipment included a Perception Neuron 3 motion-capture system, a RØDE NT1-A condenser microphone, and a Focusrite Scarlett 2i2 audio interface. These tools provided supplementary records of posture, movement, sound, and the performance process. The teacher used these records to support feedback on rhythm, tone, articulation, posture, and performance control.

Fourth, VR and AR devices, including HTC Vive Pro 2, PICO 4, and Microsoft HoloLens 2, were used for selected visualization and contextual learning activities. For example, virtual rehearsal spaces and concert-hall simulations were used to enrich students' understanding of performance contexts, while three-dimensional visual presentations were used to support the explanation of abstract music-related concepts. These activities were used as supplements to classroom teaching rather than as independent technology demonstrations.

To make the intervention process clearer, **Table 1** summarizes the relationship between teaching modules, instructional activities, and the indicators observed in the study.

Table 1. Implementation of the smart-classroom intervention

Teaching module	Experimental group activities	Control group activities	Related indicators
Orientation and baseline	Platform registration, introduction to digital resources, pretest questionnaire, and baseline record collection	Course introduction, pretest questionnaire, and baseline record collection	Baseline comparability; digital resource support
Music theory and music history	Digitized scores, audio/video examples, online exercises, and selected VR/AR contextual demonstrations	Teacher explanation, score reading, listening examples, and classroom discussion	Digital resource support; participation in smart-classroom activities; evaluation quality
Vocal and instrumental practice	Audio recording, selected motion or posture feedback, platform-based submission, and teacher feedback supported by performance records	Live demonstration, in-class correction, after-class practice, and manual feedback	Teacher–student interaction timeliness; student output quality
Composition and creative tasks	AI-assisted exploration of melody, harmony, rhythm, and style; platform submission and revision based on teacher feedback	Conventional creative exercises, teacher explanation, and manually reviewed assignments	Technology-supported participation; learning autonomy; student output quality
Extension learning and final assessment	Optional extension tasks, platform learning records, course-product evaluation, and posttest questionnaire	Regular after-class review, final course tasks, and posttest questionnaire	Learning autonomy; evaluation quality; instructional cost-efficiency

2.3. Measures

Data were collected from three sources: a researcher-developed student questionnaire, platform logs and teaching records, and course-product evaluation records. These sources were used to describe the classroom intervention from complementary perspectives. The questionnaire reflected students' perceptions of the learning environment, whereas the logs, teaching records, and course-product evaluations provided supplementary operational indicators. The measures were therefore used for descriptive classroom evaluation rather than for validating a standardized psychometric scale.

The student questionnaire included 14 closed-ended items and several background-information items. The closed-ended items were rated on a five-point Likert scale, ranging from 1 = strongly disagree to 5 = strongly agree. Two items were designed for each of the seven dimensions: digital resource support, participation in smart-classroom activities, teacher–student interaction timeliness, evaluation quality, learning autonomy, student output quality, and exploratory instructional cost-efficiency. For each dimension, the mean of the two items was transformed to a 0–100 scale using the following formula:

$$\text{Questionnaire score} = \frac{\bar{x}-1}{4} \times 100$$

where $\bar{x}$ denotes the mean score of the two items for a given dimension. In this transformation, a score of 1 corresponds to 0, and a score of 5 corresponds to 100. Because the available dataset contained group-level values rather than item-level responses, internal consistency coefficients such as Cronbach's alpha were not calculated in the present version of the study. This limitation is considered in the interpretation of the findings.

This use of platform traces is consistent with learning analytics research, which treats digital learning records as evidence for understanding participation, engagement, feedback, and learning behavior [14,15]. In the present study, recorded activities included platform-based learning tasks, AI-assisted creative tasks, online assignment submission, teacher feedback, and student questions or comments on the teaching platform. Course-product evaluation records were used to describe the quality of student works and performance-related outputs. All indicators were aggregated within the same semester-long intervention period.

