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A Human-AI Collaborative Precision Tutoring Model for Large Blended General Education Courses

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Abstract: *General education arts courses in universities often face challenges such as large class sizes, a lack of precision tutoring mechanisms, and unmet demands for personalized learning. Drawing on Human-AI collaboration theory and precision teaching theory, this study constructs a three-stage, four-step precision tutoring model characterized by "data-driven — Human-AI collaboration — iterative optimization." Taking the online elective course* Fundamentals of Photography *as a practical context, the study integrates a classroom behavior analysis system and an AI-powered artwork analysis tool into instruction. Over one semester, data on online learning behaviors, classroom behaviors, and AI-based artwork analysis were collected across four offline tutorial sessions to evaluate the model's effectiveness. The findings reveal that the precision tutoring model moderately enhances student classroom engagement and the quality of their photographic work, with significant improvements observed in technical dimensions (composition and exposure) but not in artistic dimensions (color and thematic expression). Students acknowledged the division of labor in the model, in which AI handles automated analysis of technical dimensions while the teacher focuses on guiding creative and aesthetic aspects. The introduction of technology also led to a triple transformation in the teacher's role: from "knowledge transmitter" to "data analyst," from "unified lecturer" to "differentiated instructor," and from "technology user" to "Human-AI collaboration designer." This study offers practical insights for the intelligent transformation of large-class blended teaching in universities.*

Keywords: *Human-AI collaboration, precision tutoring, classroom behavior analysis, large-class teaching, AI artwork analysis*

1. Introduction

Against the backdrop of the digital transformation of higher education and the deep integration of New Liberal Arts initiatives, general education arts courses in universities are increasingly confronted with the challenges of large class sizes, insufficient precision tutoring mechanisms, and unmet demands for personalized learning. Teachers struggle to identify individual students' weaknesses and provide timely, detailed feedback on artistic works, which hinders both teaching quality and aesthetic education goals. In response, national policies have provided clear guidance. The Opinions on Accelerating the Digitalization of Education, issued by nine ministries including the Ministry of Education in 2025, explicitly calls for "integrating artificial intelligence technology into the whole process of education and teaching, exploring new models of Human-AI collaborative teaching, and realizing large-scale personalized instruction driven by AI."[1] Likewise, the Notice on Implementing the Action for Digitally Empowering Teacher Development emphasizes "enhancing teachers' digital literacy and promoting the transformation of teaching concepts, methods, and models."[2]

Currently, classroom behavior analysis systems can capture real-time process data such as student concentration and interaction frequency, while AI tools can automatically score photographic works in technical dimensions. These technologies provide scientific support for teachers to conduct personalized precision tutoring and reform blended course instruction. However, the mere addition of technology does not guarantee improved teaching quality. AI still faces bottlenecks such as physical logic bias and insufficient emotional depth,[3] and its limitations highlight the irreplaceable role of human aesthetic judgment and life experience.[4] Thus, how to integrate behavioral data and artwork data to construct a new Human-AI collaborative teaching structure has become a critical issue for large-class general education arts courses in universities.

To address this issue, this study takes the online elective course Fundamentals of Photography as a case study and focuses on three research questions:

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- How does the Human-AI collaboration mechanism enable precision tutoring in large-class blended courses?
- How can classroom behavior data and AI artwork analysis data be integrated to achieve personalized feedback?
- What changes occur in teachers' instructional strategies and roles after the introduction of technology?

2. Theoretical Basis

2.1 Human-AI collaboration theory

Human-AI collaboration emphasizes complementarity between human intelligence and artificial intelligence rather than substitution. Zeng et al. pointed out that AI is moving from being a tool to entering a stage of "Human-AI collaboration," and future innovation lies in guiding AI toward logical self-consistency and emotional authenticity, achieving people-centered collaborative creation.[5] Li further analyzed the evolution of photographic aesthetic language from three dimensions: aesthetic carrier, creative subject, and evaluation standard, providing concrete guidance for Human-AI collaboration in photography courses.[6]

In education, AI is good at handling standardized, quantifiable tasks such as data statistics, pattern recognition, and basic scoring, which can effectively reduce teachers' workload. Teachers, on the other hand, are responsible for tasks requiring emotional resonance, creative judgment, and value guidance, such as aesthetic inspiration, personalized motivation, and creative stimulation.[7] This theory provides the core logic for constructing a precision tutoring model: AI handles quantifiable technical evaluation, while teachers focus on creative and aesthetic guidance.[8]

2.2 Precision teaching theory

Precision teaching originated from behaviorist learning theory and emphasizes making teaching decisions scientifically by frequently monitoring the frequency of learning behaviors. [9]In the digital age, the concept of precision teaching has expanded to rely on multidimensional data to accurately identify learning problems and implement targeted teaching interventions.

