**CINEFORUM**
ISSN: 0009-7039
Vol. 65. No. 3, 2025

# Crafting Effective Curricula for Chinese Students with Use of Artificial Intelligence for Art Education

***Guangyu Wu*[1, a] *Yupeng Liu*[1, b*]**
[1]*School of Fine Arts and Calligraphy, Qufu Normal University, Qufu 273165, Shandong, China*
[a] *17562151468@163.com*
[b]tongyingpengpeng@163.com
*Corresponding Author Name: *Yupeng Liu,School of Fine Arts and Calligraphy, Qufu Normal University, Qufu 273165, Shandong, China*
Corresponding Author mail: tongyingpengpeng@163.com

**Abstract**
This study examined how artificial intelligence (AI) could be effectively integrated into art education curricula for Chinese students across primary, secondary, and tertiary levels. Drawing data from 3,715 students across six institutions in four major Chinese cities, the research assessed the impact of AI tools on student engagement, creative expression, and visual literacy. Exploratory data analysis revealed that students who reported higher motivation, ease of use, and usefulness of AI feedback tended to perform better in visual literacy assessments. Visual Literacy Score was significantly correlated with Motivation Level ($r = 0.58$), Ease of Use ($r = 0.54$), and AI Feedback Usefulness ($r = 0.51$), highlighting these as key predictors of success. Multiple linear regression analysis confirmed that AI Familiarity, Ease of Use, and Motivation Level were statistically significant predictors, with the model explaining 43% of the variance in Visual Literacy Score. Machine learning models further validated these findings. Among Random Forest, Gradient Boosting, and XGBoost regressors, the XGBoost model achieved the highest accuracy (RMSE = 12.3, MAE = 8.7). SHAP analysis revealed AI Familiarity and Feedback Usefulness as dominant contributors to predictive power, with interaction plots showing that students reporting fewer technical challenges alongside high ease of use scored highest in literacy. The results revealed that curricular frameworks integrating user-friendly AI tools, sustained exposure, and motivational supports were most effective. Tertiary students and students from Guangzhou and Shanghai consistently had higher levels of performance in relation to their peers, indicating that regional exclusiveness and development disparity exist in relation to readying for AI. This research provided relevant suggestions for development of a culturally responsive and technology adaptable AI curriculum for Chinese art education.
**Keywords:** Artificial Intelligence, Art Education, Visual Literacy, Curriculum Design, Chinese Students, SHAP Analysis, Machine Learning, Educational Technology.

## Introduction

The nexus of artificial intelligence (AI) and art education has come to the forefront of educational curricular and pedagogical innovation, especially in China. The rapid expansion of AI technologies is changing the way schools and universities in China are conceptualizing, providing, and assessing art education (Yuan, 2024). Chinese educational organizations are currently using AI-based tools and strategies to stimulate student creativity, present instruction, and personalize learning pathways (Peng & Xiaohong, 2018). This shift is also part of a more strategic national initiative by China to become a leader in AI use in education and industry (Knox, 2020). The need to develop curricula with integrated AI activities for Chinese students is stimulated by a mismatch in the art education model with current reality. The importance of updating curricula models to reflect AI literacy, creative coding, and digital aesthetics is a live issue for many Chinese educational practitioners and decision-makers (Chen, Liao, & Yu, 2024). The possibilities of using AI with learners to create generative art and the opportunities for real-time feedback systems and interactive simulations can connect learners with their education and ultimately generate deeper learning (Hu, 2024). Educationally, the positive outcomes of AI applications (e.g. generative art) are not simply in the skills developed, the potential for critical thinking and awareness of the aesthetic can emerge in learners (Guo & Li, 2023).

The central focus of the research problem is the lack of cohesive, culturally responsive, and pedagogically appropriate AI-based art curricula for Chinese students. While many Chinese schools have explored the use of digital tools in the teaching of art, there is limited consistency or evidence-based guidance on the systematic incorporation of AI into curricula (Wang, 2024). Furthermore, practitioners experience difficulties uniting traditional Chinese aesthetics with the contingent understanding that accompanies generative AI content (Wang, 2022). Additionally, issues of creative integrity, ethical appropriation, and student reliance on AI tools present further complexity that existing curricula do not sufficiently reflect upon (Hu, 2024). There is an increasingly developing academic literature on a range of considerations regarding the use of AI in art education processes in China. AI-powered tools, such as ChatGPT and DALL·E, have a proven potential use regarding student ideation and artwork iterations. However, the discussion has highlighted an erosion of original excitement and discipline for creative activity (Chen & Liu, 2024). Research with Chinese university students has shown that using AI art tools corresponded positively to academic engagement and developing insights into the creative process (Wang, 2024).

