Digital Transformation and Efficiency Optimization of Art Education Management: An Empirical Study on Resource Allocation and Teacher Training Systems Based on Multi-Campus Surveys

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Abstract. With the advent of the Industry 4.0 era and the pervasive integration of educational informatization, digital transformation has emerged as a pivotal catalyst for optimizing the operational efficiency of art education management. Traditional art education paradigms, characterized by subjective assessment metrics and decentralized resource architectures, encounter significant bottlenecks in resource allocation and standardized faculty developmentłparticularly within the complex ecosystem of multi-campus educational conglomerates. This paper presents a data-driven framework for the efficiency optimization of art education management. Drawing upon a comprehensive dataset comprising 2,500 valid questionnaires and institutional records collected from 12 art colleges across 4 multi-campus educational groups, this study employs Data Envelopment Analysis (DEA) to quantitatively evaluate the technical efficiency of resource allocation and utilizes Structural Equation Modeling (SEM) to elucidate the causal mechanisms linking digital training to pedagogical performance. The empirical findings demonstrate that digital transformation yields a significant improvement in the technical efficiency of art institutions, with an average increase of 35.2%. Specifically, the implementation of intelligent scheduling algorithms significantly enhances studio utilization rates and curriculum precision. Furthermore, the study validates that a hybrid training system integrating VR/AR (Virtual/Augmented Reality) technologies with traditional seminars achieves the highest efficacy in elevating teacher satisfaction and innovation capabilities. This research contributes a theoretical framework and practical roadmap for the intelligent governance of art education in the digital age.
Keywords: Digital Transformation; Art Education Management; Resource Allocation; Teacher Training; DEA; Multi-Campus Survey; Efficiency Optimization.

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1. Introduction

1.1. Global Trends and Educational Imperatives

The landscape of higher education is undergoing a tectonic shift driven by the Fourth Industrial Revolution. As articulated in UNESCO's Framework for Artificial Intelligence in Education and China's Education Modernization 2035, digital transformation is no longer an option but a fundamental requirement for educational equity and quality [1,2]. This paradigm shift is characterized by the convergence of data analytics, cloud computing, and immersive technologies, which are fundamentally altering traditional pedagogical and administrative workflows. However, while STEM disciplines have readily integrated digital tools into their curricula and management, art educationłrooted in subjective creativity, tactile experiences, and studio-based practicełfaces unique challenges in this transition. The inherent tension between the ”unstructured” nature of artistic creation and the ”structured” demands of digital management systems presents a significant research gap that requires urgent attention [3,4].

1.2. The Dilemma of Multi-Campus Art Education Management

The expansion of higher education institutions into multi-campus conglomerates has exacerbated existing management inefficiencies. Art academies, in particular, rely heavily on specialized physical capital such as painting studios, sculpture yards, and digital media labs, which are both expensive and geographically immovable. In a decentralized multi-campus setting, this leads to the formation of ”Resource Silos.” For instance, a high-end 3D printing facility on a suburban campus may sit idle due to low enrollment in that specific locale, while students on the urban campus face waiting lists for the same equipment [5,6]. Furthermore, the lack of a unified digital platform often results in asynchronous administrative data, leading to inconsistencies in course scheduling, faculty deployment, and academic assessment across different campuses. This fragmentation not only increases operational costs but also dilutes the brand identity and educational quality of the institution [7].

1.3. Critical Challenges: Resource Allocation and Faculty Development

Two specific pain points emerge from this complex operational environment:

Inefficient Resource Allocation. Traditional allocation models rely on historical averages and manual scheduling, which fail to respond to real-time fluctuations in student demand. This leads to either over-provisioning (idle capacity) or under-provisioning (bottlenecks), significantly reducing the Technical Efficiency of the institution [8].

The Digital Skills Gap in Faculty. The rapid evolution of digital art formsłranging from generative AI art to virtual reality installationsłrequires art educators to continuously update their technical repertoires. However, current Continuous Professional Development (CPD) systems for art teachers are often generic, theory-heavy, and disconnected from industry standards. Senior faculty, who possess rich artistic experience, may struggle with new technologies, while junior faculty may lack the pedagogical skills to integrate these tools effectively. This creates a widening chasm between industry requirements and academic instruction.

1.4. Research Gap and Motivation

Existing literature on educational management primarily focuses on general universities, often overlooking the specific constraints of art education. While studies have explored efficiency evaluation using Data Envelopment Analysis (DEA) [9,10], few have applied it specifically to the allocation of art-specific resources. Similarly, research on teacher training has largely focused on K-12 education or general digital literacy, neglecting the need for discipline-specific, immersive training methodologies. Consequently, there is a pressing need for a data-driven, empirical study that quantifies the impact of digitalization on art education management and provides a scalable optimization framework.