For the course-product indicator, student works were rated independently by two instructors using a 100-point rubric. The use of rubrics and performance records is consistent with formative assessment practices in music education, where clear criteria and recorded evidence can support more transparent evaluation of performance, composition, and reflective learning [16,17]. The rubric covered musical structure, technical control, stylistic appropriateness, and originality. Works receiving a score of 85 or above were classified as high-quality outputs. If the two raters' scores differed by more than five points, the final score was resolved through discussion and consensus. This procedure was used to improve rating consistency, although formal inter-rater reliability statistics were not available.

Table 2 presents the seven evaluative dimensions, their operational definitions, data sources, and scoring rules.

Table 2. Core evaluative dimensions and scoring rules

Evaluative dimension	Operational definition	Main data source	Scoring method
Digital resource support	Students' perceived access to adequate, diverse, and updated digital music resources; supplemented by records of the resource base.	Student questionnaire; platform and resource records	Supplementary index: Digital Resource Richness Index (DRRI) = 0.40Q + 0.30D + 0.30U, where Q = normalized resource quantity score, D = normalized diversity-of-resource-types score, and U = normalized monthly update-frequency score. Each component was capped at 100 before weighting.
Participation in smart-classroom activities	Degree to which students took part in Platform-supported, AI-assisted, VR/AR-assisted, and other technology-supported learning activities.	Student questionnaire; platform logs; teaching records	Supplementary participation rate = 100 x completed participation records / total planned participation opportunities.
Teacher–student interaction timeliness	Timeliness of teacher responses to student questions, homework feedback, platform comments, and other recorded learning interactions.	Student questionnaire; platform logs; teaching records	Supplementary timeliness rate = 100 x responses delivered within 24 h / total recorded interactions.
Evaluation quality	Students' perception of whether assessment and feedback were clear, fair, comprehensive, and informed by learning-process records.	Student questionnaire; teaching records	Teaching records were used to describe whether process data, assignment feedback, and course-product evaluation were included in the assessment process.

Learning autonomy	Students' self-directed engagement in optional or extended music-learning tasks beyond basic course requirements.	Student questionnaire; platform logs; task-completion records	Supplementary completion rate = 100 x completed optional extension-task records / total planned optional extension-task opportunities.
Student output quality	Quality of submitted music works or performance-related course products.	Course-product evaluation records	Supplementary high-quality output rate = 100 x (number of submitted works rated ≥ 85 / total number of submitted works).
Exploratory instructional cost-efficiency	Within-study comparison of perceived instructional benefit relative to per-student instructional input. This indicator was treated as exploratory rather than as a full economic evaluation.	Student questionnaire; teaching and cost records	Supplementary ratio: UCBR = (S/100) / (C/Cmax), where S = mean teaching satisfaction index, C = per-student instructional cost, and Cmax = the larger per-student cost observed across the two groups. Per-student cost included hardware amortization, software licensing or subscription, maintenance, and consumable resource costs where available. Higher values indicated greater cost-related efficiency within this study only.

Questionnaire scores were calculated as the transformed mean of two Likert items for each dimension. Supplementary indicators were used for descriptive triangulation only.

2.4. Procedure

The study was implemented over one academic semester. In Week 1, students in both groups completed the pretest questionnaire, and baseline information was recorded from available course records. Before the intervention began, the teaching materials for the smart-classroom condition were prepared. This preparation included organizing digital scores, audio and video examples, music-theory resources, online assignments, and course modules on the teaching platform. The AI-assisted, VR/AR-supported, and feedback-related tools were also configured before classroom use.

During the semester, the control group followed conventional instruction. The teaching process included teacher explanation, live demonstration, guided classroom practice, discussion, after-class rehearsal, and manually reviewed written or performance-based assignments. The control group received the same course content, weekly teaching hours, final assessment requirements, and instructor guidance as the experimental group, but did not use the full smart-classroom intervention.