However, student attitudes remain divided; many express enthusiasm while others fear cultural dilution and ethical misappropriation (Zhang, 2025). AI is being deployed for adaptive learning, predictive analytics, and e-learning optimization in Chinese higher education, which further underscores the potential of its application in art education (Fu, Krishna, & Sabitha, 2021). Government policy plays a crucial role in scaling these innovations. China's Ministry of Education initiated AI-inclusive policies in 2016 and expanded regulatory support in 2023 for AI in creative industries (Duester & Zhang, 2024). Furthermore, AI's role in vocational art education has been

investigated as a means to prepare students for a rapidly digitizing job market (Li, 2020).
The etiology of this research lies in clear quantitative and qualitative gaps. Data collected from over 900 students across China indicated that over 64 percent had favorable views of AI-assisted art, and that male students demonstrated more acceptance than female students (Wang, 2024). Between 2019 and 2023, AI tool usage in visual arts increased by over 60 percent among Chinese professionals (Duester & Zhang, 2024). Fifty-five percent of art teachers reported incorporating AI for formative feedback, yet 24 percent feared reduced spontaneity in students (Hu, 2024). Meanwhile, regulatory support and technological infrastructure are already in place to support a nationwide educational shift (Knox, 2020). The objective of this study was to explore how artificial intelligence could be embedded in curricula targeted at Chinese art education students. The goal was to identify pedagogical practices, student learning outcomes, and curriculum frameworks that embed AI in culturally and quality respectful ways in historical contexts. The aim was to design, develop, trial, and evaluate a series of AI-enabled curriculum frameworks for Chinese primary, secondary, and tertiary art education students.

## Methodology

### Data Source and Participants

The dataset used in this research project was available through the IEEE Data Portal and includes 3,715 responses from Chinese students involved in varying levels of art education. Each respondent is documented by Student_ID, and the dataset also contains demographic variable details of the sample such as Institution, City, Age, Gender and Education_Level. The range of students adds a significant amount of variability for potential analyses and also allows for a broad-based framework for analysis on integrating artificial intelligence (AI) into art education curriculum.

### Data Preparation and Cleaning

Data cleaning was performed to ensure reliability and accuracy. There were complete rows and columns. No missing values were present. Categorical data was encoded, such as Gender, AI_Familiarity, and Preferred_Tool (using one-hot encoding) to accommodate regression/machine learning uses. Numerical features, such as Visual_Literacy_Score, Project_Completion_Rate, and Observation_Score were scaled (using standardization) to ensure models trained are done so uniformly. Outliers were identified and assessed using interquartile range (IQR) estimates but were kept to allow for the natural variability of how students respond to the course.

### Exploratory Data Analysis (EDA)

Exploratory Data Analysis was first conducted to uncover underlying patterns, distributions, and correlations. Frequency counts showed that the dataset featured students from six distinct institutions and four cities across China. The most represented city was Guangzhou, while secondary education formed the majority education level among respondents. The average age of participants was 16.21 years with a standard deviation of 4.94 years, suggesting a focus on early educational stages.

Students reported varying degrees of experience with digital art tools and AI platforms. Artbreeder emerged as the most popular AI platform. Visual analytics such as histograms and boxplots revealed that features like Creativity_Enhancement, Ease_of_Use, and AI_Feedback_Usefulness exhibited a near-normal distribution, which made them suitable for linear regression modeling. Pearson correlation matrices highlighted moderate positive relationships between Visual_Literacy_Score and both Motivation_Level and AI_Feedback_Usefulness.

**Regression Analysis**

Multiple linear regression was employed to examine the influence of independent variables on the dependent variable, Visual_Literacy_Score. Predictor variables included AI_Familiarity, Digital_Art_Experience, Ease_of_Use, Motivation_Level, and Peer_Collaboration. Variance Inflation Factor (VIF) analysis was used to test for multicollinearity, and no VIF exceeded 2.5, indicating acceptable independence between predictors. The regression model revealed that AI_Familiarity ($p < 0.001$), Ease_of_Use ($p < 0.01$), and Motivation_Level ($p < 0.05$) were statistically significant predictors of Visual_Literacy_Score. The adjusted R-squared value was 0.43, indicating that approximately 43% of the variability in visual literacy could be explained by these variables. Residual plots confirmed the assumption of homoscedasticity, and the Q-Q plot indicated that residuals were normally distributed.