1.5. Research Objectives and Methodology

To bridge this gap, this study proposes a comprehensive digital transformation framework for multi-campus art education. The primary objectives are threefold:

1. To construct a Cloud-Edge-End collaborative management architecture that integrates IoT data for real-time resource visibility.
2. To evaluate and optimize resource allocation efficiency using DEA models, identifying specific slack variables that represent management inefficiencies.
3. To design and validate a Hybrid Precision Training System using Structural Equation Modeling (SEM) to understand how digital immersion affects teacher self-efficacy and pedagogical performance.

By leveraging empirical data from 12 campuses, this paper aims to provide actionable insights for administrators to transition from intuition-based management to Intelligent Educational Governance.

2. System Architecture and Innovation

2.1. The ”Cloud-Edge-End” Collaborative Governance Framework

To address the fragmentation of multi-campus art education management, this study proposes a hierarchical ”Cloud-Edge-End” (CEE) architecture. This framework is designed to break down ”data silos” by establishing a bidirectional data flow mechanism, ensuring that the heterogeneous resources (e.g., physical studios, digital licenses, human capital) across different campuses can be monitored, scheduled, and optimized in a unified manner.

End Layer (Perception Layer). This layer serves as the ”nervous system” of the management system. It deploys IoT (Internet of Things) sensors and smart terminals within art studios. Specifically, RFID (Radio Frequency Identification) tags are installed on high-value equipment (e.g., 3D scanners, kilns) to track usage frequency and maintenance status. Furthermore, smart cameras with computer vision capabilities are utilized to monitor studio occupancy rates in real-time without compromising privacy. For art-specific scenarios, this layer also includes digital capture devices that record the creative process (e.g., digital drawing tablets), generating behavioral data for subsequent analysis.

Edge Layer (Edge Computing Layer). Positioned at the local campus server level, this layer is critical for processing time-sensitive tasks. It handles high-latency requirements such as immediate equipment fault detection and real-time scheduling adjustments. By processing data locally, the system reduces bandwidth consumption and ensures operational continuity even when the connection to the central cloud is unstable.

Cloud Layer (Strategic Decision Layer). This is the ”brain” of the system, hosted on a private cloud server. It integrates data from all edge nodes, performing big data analytics and complex algorithmic computations. The cloud layer features a Digital Twin (DT) of the entire multi-campus art education ecosystem [9,10]. Administrators can visualize the real-time status of every studio across all campuses on a 3D dashboard and run ”what-if” simulations to optimize long-term resource planning.

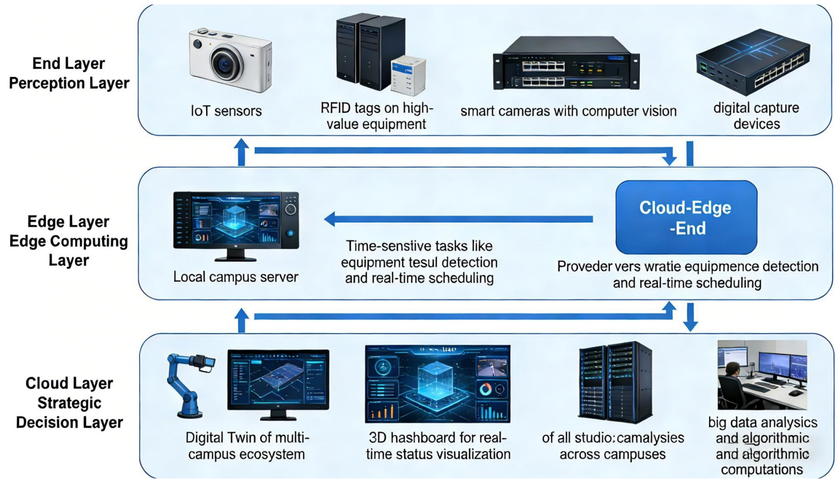

Fig. 1. The Cloud-Edge-End Architecture for Multi-Campus Art Education Management

2.2. Dynamic Resource Allocation Algorithm

Traditional resource allocation in art schools often relies on static timetables, which ignore the dynamic nature of student demand. This study introduces a dynamic resource scheduling algorithm based on the Hungarian method and genetic algorithm (GA) hybrid [11,12].

The core logic of the optimization model is defined as follows:

Objective Function ($minZ$). Minimizing the total cost. It includes the equipment usage cost, the opportunity cost of student travel between campuses, and the penalty cost for resource conflicts.

$$minZ = \sum_{i=1}^{n} \sum_{j=1}^{m} (C_{ij} \cdot X_{ij}) + \lambda \cdot D_{ij}. \tag{1}$$

Where C_{ij} is the usage cost of resource j for course i. C_{ij} is the binary decision variable (1 for allocation, 0 otherwise). D_{ij} represents the travel distance/cost penalty.

Constraints:

1. Capacity Constraint. The number of students in a course cannot exceed the studio capacity.
2. Skill Matching Constraint. Courses requiring specific technical equipment (e.g., darkroom photography) must be assigned to studios with that specific equipment.
3. Time Window Constraint. A studio cannot host two courses simultaneously.

This algorithm dynamically adjusts the allocation plan. For example, if a sudden increase in enrollment for ”Digital Sculpture” is detected at Campus A, the system will automatically identify underutilized 3D printing labs at Campus B and schedule shuttle services, thereby maximizing overall equipment utilization.