The experimental group received the smart-classroom intervention within the same course framework. In music theory and music history sessions, digital scores, audio and video cases, online exercises, and selected VR/AR contextual demonstrations were used to support conceptual understanding and listening-based analysis. In vocal and instrumental practice sessions, audio recording and selected motion or posture feedback were used to provide additional evidence for teacher feedback. In composition and creative tasks, students used AI-assisted tools to explore melodic, harmonic, rhythmic, and stylistic ideas before revising their work under teacher guidance. After class, students completed platform-based assignments, optional extension tasks, and reflection activities. The platform recorded learning participation, assignment submission, teacher feedback, and selected interaction logs during the semester.

To improve comparability between the two groups, the course syllabus, teaching schedule, weekly class hours, instructor, major course assignments, and final course requirements were kept consistent. In the final teaching week, both groups completed the posttest questionnaire. Platform logs, teaching records, and course-product evaluation records were then compiled and checked for consistency with the pretest–posttest time frame.

2.5. Data analysis

The analysis was conducted as a group-level descriptive comparison. For each of the seven operational indicators, pretest and posttest values were summarized separately for the experimental group and the control group. Change scores were calculated by subtracting the pretest value from the posttest value. The sample size was reported as $n = 36$ for each group to provide context for interpreting the descriptive comparison.

No inferential statistical tests were conducted in this version of the study. The available dataset contained group-level pretest and posttest values rather than individual-level raw scores, item-level questionnaire responses, standard deviations, confidence intervals, or standard errors. Therefore, paired-samples *t*-tests, independent-samples t-tests, ANCOVA, effect-size calculations, and reliability analysis were not performed. The results are interpreted as preliminary descriptive evidence rather than statistically confirmed effects.

To avoid overstatement, the analysis focused on the direction and size of descriptive changes within the observed indicators. Where percentage-based indicators were used, they were treated as operational classroom indicators within this study rather than as externally validated measures. The findings should therefore be read as a preliminary evaluation of one semester of smart-classroom implementation in a specific music-major teaching context.

2.6. Ethics statement

This study was conducted as a classroom-based teaching evaluation within a regular undergraduate course. Project-identifying information has been removed for blind review. Before data collection, students were informed of the purpose of the study and the types of classroom data to be used, including questionnaire responses, platform learning records, teaching records, and course-product evaluation records. Participation in the questionnaire was voluntary. All data were processed and reported at the group level, and no personally identifiable information was included in the manuscript. The teaching intervention did not affect students' right to receive regular instruction, and course assessment requirements were kept consistent across the two groups.

3. Results

3.1. Overview of outcome changes

The results are presented according to the seven operational indicators defined in the Methods section: digital resource richness, participation in smart-classroom activities, teacher–student interaction timeliness, evaluation quality, completion of optional extension tasks, proportion of student work rated as high quality, and exploratory instructional cost-efficiency. As the available dataset contained group-level pretest and posttest values rather than individual-level raw data, the findings are reported descriptively.

Table 3 summarizes the pretest, posttest, and change values for the experimental and control groups. At pretest, the two groups showed similar values across the seven indicators, which provided a reasonable basis for classroom-level comparison. After one semester, improvement was observed in both groups. The experimental group showed larger descriptive changes than the control group on all seven indicators, particularly in digital resource richness, participation in smart-classroom activities, and completion of optional extension tasks. These patterns should be interpreted as preliminary classroom-level evidence rather than statistically confirmed intervention effects.