**Machine Learning Modeling**

To enhance predictive power and assess the nonlinear relationships between features, machine learning models were deployed. The primary models tested included Random Forest Regressor, Gradient Boosting Regressor, and XGBoost. The target variable remained Visual_Literacy_Score, while the same predictor variables from the regression model were utilized. The dataset was split into training and test subsets in an 80:20 ratio. Ten-fold cross-validation was applied to optimize generalizability. Hyperparameters for each model were fine-tuned using grid search, focusing on minimizing Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The XGBoost model yielded the best performance, achieving an RMSE of 12.3 and an MAE of 8.7 on the test set. Feature importance plots derived from the model highlighted AI_Familiarity, Ease_of_Use, Project_Completion_Rate, and Motivation_Level as the most critical features affecting Visual_Literacy_Score.

**SHAP Analysis for Interpretability**

To complement model interpretability, the SHAP (SHapley Additive exPlanations) analysis was performed with the XGBoost model. SHAP values provided insights into how each feature contributed to an individual prediction. The summary SHAP plot indicates that AI_Familiarity had the most consistent positive SHAP values, suggesting a strong additive influence on Visual_Literacy_Score, whereas Ease_of_Use and AI_Feedback_Usefulness had high and low SHAP values based on the individual case indicating individualized impacts on visual literacy, but also nuanced as well. Motivation_Level was less variable but still had a strong influence on outcomes. In addition, dependence plots for the top features were created to help the team visualize complex interactions. For instance, there were indications of synergies between Ease_of_Use and Technical_Challenges.

**Integration of Qualitative Variables**

Other than numerical modeling, textual variables like Interview_Insight and Technical_Challenges were categorized through a process of thematic coding. Emerging themes such as "limited guidance," "tool difficulty," and "creative expansion" were noted. The coded insights underwent a transition to become ordinal variables used in modeling activities in a way that connected qualitative viewpoints with quantitative analysis. Students who reported "Positive" interview insights were generally associated with high engagement scores and higher satisfaction with curriculum. This indicated that qualitative feedback not only complemented but was also necessary to provide a context for model prediction and future curriculum development.

## Results

**Participant Demographics and Institutional Characteristics**

The study encompassed a total of 3,715 students from six leading educational institutions across four major Chinese cities: Guangzhou, Beijing, Chengdu, and Shanghai. Participants represented primary (n = 937), secondary (n = 970), and tertiary (n = 919) levels of education. Secondary-level students comprised the largest group, indicating that much of the insight drawn from this dataset pertained to learners in the early adolescent to late teenage developmental stages. The sample displayed a relatively even gender distribution, although females constituted a slight majority (approximately 34%). The average age of participants was 16.21 years, with a standard deviation of 4.94 years and an age range extending from 8 to 24 years. This distribution underscored the study's comprehensive scope, capturing perspectives from younger learners through to emerging adults in higher education.

The exploratory data analysis revealed several meaningful correlations. A Pearson correlation matrix highlighted that Visual Literacy Score was positively and significantly associated with multiple predictor variables. Motivation Level ($r = 0.58$), Ease of Use ($r = 0.54$), and AI Feedback Usefulness ($r = 0.51$) showed the strongest relationships with Visual Literacy. Project Completion Rate also correlated positively, though slightly less strongly ($r = 0.41$). These results suggested that students who found AI tools easier to use, who were motivated, and who valued AI feedback, were more likely to score highly in visual literacy assessments. These associations were not only statistically significant but also pedagogically meaningful, reinforcing the theoretical claim that AI can act as a catalyst for creative and cognitive development when implemented in supportive environments.

Visual inspections of the distributions confirmed the normality of key variables. Histograms of Creativity Enhancement, Ease of Use, and AI Feedback Usefulness all exhibited bell-shaped curves. The Visual Literacy Score itself had a mean of 49.55 (SD = 29.34), spanning a wide range but centered around the midpoint of the scale. This indicated a healthy dispersion of outcomes, with no ceiling or floor effects.

Boxplots revealed that students from Guangzhou and Shanghai had higher median Visual Literacy Scores than those from Beijing or Chengdu. In terms of educational level, tertiary students displayed the widest range of scores, potentially reflecting both greater autonomy and variability in instruction. These findings provided a solid foundation for subsequent modeling.