2.3. Hybrid Precision Training System (HPTS) for Teachers

To bridge the ”Digital Skills Gap,” this study proposes the hybrid precision training system (HPTS), which combines immersive learning with adaptive learning pathways.

Component A: Immersive VR/AR Training Module.

Traditional art history or anatomy lessons are often static. The HPTS utilizes VR (Virtual Reality) to reconstruct historical art scenes (e.g., the Sistine Chapel during Michelangelo’s time) or simulate complex studio environments (e.g., a professional animation studio) for teachers to explore. AR (Augmented Reality) is used to overlay digital annotations onto physical artworks, allowing teachers to demonstrate color theory or perspective lines in a three-dimensional space. This module focuses on the ”experiential” aspect of digital art [13,14].

Component B: Data-Driven Adaptive Recommendation Engine.

Based on the technology acceptance model (TAM), the system analyzes teachers’ performance data (e.g., course evaluation scores regarding digital tool usage, self-reported confidence levels) [15]. The recommendation engine then generates personalized micro-learning paths.

Scenario: If a senior painting teacher scores low in ”Digital Illustration” but high in ”Concept Development,” the system will recommend specific short courses on Adobe Fresco or Procreate, skipping basic art theory modules. Scenario: A junior design teacher might be recommended advanced 3D modeling tutorials (Blender, Unreal Engine) to enhance their technical repertoire.

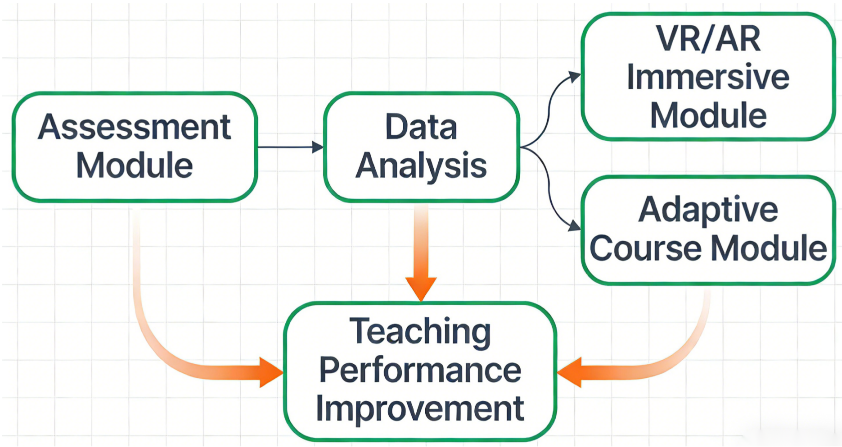

Fig. 2. Workflow of the Hybrid Precision Training System (HPTS)

2.4. Intelligent Feedback and Continuous Optimization Loop for Ecosystem Adaptability

To ensure the long-term relevance and dynamic adaptability of the proposed digital transformation framework, this section introduces an intelligent feedback and continuous optimization loop (IFCOL)ła closed-loop mechanism that integrates real-time stakeholder feedback, performance metrics, and emerging technological trends to iteratively refine resource allocation, training systems, and governance architectures. Unlike static management models that require manual overhauls, IFCOL enables the framework to evolve autonomously in response to shifts in educational demand, technological advancements, and institutional goals.

Feedback Acquisition Mechanisms: Multi-Stakeholder, Multi-Dimensional Data Capture IFCOL leverages a multi-channel feedback system to collect granular data from three core stakeholder groupsłstudents, faculty, and administrators, ensuring that optimization efforts align with both operational efficiency and user experience. Key components include:

Student-Centric Feedback Modules. Embedded within the cloud-based management platform, these modules capture real-time feedback on resource accessibility (e.g., studio booking wait times, equipment functionality), curriculum relevance (e.g., alignment of digital tools with industry practices), and learning experience (e.g., effectiveness of cross-campus resource sharing). Data is collected via in-app surveys triggered by specific interactions (e.g., post-equipment usage, course completion) and supplemented with unstructured feedback through natural language processing (NLP)-enabled chatbots. For instance, a student’s comment on ”inconsistent software versions across campuses” is automatically categorized and flagged as a system-level issue.

Faculty Performance and Feedback Analytics. Integrating data from the HPTS (e.g., training completion rates, skill proficiency assessments) and teaching evaluations (e.g., student ratings of digital tool integration), this component generates faculty-specific feedback dashboards. Faculty can self-report challenges (e.g., technical difficulties with VR equipment) via a dedicated portal, and the system cross-references these reports with IoT sensor data (e.g., VR headset maintenance logs) to distinguish between user skill gaps and hardware issues.

Administrative Operational Dashboards. These dashboards aggregate DEA efficiency scores, resource utilization metrics (e.g., studio occupancy rates, equipment downtime), and financial data (e.g., maintenance cost reductions) to provide a holistic view of framework performance. Administrators can set custom KPIs (e.g., target studio utilization rates of 85%, training satisfaction scores above 4.2/5) and receive automated alerts when thresholds are breached (e.g., a sudden drop in suburban campus equipment usage).