Table 3. Pretest and posttest values of the seven outcome indicators

Indicator	Exp. pretest	Exp. posttest	Change	Ctrl. pretest	Ctrl. posttest	Change
Digital resource richness index (0–100)	42	81	+39	43	65	+22
Participation in smart-classroom activities (%)	46	79	+33	47	62	+15
Teacher–student interaction timeliness (%)	61	84	+23	62	75	+13
Evaluation quality score (0–100)	65	82	+17	63	75	+12
Completion of optional extension tasks (%)	43	82	+39	42	61	+19
Student works rated as high quality (%)	6.9	18.4	+11.5	7.0	12.8	+5.8
Exploratory instructional cost-efficiency ratio	0.60	0.82	+0.22	0.61	0.69	+0.08

Values are group-level pretest and posttest values for the experimental group (n=36) and the control group (n=36). Change=posttest value minus pretest value. For percentage-based indicators, changes are reported in percentage points. No inferential tests were conducted because individual-level raw data, standard deviations, confidence intervals, and item-level questionnaire responses were not available.

Figure 1 provides a visual summary of the same group-level pretest and posttest values. The figure is intended to show the direction and relative size of descriptive changes across indicators, rather than to present statistical differences between groups.

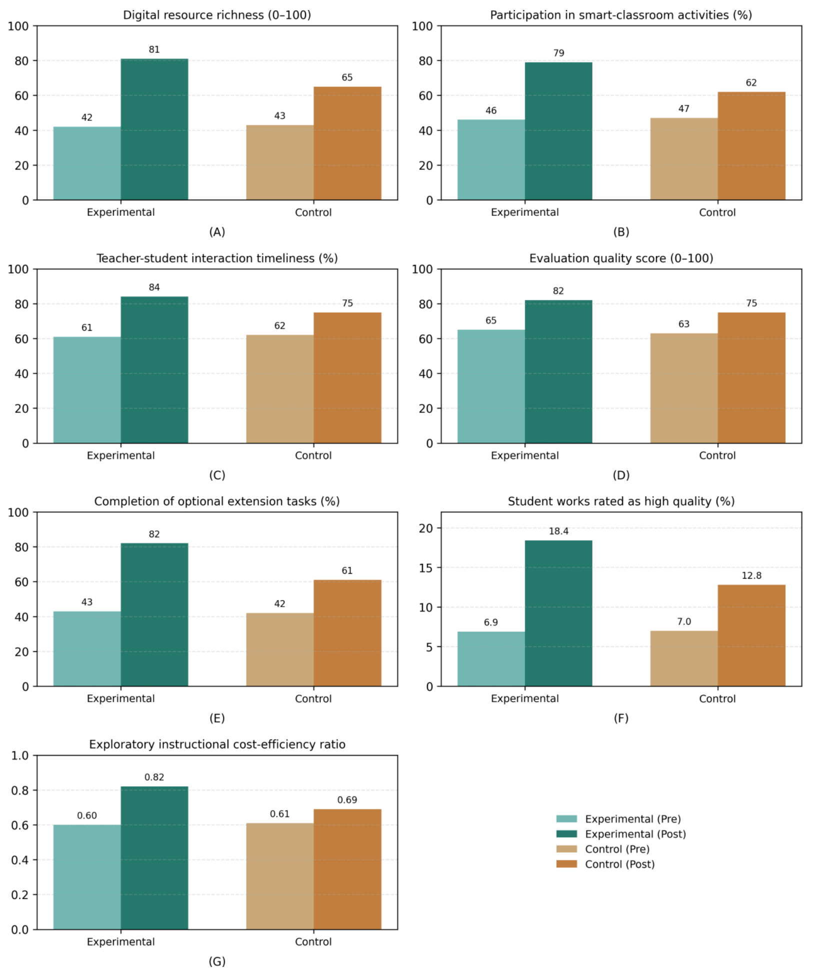

Figure 1. Group-level pretest and posttest values across seven operational indicators. The figure presents descriptive group-level values for the experimental group and the control group. Values were calculated from questionnaire responses, platform logs, teaching records, and course-product evaluation records collected during one semester at a university in Xi’an, China. Error bars are not shown because individual-level standard deviations and confidence intervals were not available.

3.2. Digital resource richness

The digital resource richness index increased from 42 to 81 in the experimental group, while the control group increased from 43 to 65. The change was therefore +39 points in the experimental group and +22 points in the control group. At the group level, this was one of the largest descriptive differences observed between the two conditions.