Fu et al. constructed a comprehensive framework for Human-AI collaborative precision teaching, proposing a three-level intervention mechanism (whole-class, group-level, and individual-level) to resolve the fundamental contradiction between large-scale instruction and personalized cultivation.[10] Wang et al. proposed a precision teaching model that returns to pedagogy, taking Human-AI collaboration as its main feature and dividing precision teaching into nine aspects: precise guidance, precise objectives, precise learning, precise diagnosis, precise intervention, precise feedback, precise evaluation, precise reflection, and precise extension. The precision tutoring model in this study focuses on the three core aspects of "precise diagnosis," "precise intervention," and "precise feedback."

3. Precision Tutoring Model Construction

The "Human-AI collaborative precision tutoring model" proposed in this study refers to a teaching approach in large-class blended courses in universities that, guided by Human-AI collaboration theory and precision teaching theory, integrates multi-source data from classroom behavior analysis systems and AI artwork analysis tools. It constructs a three-stage, four-step integrated model of "data-driven — Human-AI collaboration — iterative optimization" to achieve a whole-process learning profile of students and personalized teaching interventions.

3.1 Stage 1: Data-driven

This stage includes two steps: data collection and intelligent analysis. Data collection gathers three types of data through the course platform, smart classroom behavior analysis system, and AI artwork analysis tool: online learning behaviors (video viewing, chapter quizzes, discussion participation), classroom behaviors (concentration, eye-contact rate, interaction frequency), and AI artwork analysis (scores in composition, exposure, color, thematic expression, and problem tags). Intelligent analysis comprehensively analyzes the collected multi-source data to generate class learning portraits, individual learning trajectories, and distribution of artwork defects, providing data support for teaching decisions.

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3.2 Stage 2: Human-AI collaboration

This stage focuses on the step of precision feedback, adopting a three-tier mechanism of "AI automatic analysis — teacher differentiated feedback — precise resource push." AI automatically scores all works in technical dimensions and generates problem tags, providing immediate feedback to all students. Teachers then implement differentiated feedback based on AI analysis results: excellent works (AI total score ≥32) receive in-depth comments and are recommended for exhibitions; problematic works (AI total score ≤20) receive detailed modification suggestions; average works (AI total score 21–31) receive template feedback combined with in-class collective comments. Meanwhile, the system automatically pushes corresponding micro-course resources based on the problem tags.

3.3 Stage 3: Iterative optimization

This stage includes strategy adjustment and iterative cycles. Based on the data analysis results and feedback effects, teachers reflect on the effectiveness of teaching strategies and adjust subsequent tutoring priorities, intervention methods, and resource push strategies. After each round of tutoring, a closed loop is formed through strategy adjustment, and the next round of data collection begins, continuously bringing teaching strategies closer to students' actual needs, achieving the goal of "teaching on demand."

The three stages are progressive, and the four steps are interlocking, together forming the complete operation system of the precision tutoring model.

4. Materials and Methods

4.1 Research design

This study applied the precision tutoring model to the online elective course Fundamentals of Photography. The whole process of four offline tutoring sessions was tracked, and multi-source data were collected to evaluate the model's effectiveness.

4.2 Data collection

The study was conducted in the online general education elective course Fundamentals of Photography at Guangdong Ocean University. The course had a total of 32 credit hours, of which 24 hours were online theoretical learning (students independently watched videos and completed quizzes), and 8 hours were offline tutoring (four sessions, each 2 hours). The offline tutoring was delivered by one of the authors. A total of 156 students enrolled, from various majors across the university, with 82 males and 74 females, distributed from freshman to senior years, none with a photography background.

4.3 Implementation process

Data collection (before class): Before each offline tutoring session, the teacher integrated multi-source data for learning analysis: online learning behavior data from the course platform, the previous session's classroom behavior report from the behavior analysis system, and the AI artwork analysis report from the previous assignment. These three types of data mutually verified each other to form a class learning portrait, based on which the tutoring focus was determined.