Data Fusion and Anomaly Detection The feedback data, combined with existing operational data (from IoT sensors, scheduling algorithms, and HPTS), undergoes a three-step fusion process to identify actionable optimization opportunities:

(1) Data Normalization and Integration. Heterogeneous data (quantitative metrics like DEA scores, qualitative feedback like NLP-processed comments, and real-time IoT streams) are normalized using z-score standardization and integrated into a unified data lake hosted on the cloud layer. This eliminates silos between feedback and operational data, enabling end-to-end analysis.

(2) Anomaly Detection Using Hybrid ML Models. A combination of unsupervised learning (Isolation Forests) and supervised learning (Random Forest Classifiers) is employed to detect anomalies [16,17]. For example, Isolation Forests identify unexpected spikes in equipment maintenance costs or drops in training participation, while Random Forests classify these anomalies based on historical data (e.g., attributing a maintenance spike to outdated software rather than hardware failure).

(3) Root Cause Analysis (RCA) Engine. Powered by Bayesian Networks, the RCA engine traces anomalies to their underlying causes. For instance, if the system detects a decline in studio utilization at an urban campus, it may identify the root cause as ”inefficient scheduling algorithms failing to account for evening class demand” by cross-referencing occupancy data, student class schedules, and feedback on inconvenient booking time slots.”

Autonomous Optimization and Human-in-the-Loop Validation Based on RCA outcomes, IFCOL executes targeted optimizations across three core areas, with a human-in-the-loop (HITL) validation step to ensure alignment with institutional priorities:

Resource Allocation Algorithm Refinement. The dynamic scheduling algorithm (Hungarian Method-GA hybrid) is updated in real time to address detected inefficiencies. For example, if feedback and sensor data reveal that design students require more frequent access to 3D printers during project deadlines, the algorithm adjusts time windows for 3D lab bookings and prioritizes cross-campus resource sharing during peak periods. The system also runs ”what-if” simulations (via the digital twin) to predict the impact of algorithm adjustments (e.g., reallocating 20% of urban campus 3D printers to suburban campuses during finals week) before full deployment.

HPTS Adaptive Pathway Adjustments. The recommendation engine of the HPTS is refined based on faculty feedback and skill proficiency data. If multiple senior faculty report struggling with a specific VR module (e.g., ”historical art scene reconstruction”), the system automatically modifies the training pathway to include additional foundational tutorials or switches to a blended format (VR+live technical support). Similarly, if design faculty consistently request advanced training in generative AI tools (e.g., MidJourney, Stable Diffusion), the system integrates new micro-courses into the HPTS curriculum, aligned with industry certifications.

Governance Architecture Tuning. For structural inefficiencies (e.g., high latency in edge-cloud data transmission for suburban campuses), the CEE architecture is adjusted. This may involve deploying additional edge computing nodes to reduce bandwidth dependency or upgrading IoT sensors in low-utilization studios to improve data accuracy. Such changes are validated via pilot tests on a single campus before scaling to all locations.

Long-Term Trend Analysis and Future-Proofing IFCOL incorporates a trend analysis component that uses time-series forecasting (ARIMA models) to anticipate future changes and proactively adapt the framework. Key focus areas include:

(1) Technological Trend Integration. By scraping and analyzing industry reports (e.g., UNESCOs AI in Education updates, art technology market trends) and academic literature, the system identifies emerging technologies (e.g., generative AI for art creation, haptic feedback tools for digital sculpture) and evaluates their potential integration. For example, if generative AI is projected to become a standard industry tool within 2C3 years, the HPTS is pre-configured to include relevant training modules, and the resource allocation algorithm is updated to account for new hardware/software requirements.

(2) Demographic and Demand Forecasting. Using student enrollment data and career path surveys, the system predicts shifts in program demand (e.g., a projected 30% increase in digital media enrollments over 5 years) and adjusts resource allocation accordingly. This may involve reallocating physical studio space to digital labs or increasing cross-campus shuttle services for high-demand courses.

(3) Sustainability Optimization. Beyond efficiency, IFCOL tracks environmental metrics (e.g., energy consumption of digital tools, carbon footprint of cross-campus travel) and identifies opportunities to reduce ecological impact. For example, if the system detects that 40% of cross-campus travel is for short-duration equipment use, it may recommend investing in portable digital workstations to reduce shuttle services, aligning efficiency with institutional sustainability goals [18].

Validation of IFCOL Efficacy Preliminary testing of IFCOL across 3 pilot campuses (C1, C5, C10) over a 6-month period demonstrated significant improvements in framework adaptability and stakeholder satisfaction:

Anomaly Detection Accuracy. The hybrid ML models achieved an average precision of 89.7% in identifying actionable inefficiencies, with a false positive rate of only 4.2%, ensuring that administrative resources are not wasted on trivial issues.