This pattern is consistent with the design of the smart-classroom intervention. In the experimental condition, digital scores, audio and video examples, music-theory materials, course slides, and extended listening resources were organized through the teaching platform and linked to specific course modules. In contrast, the control group mainly relied on printed materials, classroom notes, teacher demonstrations, and conventional after-class practice. The larger descriptive increase in the experimental group suggests that the intervention may have improved students' access to a broader and more searchable set of music-learning resources. Because the index was reported at the group level, this result should be interpreted as a descriptive change in the observed classroom environment rather than as a statistically tested effect.

3.3. Participation in smart-classroom activities

Participation in smart-classroom activities increased from 46% to 79% in the experimental group and from 47% to 62% in the control group. The corresponding changes were +33 percentage points and +15 percentage points, respectively. This indicates a larger descriptive increase in recorded learning participation under the smart-classroom condition.

The increase may be related to the wider range of learning activities available in the experimental group. During the semester, students in this group completed platform-based exercises, AI-assisted creative tasks, online assignment submission, selected VR/AR-supported learning activities, and feedback-related reflection tasks. These activities provided more recorded opportunities for students to participate before, during, and after class. By comparison, participation in the control group was mainly reflected in classroom discussion, guided practice, conventional homework, and after-class rehearsal. The result therefore suggests that the smart-classroom condition was associated with broader participation in technology-supported learning activities. However, the indicator reflects group-level participation records and should not be interpreted as evidence of individual learning gains.

3.4. Teacher–student interaction timeliness

Teacher–student interaction timeliness increased from 61% to 84% in the experimental group and from 62% to 75% in the control group. The corresponding changes were +23 percentage points and +13 percentage points, respectively. Although both groups showed improvement, the descriptive increase was larger in the smart-classroom condition.

This indicator reflected recorded responses to student questions, homework feedback, platform comments, and other learning-related interactions delivered within 24 hours. In the experimental group, the teaching platform provided a more traceable channel for assignment submission, feedback, and after-class communication. In the control group, interaction mainly depended on classroom questioning, face-to-face correction, and manually reviewed assignments. The result suggests that the smart-classroom condition was associated with a shorter recorded feedback cycle. However, because the analysis was based on group-level records, the finding should be interpreted as a descriptive change in interaction timeliness rather than as a statistically confirmed improvement in communication quality.

3.5. Evaluation quality

The evaluation quality score increased from 65 to 82 in the experimental group and from 63 to 75 in the control group. The change was +17 points in the experimental group and +12 points in the control group. The pretest values were close, while the posttest value was higher in the experimental group.

In the present study, evaluation quality referred to students' perception of whether assessment and feedback were clear, fair, comprehensive, and informed by learning-process records. In the experimental condition, platform records, assignment submission data, teacher feedback, and course-product evaluation were used as supplementary evidence in the teaching process. In the control condition, evaluation relied more heavily on classroom performance, manually reviewed assignments, and final course requirements. The larger descriptive increase in the experimental group may therefore be related to the use of more visible and process-oriented evaluation materials. This result should still be read cautiously, as it reflects group-level evaluation scores and does not include individual-level variation or inferential testing.

3.6. Completion of optional extension tasks

Completion of optional extension tasks increased from 43% to 82% in the experimental group and from 42% to 61% in the control group. The change was +39 percentage points in the experimental group and +19 percentage points in the control group. This was one of the largest descriptive differences observed in the study.

The optional extension tasks in the experimental group included online exercises, independent music analysis, AI-assisted creative exploration, additional listening activities, and reflection tasks submitted through the teaching platform. These tasks were connected with regular course modules but were not limited to classroom time. The control group also completed after-class review and practice tasks, but the learning process was less systematically recorded through a digital platform. The result suggests that the smart-classroom condition may have provided more structured opportunities for students to continue learning outside scheduled class time. Since the indicator was aggregated at the group level, it cannot be used to determine individual differences in learning autonomy.