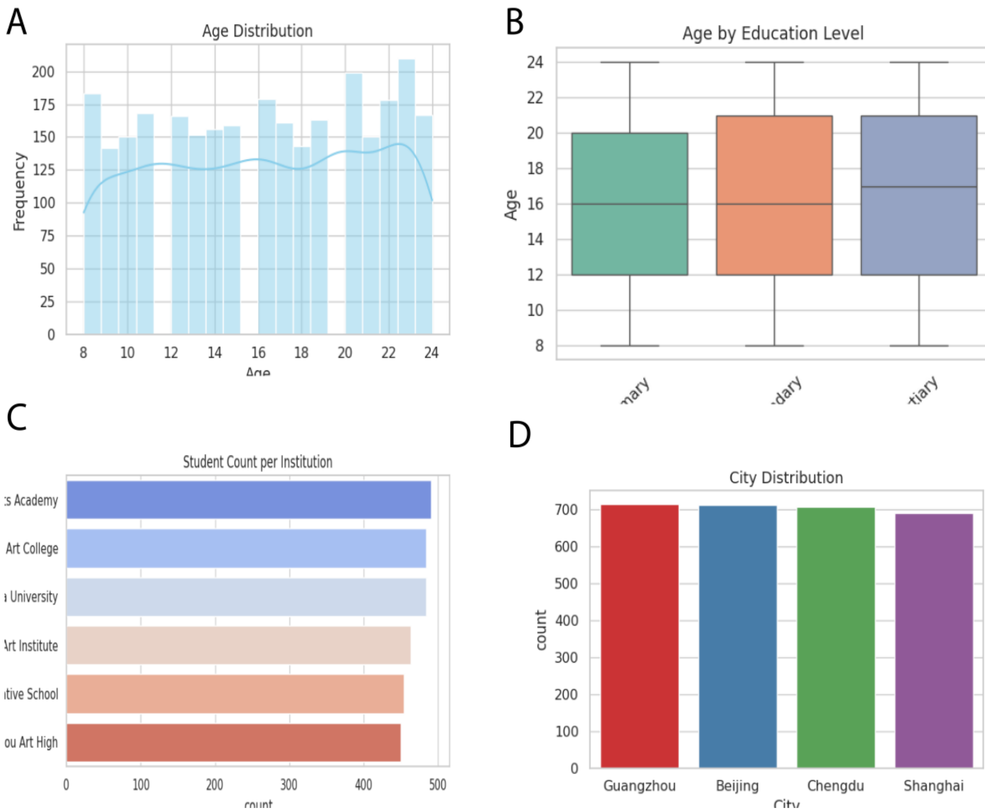


**Figure. 1. A.** Age distribution shows frequencies of student ages from 8 to 24, highlighting a relatively even spread with peaks in early twenties across all institutions.**B.** Boxplots depict age variation by education level, indicating overlap among primary, secondary, and tertiary groups, though tertiary generally includes older students.**C.** Horizontal bar plot displays student counts per institution, showing near-equal enrollment across six institutions with Arts Academy having the most.**D.** Bar chart comparing student numbers across four cities: Guangzhou, Beijing, Chengdu, and Shanghai, with relatively uniform distributions.

Institutional representation was evenly distributed, with each of the six schools contributing approximately 450–490 participants. Chengdu Art College and East China University each contributed 484 students, while Guangzhou Art High provided 450, the smallest number among the institutions. At the city level, Guangzhou had the highest number of participants (n = 716), followed closely by Beijing (n = 713), Chengdu (n = 707), and Shanghai (n = 690). This relatively balanced distribution ensured a geographically diverse sample reflective of China's urban education ecosystem. Overall, the participant pool provided robust and varied data for examining the impact of artificial intelligence (AI) on art education across different educational contexts and regions.