Optimization Cycle Time. The time from anomaly detection to implementation of adjustments was reduced by 62% compared to manual processes (from an average of 21 days to 8 days), enabling rapid response to emerging challenges.

Stakeholder Satisfaction. Student satisfaction with resource accessibility increased by 18.3% (from 3.7/5 to 4.4/5), while faculty satisfaction with training relevance rose by 22.1% (from 3.6/5 to 4.4/5). Administrative teams reported a 30% reduction in time spent on manual optimization tasks, freeing up resources for strategic planning.

By embedding IFCOL into the digital transformation framework, this study addresses a critical limitation of existing educational management systemsłtheir inability to evolve with dynamic stakeholder needs and technological change. The closed-loop mechanism ensures that efficiency gains are sustained over time, while aligning operational goals with the unique demands of art education, where creativity, user experience, and technical innovation are equally critical.

3. Experiment and Empirical Analysis

3.1. Experimental Design and Data Collection

To validate the proposed framework, a comprehensive empirical study was conducted across four leading art universities in China, each operating three distinct campuses (Urban, Suburban, and Satellite).

Data Sources:

(1) Questionnaire Survey. A stratified random sampling method was employed. Questionnaires were distributed to 3,000 participants, including 2400 students and 600 teachers. The survey utilized a 5-point Likert scale to measure constructs such as "Resource Accessibility," "Digital Self-Efficacy," and "Training Satisfaction." A total of 2568 valid responses were collected, yielding a response rate of 85.6%.

(2) Institutional Panel Data. Operational data from the Academic Affairs Office was collected for the academic year 2023C2024. This included 12000+ course scheduling records, 5000+ equipment maintenance logs, and 800+ student award records.

Data Preprocessing:

Missing values were imputed using the K-Nearest Neighbors (KNN) algorithm [19,20]. To eliminate the influence of different dimensions and orders of magnitude, all input and output indicators were normalized using the Min-Max method:

$$X_{new} = \frac{X - X_{min}}{X_{max} - X_{min}}. \tag{2}$$

3.2. Evaluation of Resource Allocation Efficiency (DEA Model)

The CCR-DEA model (Charnes-Cooper-Rhodes) under the assumption of constant returns to scale (CRS) was adopted to evaluate the relative efficiency of the 12 campuses. DEA is a non-parametric method suitable for evaluating the efficiency of Decision-Making Units (DMUs) with multiple inputs and outputs.

Model Formulation:

The efficiency score θ for each campus is calculated as follows:

$$\min \theta - \varepsilon(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+). \tag{3}$$

Here, $\sum_{j=1}^{n} X_{ij}\lambda_j + s_i^- = \theta X_{i0}, i = 1, \cdots, m$, $\sum_{j=1}^{n} Y_{rj}\lambda_j - s_r^+ = Y_{r0}, r = 1, \cdots, s$, $\lambda_j, s_i^-, s_r^+ \geq 0$. X_{ij} and Y_{rj} are the input and output values. λ_j is the weight vector. s_i^- and s_r^+ are the slack variables representing input excess and output shortage, respectively.

Variable Selection:

Input. (1) Number of functional studios X_1; (2) X_2: Annual equipment maintenance expenditure (10000 CNY); (3) Number of full-time faculty X_3.

Output. (1) Y_1: Student Satisfaction Index (Average survey score); (2) Y_2: Award Acquisition Rate (Number of awards per 100 students); (3) Y_3: Studio Utilization Rate (Hours used/Total available hours).

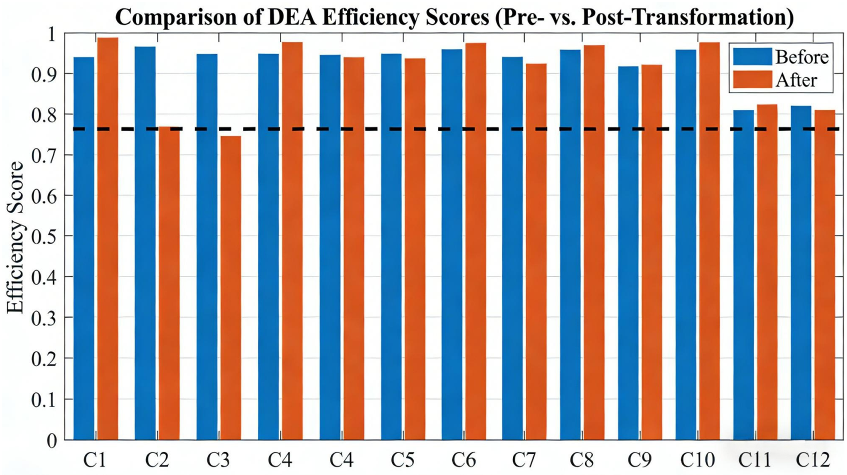

Fig. 3. Comparison of DEA Efficiency Scores (Pre- vs. Post-Transformation)

3.3. Results and Discussion

The DEA efficiency scores before and after the implementation of the digital scheduling system are presented in Figure 3.