Intelligent analysis (before class): The teacher comprehensively analyzed the collected multi-source data: correlating online learning behavior with classroom behavior to identify different types of students (e.g., high concentration but low quiz scores vs. low concentration but excellent works), and correlating AI artwork analysis with behavior to assess relationships between artwork defects and learning behavior. Based on the analysis results, the tutoring focus was determined.

Precision feedback (during and after class): During class, the teacher monitored the concentration curve and activity heatmap in real time via the system. When concentration dropped or interaction frequency decreased, the teacher immediately adjusted teaching strategies. After class, AI completed scoring and generated problem tags within 5 minutes, providing immediate feedback to all students. The teacher then implemented differentiated feedback based on AI score distribution: excellent works (AI total score ≥32) received in-depth comments and were recommended for exhibitions; problematic works (AI total score ≤20) received detailed modification suggestions; average works (AI total score 21–31) received template feedback combined with in-class collective comments. Meanwhile, the system automatically

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pushed corresponding micro-course resources based on problem tags.

Strategy adjustment and iteration (after class): After each tutoring session, the teacher reflected on the effectiveness of teaching strategies based on data analysis results and feedback effects, and adjusted subsequent tutoring priorities and intervention methods. The four tutoring sessions formed four iterative cycles, continuously optimizing teaching strategies.

4.4 Data analysis

Descriptive statistics were first used to present changes in learning behaviors and improvements in artwork quality. Paired-sample *t*-tests were used to test the significance of differences in concentration and artwork scores before and after the intervention. Satisfaction analysis of post-test questionnaires revealed students' subjective evaluations. Finally, Pearson correlation analysis was used to explore correlations among online learning behavior, classroom behavior, and artwork scores to verify the effectiveness of data integration.

5. Results

5.1 Changes in classroom behavior

The classroom behavior data for the four offline tutoring sessions and the statistical test results are shown in Table 1.

Table 1 Classroom behavior statistics.

Indicator	Session 1	Session 2	Session 3	Session 4	Comparison (Session 1 vs. Session 4)
Concentration (%)	74.2%	68.5%	71.8%	75.1%	$t=1.42$, $p>0.05$
Interaction frequency (times/person)	0.1	0.2	0.2	0.3	$t=2.86$, $p<0.05$
Attendance rate (%)	94%	92%	93%	95%	$t=1.21$, $p>0.05$

Concentration decreased by 5.7 percentage points in the second session, then gradually recovered after strategy adjustments, reaching 75.1% in the fourth session, surpassing the level of the first session. The paired-sample *t*-test showed a significant difference between the second and fourth sessions ($t=2.93$, $p<0.05$), indicating that the model effectively improved student engagement. Interaction frequency increased from 0.1 times/person in the first session to 0.3 times/person in the fourth session, a significant increase ($t=2.86$, $p<0.05$). Attendance rate fluctuated between 92% and 95%, with no significant change ($t=1.21$, $p>0.05$), suggesting it was influenced by external factors.

5.2 Changes in artwork quality

The AI analysis data of student artworks and the statistical test results are shown in Table 2.

Table 2 AI analysis statistics of student artworks.

Dimension	Pre-test mean (max 10)	Post-test mean (max 10)	t-value	p-value
Composition	6.2	7.1	2.85	<0.01
Exposure	5.8	6.5	2.31	<0.05
Color	6.5	6.9	1.52	>0.05
Thematic expression	5.5	6.1	1.96	>0.05
Total score (max 40)	24.0	26.6	2.73	<0.01
Standard deviation	4.8	4.2	1.68	>0.05

The total score increased from 24.0 to 26.6, an increase of 2.6 points (10.8%). Technical dimensions (composition, exposure) improved significantly, while artistic dimensions (color, thematic expression) did not show significant improvement, which is consistent with the laws of art education (creativity and aesthetics require long-term accumulation). The standard deviation decreased from 4.8 to 4.2, indicating a slight narrowing of the gap between students, though not statistically significant.

5.3 Student satisfaction

The post-test questionnaire had 142 valid responses. Student satisfaction with various dimensions is shown in Table 3.

Table 3 Student satisfaction evaluation.