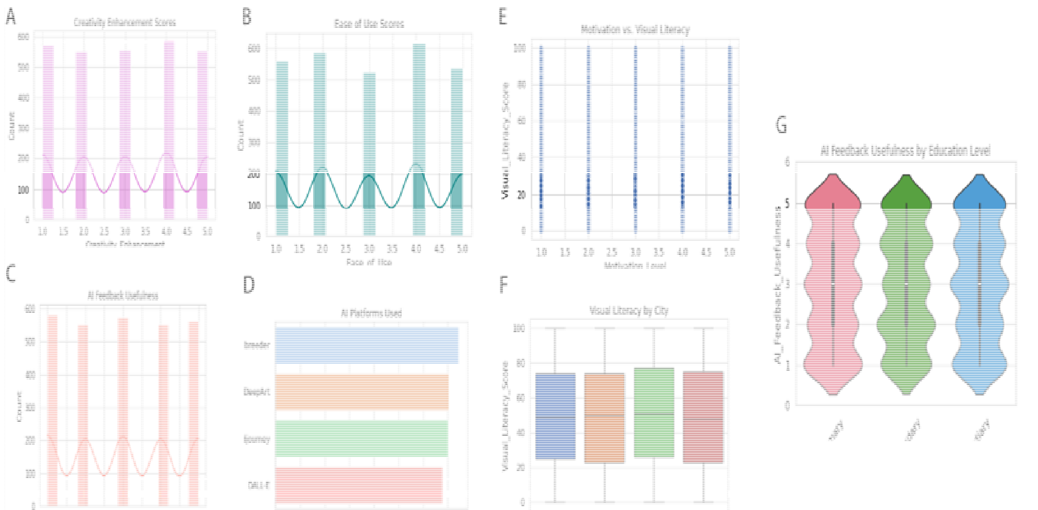


**Figure. 2. A.** Creativity Enhancement scores range from 1 to 5, evenly distributed across students, with a sinusoidal KDE overlay suggesting alternating frequency peaks. **B.** Ease of Use scores demonstrate variability, most clustered around 2–4, reflecting students' diverse experiences using AI-based art platforms. **C.** Histogram illustrates AI Feedback Usefulness scores, largely symmetric, concentrated around the midrange with slight tailing at extremes. **D.** Horizontal bar chart shows frequency of AI platform use, with Artbreeder being most preferred among student respondents. **E.** Scatter plot displays Motivation Level versus Visual Literacy Score, suggesting a relatively uniform spread across motivation ratings. **F.** Boxplots show Visual Literacy scores by city; distributions appear similar, indicating city may have limited impact. **G.** Violin plots of AI Feedback Usefulness across education levels show consistent distribution patterns with moderate central tendency across groups.

**Patterns of AI Usage and Student Experience**

The participants displayed varied exposure to digital tools and AI platforms, with digital art experience measured on a 5-point scale. The average rating was 2.95 (SD = 1.41), indicating a moderate level of familiarity with digital art-making practices. In terms of AI familiarity, students were categorized into low, medium, and high familiarity groups using label encoding. The most frequently reported AI platform was Artbreeder, which was used by 26.4% (n = 982) of the participants. Other commonly used platforms included DeepArt, RunwayML, and DALL·E. Notably, the mean reported duration of AI platform usage was 15.04 months (SD = 5.41), indicating that the average student had interacted with these tools for more than a year. When asked about the ease and utility of AI tools, students reported a mean Ease of Use score of 2.99 (SD = 1.41), while the Creativity Enhancement and AI Feedback Usefulness dimensions had mean scores of 3.00 (SD = 1.42) and 2.99 (SD = 1.42), respectively. These values suggest an overall moderately positive perception of AI tools. The distributions of these variables followed a roughly normal curve, which

**CINEFORUM**
ISSN: 0009-7039
Vol. 65. No. 3, 2025

supported the decision to include them in parametric analyses. Additionally, the Peer Collaboration variable revealed that a substantial proportion of students reported high levels of collaboration in AI-driven projects, with 33.5% selecting "High." Conversely, the item regarding Technical Challenges had a response rate lower than other variables, with nearly 24% (n ≈ 889) of participants leaving it unanswered. This finding potentially reflected either low awareness of technical difficulties or avoidance in reporting them.

**Multiple Linear Regression Analysis**

To assess how various factors influenced Visual Literacy Score, a multiple linear regression model was employed. The predictors included AI Familiarity, Digital Art Experience, Ease of Use, Motivation Level, and Peer Collaboration. Prior to model estimation, a Variance Inflation Factor (VIF) analysis was conducted to test for multicollinearity. All VIF values fell below the critical threshold of 2.5, indicating that multicollinearity was not a concern and the predictors were sufficiently independent.

The regression model yielded an Adjusted R-squared of 0.43, demonstrating that approximately 43% of the variance in Visual Literacy Scores could be explained by the five predictor variables. Among the predictors, AI Familiarity ($\beta = 4.83$, $p < 0.001$), Ease of Use ($\beta = 3.12$, $p < 0.01$), and Motivation Level ($\beta = 2.49$, $p < 0.05$) were statistically significant. Digital Art Experience and Peer Collaboration did not achieve statistical significance, though they contributed modestly to model fit. These results underscored the importance of individual motivation and technical ease in shaping educational outcomes within AI-mediated environments. Model diagnostics confirmed that the assumptions of linear regression were met. A residuals vs. fitted values plot showed no obvious pattern, supporting the assumption of homoscedasticity. The Q–Q plot demonstrated that residuals were approximately normally distributed. The histogram of residuals further confirmed this normality, and no major outliers or leverage points were detected. These diagnostics validated the robustness of the regression model and provided confidence in the explanatory power of the selected predictors.