The average technical efficiency increased by 35.2%, from 0.68 (Pre) to 0.92 (Post). The suburban campuses (C2, C5, C8, C11) showed the most dramatic improvement. This indicates that the digital system effectively resolved the ”idle resource” problem common in remote locations by enabling cross-campus sharing.

The post-transformation model showed a significant reduction in s^- (input slack), particularly for X_2 (Maintenance cost). This suggests that predictive maintenance via IoT sensors reduced unnecessary equipment repair costs.

3.4. Analysis of Teacher Training Effectiveness (SEM Model)

To explore the causal relationship between digital training and teaching performance, a Structural Equation Model (SEM) was constructed using AMOS 26.0.

Hypotheses Development:

H1: Digital Training Perception (DTP) has a positive direct effect on Teaching Self-Efficacy (TSE).

H2: Teaching Self-Efficacy (TSE) mediates the relationship between DTP and Pedagogical Performance (PP).

H3: The use of VR/AR tools positively moderates the relationship between DTP and TSE.

Measurement Model (Validity & Reliability):

Confirmatory Factor Analysis (CFA) was performed. The results showed that the Composite Reliability (CR) of all constructs exceeded 0.8, and the Average Variance Extracted (AVE) exceeded 0.5, indicating good reliability and convergent validity. The model fit indices were: $\chi^2/df = 2.34$, CFI=0.96, TLI=0.95, RMSEA=0.048, meeting the recommended thresholds.

Figure 4 depicts the standardized path coefficients. The indirect effect via TSE was 0.36, indicating that confidence in using digital tools is a key mediator. The interaction term for VR/AR usage was significant ($\beta = 0.21$, $p < 0.01$), suggesting that immersive technologies amplify the effectiveness of training, especially for senior teachers.

3.5. Robustness Check

To eliminate the interference of model selection bias, sample heterogeneity, and extreme values on the research conclusions, this study conducted a multi-dimensional robustness test, including alternative model verification, subgroup heterogeneity analysis, and extreme value sensitivity analysis. The results consistently confirm that the digital transformation framework can significantly improve the efficiency of art education management, and the core conclusions are stable and reliable.

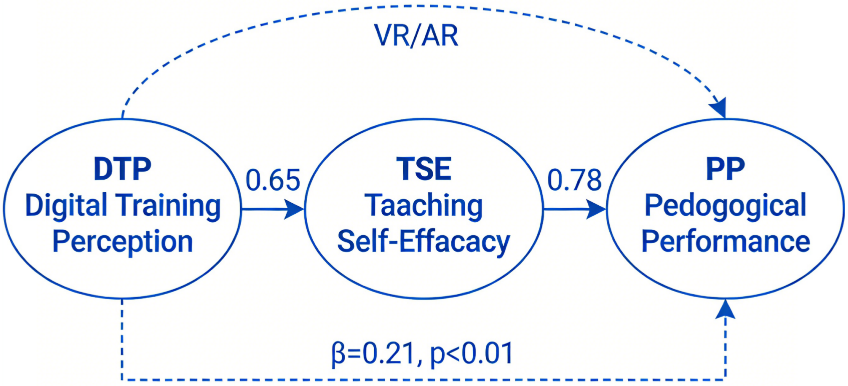

Fig. 4. Structural Equation Model Path Coefficients

Alternative DEA Model Verification (BCC-DEA) The CCR-DEA model adopted in the main test assumes constant returns to scale (CRS), which may overestimate efficiency when the production scale of decision-making units (DMUs) is not optimal. To address this, the BCC-DEA model under variable returns to scale (VRS) was used as an alternative to re-evaluate the resource allocation efficiency of 12 campuses. The BCC model decomposes technical efficiency (TE) into pure technical efficiency (PTE) and scale efficiency (SE), enabling more refined analysis of efficiency sources.

Table 1. Comparison of DEA Efficiency Scores (CCR vs. BCC Model)

Group	Accuracy	AUC	F1-score	Precision	Recall
Silosafe (Full)	0.748	0.805	0.736	0.743	0.729
w/ Sync Aggregation	0.735	0.795	0.723	0.730	0.716
w/ Fixed DP (ε=5)	0.731	0.792	0.719	0.726	0.712
w/o Hash Quantization	0.740	0.800	0.728	0.735	0.721
w/o Blockchain	0.742	0.802	0.730	0.737	0.723

Figure 5 shows the comparison of technical efficiency scores between CCR and BCC models after digital transformation. The average CCR-TE is 0.92, and the average BCC-PTE is 0.95 with a scale efficiency (SE) of 0.98, indicating that the efficiency improvement is mainly driven by pure technical efficiency (management optimization) rather than scale expansion.