Dimension	Mean (5-point scale)	Standard deviation	Satisfaction rate (%)
Timeliness of AI analysis	4.6	0.6	92%
Accuracy of AI analysis	3.7	0.9	72%
Usefulness of teacher feedback	4.3	0.8	85%
Matching of resource push	4.1	0.8	78%
Overall experience	4.2	0.7	83%

Students rated the timeliness of AI analysis highest (92% satisfied) and its accuracy lowest (68% satisfied), reflecting the high efficiency but limited accuracy of AI technology. The usefulness of teacher feedback (mean 4.3) was significantly higher than the accuracy of AI analysis ($p<0.01$), confirming the value of the Human-AI division of labor.

5.4 Verification of Human-AI collaboration mechanism

To verify the effect of multi-source data integration, Pearson correlation analysis was conducted on online learning behavior, classroom behavior, and AI artwork analysis data for 156 students. The results are shown in Table4.

Table 4 Correlation analysis results of three types of data.

Variable pair	n	Correlation coefficient (r)	Coefficient of determination (r^2)	t-value	p-value
Online behavior vs. classroom behavior	156	0.31	0.10	4.03	<0.01
Online behavior vs. total artwork score	156	0.24	0.06	3.07	<0.05
Classroom behavior vs. total artwork score	156	0.42	0.18	5.73	<0.01

Online learning behavior was significantly positively correlated with classroom behavior ($r=0.31$, $p<0.05$), indicating that students with better self-directed learning habits also showed higher concentration and interaction in class. Classroom behavior was moderately positively correlated with total artwork score ($r=0.42$, $p<0.01$), with a coefficient of determination of 0.18, indicating that classroom engagement directly influenced artwork quality. Online learning behavior was weakly positively correlated with total artwork score ($r=0.24$, $p<0.05$), with a coefficient of determination of only 0.06, confirming that the core improvement in photography skills depends on offline practice rather than online theoretical learning alone.

These correlations provided data support for teachers to implement differentiated instruction: for “low concentration but excellent artwork” students (about 8%), who had high online learning input, teachers encouraged personalized creation; for “high concentration but poor artwork” students (about 12%), who had low chapter quiz scores, teachers strengthened basic knowledge explanations. This differentiated instruction based on data fusion achieved a shift from “experience-based judgment” to “data-assisted decision-making.”

6. Conclusions

This study constructed a Human-AI collaborative precision tutoring model of “data-driven — Human-AI collaboration — iterative optimization” with three stages and four steps, and validated its effectiveness through one semester of practice in the online elective course Fundamentals of Photography. The results show that the model moderately improved student classroom engagement and artwork quality, with significant improvements in technical dimensions but not in artistic dimensions, which aligns with the laws of art education. AI and teachers formed an effective complementary division of labor: AI handled quantifiable, repeatable evaluation tasks with high speed and full coverage, solving the problem of delayed feedback in large-class teaching, while teachers’ differentiated feedback focused on creative and emotional guidance, addressing aesthetic biases that AI cannot handle. This division was recognized by students, though AI accuracy still requires further improvement. Data integration revealed that online learning behavior had a limited correlation with artwork quality, while classroom behavior showed a stronger correlation, confirming that photography skill improvement depends primarily on offline practice.

Several limitations should be noted. First, students’ hands-on operations can be misjudged by the system as inattention, creating a “data gap” that requires teacher observation for correction. Second, the study period was only one semester, and the sample was drawn from a single university, limiting the

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generalizability of the findings. Future research can explore multi-modal data fusion to improve data accuracy, investigate generative AI-assisted creation guidance to expand the role of AI from "analyzer" to "collaborator," and conduct cross-university comparative studies to further validate the model's applicability across different disciplines and class sizes.

After the introduction of technology, teachers' instructional strategies shifted from unified lecturing to differentiated guidance, and their roles transformed from knowledge transmitter to data analyst, from unified lecturer to differentiated instructor, and from technology user to Human-AI collaboration designer. This study offers practical insights for the intelligent transformation of large-class blended teaching in universities, demonstrating that introducing intelligent technology to build a Human-AI collaborative precision tutoring model can, to a certain extent, improve teaching efficiency and personalization. However, it is essential to clearly recognize the limitations of technology and adhere to the principle of "human-centered, machine-assisted."

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