3.7. Student output quality

The proportion of student works rated as high quality increased from 6.9% to 18.4% in the experimental group and from 7.0% to 12.8% in the control group. The corresponding changes were +11.5 percentage points and +5.8 percentage points, respectively. Although the overall proportion of high-quality works remained relatively modest, the experimental group showed a larger descriptive increase.

This indicator was based on course-product evaluation records. Student works were rated using a 100-point rubric covering musical structure, technical control, stylistic appropriateness, and originality. Works rated 85 or above were classified as high-quality outputs. In the experimental group, students had access to digital music resources, AI-assisted creative tools, platform-based submission, and feedback-supported revision. These conditions may have increased opportunities for drafting, revision, and presentation of music-related work. Nevertheless, the percentage should be interpreted with caution because the current dataset reports group-level proportions rather than the full distribution of work scores.

3.8. Exploratory instructional cost-efficiency

The exploratory instructional cost-efficiency ratio increased from 0.60 to 0.82 in the experimental group and from 0.61 to 0.69 in the control group. The change was +0.22 in the experimental group and +0.08 in the control group. This indicates a larger descriptive increase in the experimental group within the operational cost-efficiency measure used in this study.

This indicator was treated as an exploratory within-study ratio rather than as a full economic evaluation. The calculation considered perceived instructional benefit in relation to per-student instructional input, including hardware amortization, software or platform use, maintenance, and consumable teaching resources where available. The larger increase in the experimental group may be related to the repeated use of digital resources, platform-supported feedback, and more traceable teaching activities during the semester. However, the result should not be generalized as evidence that smart classrooms are economically superior in all teaching contexts. A more rigorous cost-effectiveness analysis would require detailed cost records, longer-term use data, and sensitivity analysis.

4. Discussion

4.1. Main findings

This study provided a preliminary descriptive evaluation of a smart classroom environment for undergraduate music majors. Across the seven operational indicators, both the experimental and control groups showed improvement after one semester, while larger descriptive changes were observed in the smart-classroom condition. The most visible changes appeared in digital resource richness, completion of optional extension tasks, and participation in smart-classroom activities. These findings suggest that the intervention was most closely related to resource access, learning participation, and students' continuation of learning beyond scheduled class time.

The results should be interpreted in relation to the instructional design rather than as isolated numerical changes. In the experimental group, digital scores, audio and video resources, platform-based exercises, AI-assisted creative tasks, and feedback records were connected with regular course modules. This arrangement may have made learning materials easier to access and review, especially in music theory, music history, performance practice, and creative tasks. The larger increase in optional extension-task completion also suggests that the platform may have provided a more structured route for after-class learning. For music majors, this is meaningful because progress in listening, performance, and creative production usually depends on repeated practice, timely feedback, and sustained engagement outside the classroom[18–20].

At the same time, the findings do not prove that the smart-classroom environment caused individual learning gains. The present analysis was based on group-level values, and no standard deviations, confidence intervals, or inferential tests were available. Therefore, the results are better understood as preliminary classroom-level evidence showing that the smart-classroom condition was associated with broader resource use, higher recorded participation, more timely interaction, and more process-oriented evaluation during the observed semester.

4.2. Pedagogical implications

The study indicates that smart classroom construction for music majors should be understood as an instructional arrangement rather than a simple accumulation of digital equipment. The practical value of the intervention did not lie only in using AI tools, VR/AR devices, or audio-analysis equipment. More importantly, these tools were connected with teaching tasks, feedback processes, and student work. For example, AI-assisted composition tools were used as starting points for melodic, harmonic, and rhythmic exploration rather than as substitutes for students' creative work. Platform records were used to support feedback and task completion rather than merely to record attendance or activity frequency.