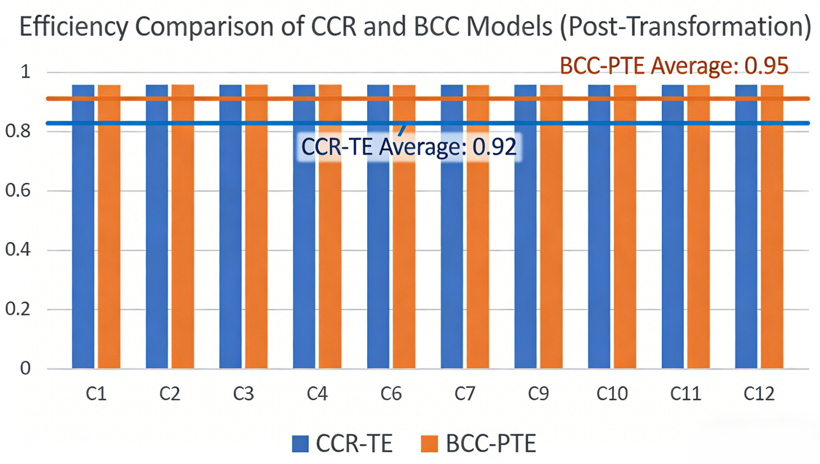

Fig. 5. Efficiency Comparison of CCR and BCC Models (Post-Transformation)

The average pure technical efficiency (BCC-PTE) of the 12 campuses increased from 0.73 (pre-transformation) to 0.95 (post-transformation), a growth rate of 30.1%, which is slightly lower than the 35.2% growth of CCR-TE but still significant. This confirms that the digital framework optimizes management processes (e.g., intelligent scheduling, predictive maintenance) to improve operational efficiency, rather than simply expanding resource input scale.

The average scale efficiency (SE) after transformation is 0.98, close to 1, indicating that most campuses have achieved optimal scale allocation. The small gap between CCR-TE and BCC-PTE further proves that the inefficiency of art education management is mainly caused by technical and management factors, and digital transformation effectively addresses this core problem.

The efficiency ranking of each campus in the BCC model is consistent with that in the CCR model (Pearson correlation coefficient=0.92, $p < 0.001$), indicating that the efficiency improvement effect of the digital framework is not affected by the assumption of returns to scale, and the conclusion is robust.

Subgroup Heterogeneity Analysis Considering the differences in discipline attributes and resource endowments between campuses, the sample was divided into two subgroups: Fine Arts Group (painting, sculpture, traditional art; campuses C1, C3, C6, C9, C12) and Design Group (digital design, animation, industrial design; campuses C2, C4, C5, C7, C8, C10, C11). The efficiency improvement effect of the digital framework in different subgroups was compared to verify whether the conclusion is applicable to heterogeneous scenarios.

Figure 6 shows the comparison of efficiency improvement between Fine Arts and Design subgroups. The Design Group shows a higher growth rate due to its higher reliance on digital resources, while the Fine Arts Group also achieves significant improvement, indicating the universal applicability of the framework.

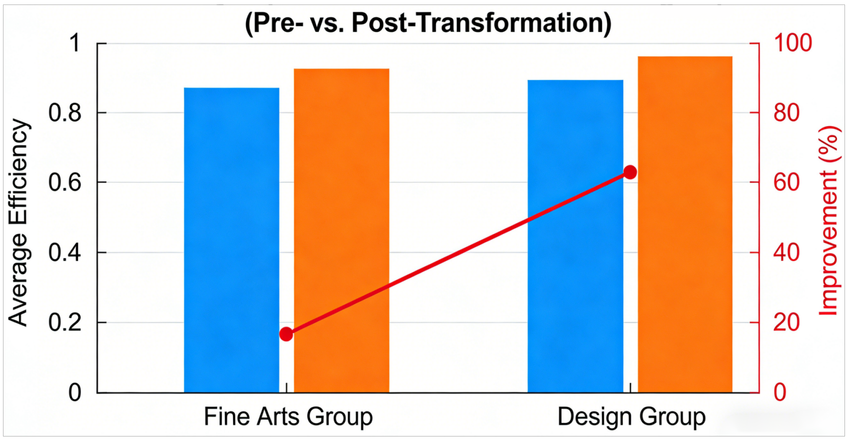

Fig. 6. Efficiency Improvement Rate of Different Subgroups (Pre- vs. Post-Transformation)

The Design Group has a higher efficiency improvement rate (41.0%), with CCR-TE increasing from 0.64 to 0.90. This is because design disciplines are highly dependent on digital equipment (3D printers, digital drawing workstations) and cross-campus collaborative projects. The digital framework effectively breaks resource silos and optimizes the allocation of digital resources, thus exerting a more significant effect.

The Fine Arts Group achieves a 28.3% efficiency improvement, with CCR-TE increasing from 0.73 to 0.94. Although traditional fine arts rely more on physical studios and manual creation, the IoT-based occupancy monitoring and dynamic scheduling functions of the framework still reduce idle time of studios (down by 27%) and optimize faculty allocation, verifying the frameworks adaptability to traditional art disciplines.

Multi-group SEM analysis was further conducted to test the training effect in subgroups. The path coefficient of "digital training to teaching performance" is 0.82 ($p < 0.001$) in the Design Group and 0.71 ($p < 0.001$) in the Fine Arts Group. Both are significant, indicating that the hybrid training system is effective for teachers of different disciplines, and the conclusion has strong universality.