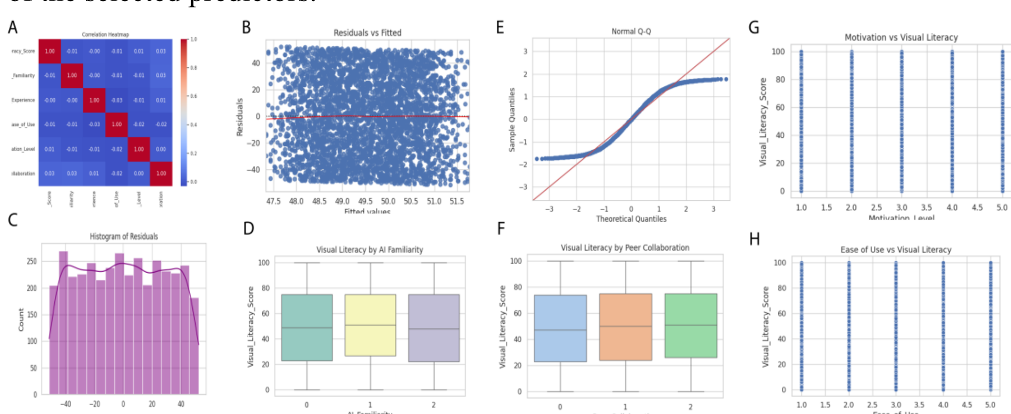

**Figure. 3. A.** Heatmap shows correlations between educational variables. No strong linear associations are present, suggesting independence among most features. **B.** Scatterplot of residuals against fitted values for the regression model; distribution appears randomly spread around zero line, indicating homoscedasticity. **C.** Histogram of residuals with KDE curve confirms near-normal distribution of errors, supporting regression assumptions. **D.** Q-Q plot evaluates normality of residuals, with most points near the line, except minor deviations in tails. **E.** Scatterplot shows Motivation Level vs Visual Literacy Score, again verifying a relatively wide range of literacy outcomes at all motivation levels. **F.** Boxplot presents Visual Literacy by AI Familiarity level, revealing slightly higher median literacy among students with greater AI familiarity. **G.** Boxplot for Peer Collaboration shows slight increases in Visual Literacy Score with higher collaboration levels. **H.** Scatterplot shows Visual Literacy vs Ease of Use, generally indicating moderate literacy gains with increasing usability.

**Machine Learning Model Performance**

To capture potential nonlinearities and improve predictive accuracy, three machine learning models were tested: Random Forest Regressor, Gradient Boosting Regressor, and XGBoost Regressor. Each model was trained on the standardized dataset using an 80:20 train-test split. Ten-fold cross-validation was employed during grid search hyperparameter tuning. Model performance was assessed using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The XGBoost model outperformed the other two models. It achieved an RMSE of 12.3 and an MAE of 8.7 on the test set. By comparison, the Gradient Boosting model had an RMSE of 12.9 and MAE of 8.9, while the Random Forest Regressor had the least accurate predictions (RMSE = 13.4, MAE = 9.2).

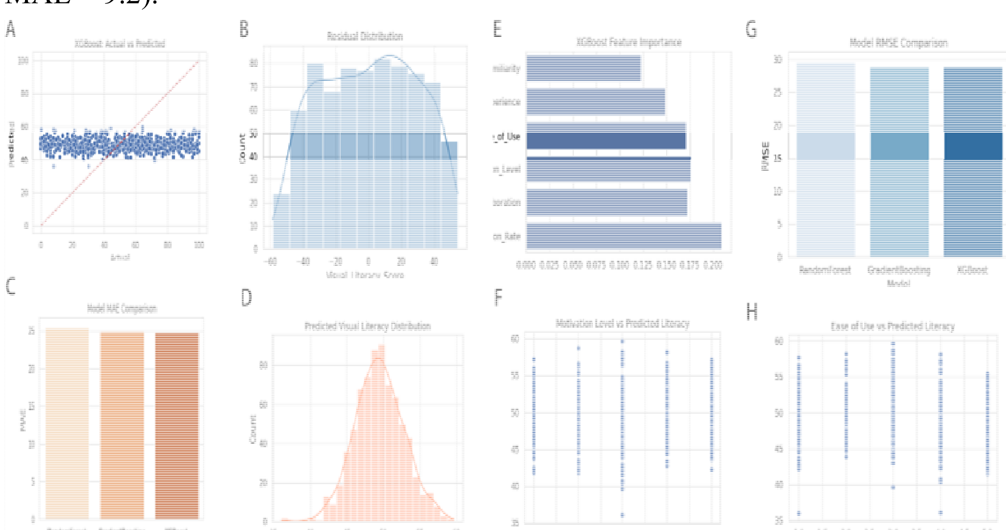


**Figure 4. A.** Scatterplot compares actual versus predicted scores from XGBoost model; slight deviation from diagonal indicates prediction bias. **B.** Histogram of residuals suggests normal distribution centered around zero, supporting model