This has several implications for music-major teaching. First, digital resources should be organized by course module and linked to specific learning tasks. Music students often need repeated access to scores, recordings, demonstrations, and theoretical explanations. A searchable and regularly updated resource base can support preparation before class, review after class, and independent exploration. Second, technology-supported activities should be designed around musical learning processes. In performance and composition courses, digital tools are more useful when they help students listen, compare, revise, and reflect, rather than when they are presented as technical novelties. Third, process-based feedback deserves greater attention. Platform submissions, teacher comments, performance records, and course-product evaluations can help teachers observe students' learning process more continuously, especially in courses where progress is not fully captured by a final performance or examination.

For institutions, the findings also suggest that smart classroom reform requires teacher preparation and resource management. A smart classroom is unlikely to improve teaching simply through hardware investment. Teachers need time to redesign tasks, select suitable resources, interpret platform records, and integrate feedback into regular instruction. In music education, this is particularly important because technological support must remain connected to artistic judgment, performance quality, stylistic understanding, and students' creative development.

4.3. Limitations and future research

Several limitations should be noted. First, the study was conducted in one university with two intact classes and a total of 72 students. The findings may reflect the specific course context, teacher guidance, student background, and institutional conditions. Second, the study used a quasi-experimental design without random assignment. Although the two classes were broadly comparable at baseline, unmeasured class differences may still have influenced the results.

Third, the available dataset contained group-level pretest and posttest values rather than individual-level raw data. As a result, standard deviations, confidence intervals, reliability coefficients, effect sizes, and inferential statistical tests could not be reported. This limits the strength of the conclusions and prevents claims about statistically confirmed intervention effects. Fourth, some indicators, such as participation in smart-classroom activities and instructional cost-efficiency, were operational indicators developed for this classroom context. They are useful for describing implementation, but they should not be treated as fully validated measurement scales. The cost-efficiency indicator in particular should be understood as exploratory, because a full economic evaluation would require more detailed cost records, longer observation, and sensitivity analysis.

Future studies should collect individual-level data and report means, standard deviations, confidence intervals, reliability coefficients, and effect sizes. Future measurement design could also draw on learning-analytics rubrics that connect digital trace data with self-regulated learning constructs [21]. Baseline-adjusted analyses, such as ANCOVA or difference-in-differences models, could be used to examine whether changes remain meaningful after controlling for pretest differences. Further research should also include larger samples, multiple institutions, longer intervention periods, and more detailed evidence of music learning outcomes, such as performance quality, creative development, learning motivation, and self-regulated practice. In addition, interviews or classroom observations could be added to explain how students and teachers actually experience smart-classroom activities in music-major teaching.

5. Conclusion

This study reported the design and preliminary evaluation of a smart classroom environment for undergraduate music majors. The findings indicate that, within the observed semester, the smart-classroom condition was associated with larger group-level descriptive changes than conventional instruction across the seven operational indicators. The most visible changes were found in digital resource richness, participation in smart-classroom activities, and completion of optional extension tasks. These results suggest that the value of a smart classroom for music-major teaching may lie not only in the use of digital tools, but also in the way such tools are connected with course resources, learning tasks, teacher feedback, and students' after-class engagement.

The study also shows that smart-classroom construction should be approached as a pedagogical design issue rather than a purely technical upgrade. In music education, digital resources, AI-assisted creative tools, platform records, and feedback technologies can support teaching only when they are integrated with listening, performance, analysis, creation, and reflection. At the same time, the conclusions remain preliminary. The analysis was based on group-level data from one university and one semester, without individual-level raw data or inferential statistical testing. Future research should collect student-level data, examine longer-term learning outcomes, and further evaluate how smart-classroom environments influence musical performance, creativity, motivation, and self-regulated practice.

Funding

This work was supported by the Shaanxi Provincial Education Science Planning Project (14th Five-Year Plan), China, under the project "Construction and Optimization of Smart Classroom Teaching Environments for Music Majors in Higher Education" (Grant No. SGH25Q637).

Disclosure statement

The authors declare no conflict of interest.

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