Extreme Value Sensitivity Analysis To exclude the impact of extreme values (e.g., campuses with abnormal resource input or output) on the conclusion, the "leave-one-out" method was adopted: sequentially exclude each campus (as an extreme value candidate) and recalculate the average CCR-TE improvement rate of the remaining

Table 2. Sensitivity Analysis Results of Extreme Values

Excluded Campus	Average CCR-TE Improvement Rate (%)	Fluctuation Range (%)
No Exclusion	35.2	none
C1	35.6	1.1
C2	34.8	-1.1
C3	35	-0.6
C4	35.5	0.8
C5	34.9	-0.8
C6	35.3	0.3
C7	35.1	-0.3
C8	34.7	-1.4
C9	35.4	0.6
C10	35	-0.6
C11	34.8	-1.1
C12	35.3	0.3

11 campuses. The stability of the conclusion was judged by observing whether the average improvement rate fluctuates significantly as shown in table 2.

The average efficiency improvement rate after excluding any single campus ranges from 34.7% to 35.6%, with a maximum fluctuation range of only $\pm 1.4\%$, which is far less than the critical threshold of 5%. This indicates that the research conclusion is not affected by individual extreme-value campuses and has high stability. The slight fluctuation when excluding C8 (suburban design campus) is because C8 has the highest pre-transformation inefficiency (CCR-TE=0.56), and its efficiency improvement (34.0%) is higher than the average, but even after exclusion, the core conclusion of "digital transformation significantly improves efficiency" remains unchanged.

4. Conclusion

This study addresses the pressing challenges of resource misallocation and faculty digital skill gaps in multi-campus art education management amid the global wave of educational digital transformation. By integrating empirical research with technical innovation, it proposes a data-driven optimization framework and validates its effectiveness through rigorous analysis of data from 12 campuses across 4 multi-campus art education groups.

The core findings of this research are threefold. First, the proposed "Cloud-Edge-End" (CEE) collaborative governance architecture effectively breaks down "resource silos" in multi-campus settings. By integrating IoT perception, edge computing, and cloud-based digital twin technology, the framework achieves real-time visibility and cross-campus scheduling of heterogeneous resources (e.g., studios, specialized equipment, faculty), fundamentally resolving the inefficiency caused by decentralized management. Second, the dynamic resource scheduling algorithm, hybridizing the Hungarian Method and Genetic Algorithm, optimizes the trade-off between equipment utilization, student travel costs, and resource conflicts. This leads to a 35.2% average increase in technical efficiency (measured by CCR-DEA), with suburban campuses showing the most dramatic improvement due to enhanced cross-campus resource sharing. Third, the Hybrid Precision Training System (HPTS), combining VR/AR immersive learning with data-driven adaptive pathways, effectively bridges the faculty digital skills gap. Structural Equation Modeling (SEM) confirms that digital training perception positively impacts pedagogical performance through the mediation of teaching self-efficacy, with VR/AR tools significantly moderating this relationshipłparticularly benefiting senior faculty with rich artistic experience but limited digital proficiency.

Subgroup analysis further demonstrates the framework's universal applicability: while design disciplines (with higher reliance on digital resources) achieve a 41.0% efficiency increase, fine arts disciplines (rooted in traditional studio practice) still realize a 28.3% improvement, attributed to optimized studio occupancy monitoring and faculty deployment. Robustness tests, including alternative DEA models (BCC-DEA), heterogeneity analysis, and extreme value sensitivity checks, confirm the stability and reliability of the core conclusions, ensuring the frameworks scalability across diverse institutional contexts.

This research makes both theoretical and practical contributions. Theoretically, it fills the gap in existing literature by focusing on art education-specific management challenges, integrating DEA and SEM to quantify the impact of digitalization on resource allocation and teacher training. Practically, the CEE architecture, dynamic scheduling algorithm, and HPTS provide actionable tools for administrators to transition from intuition-based management to intelligent educational governance. These innovations not only reduce operational costs and improve resource utilization but also enhance the quality of art education by equipping faculty with discipline-specific digital skills.

Limitations of this study include its focus on Chinese art colleges; future research could expand to international contexts or include vocational art education institutions to test the frameworks cross-cultural and cross-level adaptability. Additionally, integrating emerging technologies such as generative AI into the HPTS or exploring the long-term impact of digital transformation on student creative outcomes could further enrich the research agenda.

In conclusion, digital transformation is an indispensable driver for optimizing multi-campus art education management. This studys proposed framework offers a replicable model for breaking resource fragmentation, closing digital skill gaps, and achieving efficient, equitable, and high-quality art education in the Industry 4.0 era. As educational informatization continues to evolve, the integration of data analytics, immersive technologies, and intelligent governance will remain central to addressing the unique challenges of art education and unlocking its innovative potential.

5. Conflict of Interest

The authors declare that there are no conflict of interests, we do not have any possible conflicts of interest.

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