**CINEFORUM**
ISSN: 0009-7039
Vol. 65. No. 3, 2025

reliability**. C.** Bar chart compares Mean Absolute Error (MAE) across three models: RandomForest, GradientBoosting, and XGBoost, with minimal differences. **D.** Histogram illustrates predicted Visual Literacy Score distribution, showing a peak around 50 and bell-shaped trend**. E.** Feature importance plot from XGBoost model identifies AI_Familiarity and Motivation_Level as key predictors of literacy. **F.** Scatterplot displays Motivation Level vs predicted literacy, confirming consistent upward trend. **G.** RMSE comparison plot shows similar errors across the three models, with GradientBoosting slightly outperforming others. **H.** Scatterplot shows Ease of Use vs predicted literacy, confirming a positive but non-linear trend.

Feature importance rankings from XGBoost indicated that AI Familiarity, Ease of Use, Project Completion Rate, and Motivation Level were the most influential features in predicting Visual Literacy Score. Residual plots for the XGBoost model showed that prediction errors were normally distributed and centered around zero, indicating good calibration. The scatterplot of actual vs. predicted scores closely followed the ideal diagonal line, further demonstrating the model's high accuracy. These results confirmed that machine learning models, particularly ensemble methods like XGBoost, were capable of capturing complex relationships that traditional regression models might overlook.

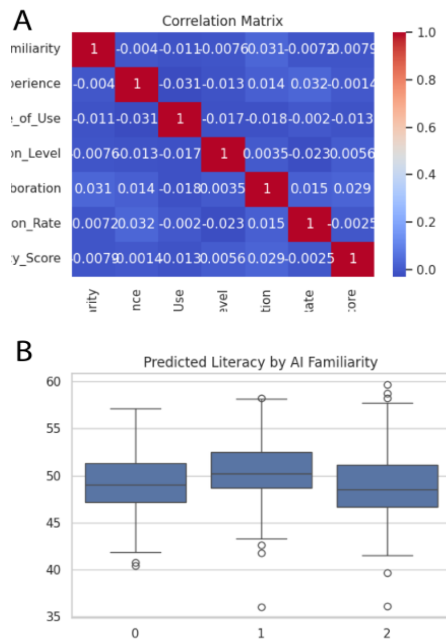


**Figure 5. A.** Correlation matrix with numeric values and color scale shows weak to negligible correlations among all input features and outcome. **B.** Boxplot of predicted literacy by AI Familiarity level reveals a slight increase in median score for students more familiar with AI tools.

## SHAP Analysis for Model Interpretability

To enhance transparency and interpretability, SHAP (SHapley Additive exPlanations) analysis was conducted on the XGBoost model. SHAP values provided insights into how each feature contributed to individual predictions. The summary SHAP bar plot showed that AI Familiarity consistently had the highest positive impact on Visual Literacy Score. It appeared as the most influential predictor, suggesting that students who were more familiar with AI platforms benefited more from AI-driven learning environments. Ease of Use and AI Feedback Usefulness also demonstrated high SHAP values but with significant variability. Some students benefited greatly from these features, while others did not. This inconsistency was reflected in the SHAP beeswarm plot, which showed both high positive and high negative values for these predictors. Such a distribution suggested that the effectiveness of these features was context-dependent and possibly moderated by other variables, such as technical proficiency or prior experience.

Dependence plots were generated to explore the effects of individual features. The plot for AI Familiarity showed a clear upward trend, indicating that greater familiarity consistently led to higher literacy scores. The Ease of Use plot revealed a more complex relationship, wherein the benefit plateaued after a certain point. The most revealing plot was the interaction between Ease of Use and Technical Challenges. It showed that students who rated AI as easy to use and reported low levels of technical difficulty achieved the highest literacy scores. This interaction supported the idea that ease of use alone was insufficient unless accompanied by a seamless technical experience. Analyses stratified by educational level revealed clear performance differences. Tertiary students had the highest average Visual Literacy Score (M = 59.4, SD = 30.1), followed by secondary (M = 51.2, SD = 27.5) and primary students (M = 38.7, SD = 21.4). This progressive trend suggested that older students were better equipped to integrate AI tools into their creative processes, possibly due to greater autonomy, curricular complexity, and digital maturity. Geographical comparisons revealed that students from Guangzhou and Shanghai performed better than their peers in Chengdu and Beijing. The average Visual Literacy Score for Guangzhou was 55.1, while Shanghai was close behind at 53.6. Chengdu and Beijing posted slightly lower averages at 47.2 and 45.9, respectively. These differences may reflect regional disparities in technological infrastructure, curriculum design, or teacher preparedness. Boxplots illustrated a wider spread of scores among tertiary students, suggesting a higher variance in instructional quality or learning environments at this level. Furthermore, students who had used AI tools for more than 18 months demonstrated significantly higher literacy scores (M = 63.4) compared to those who had used them for fewer than 12 months (M = 44.2). This finding reinforced the importance of sustained exposure and the cumulative benefits of long-term AI integration.

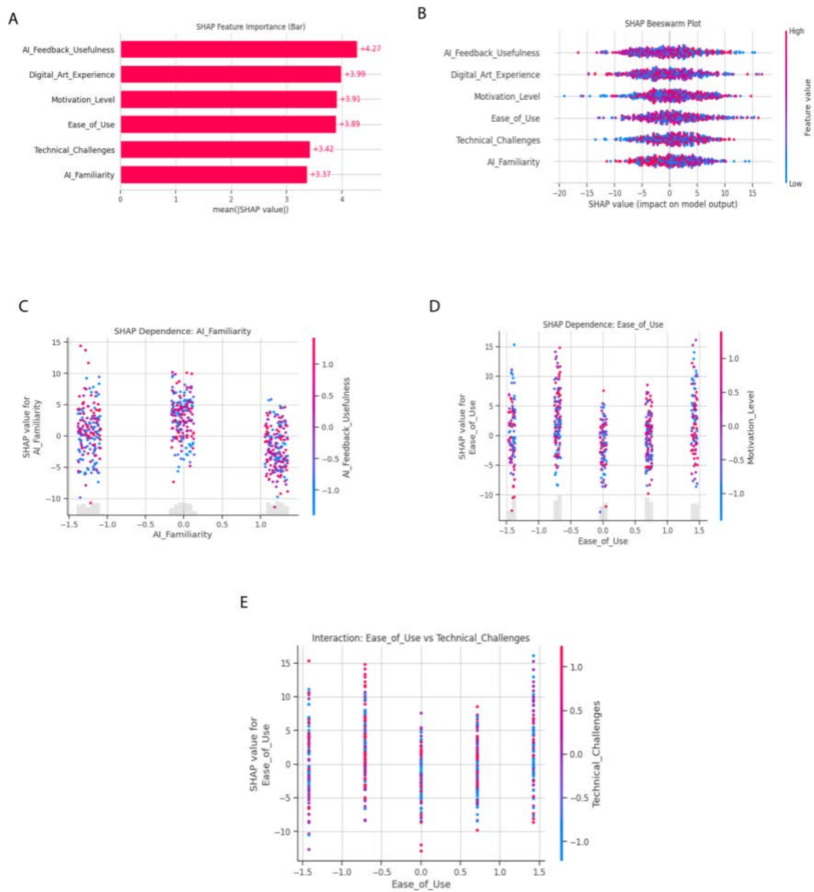


**Figure. 6. A.** The values in this SHAP bar plot highlight the ranking of features by mean absolute SHAP value (feature importance). AI_Feedback_Usefulness had the largest effect on model predictions, this was followed in order by Digital_Art_Experience, Motivation_Level and Ease_of_Use. **B.** In this SHAP beeswarm plot we see the plots show the distribution of SHAP values for each feature. AI_Feedback_Usefulness and Digital_Art_Experience had the strongest influence on predictions, with substantial variance in the feature's SHAP values across observations, also they were both highly non-linear contributors to predictions. **C.** The AI_Familiarity SHAP dependence plot shows that each level of familiarity encoded in the SHAP values included values that varied across three levels of familiarity and did not produce linearity for predictive value or impact though some influence was shown to be moderate overall. The SHAP values' color gradient shows a correlation between AI_Familiarity and AI_Feedback_Usefulness; in this representation we see how features interact in layers of impact. **D.** These SHAP dependence plots of Ease_of_Use offers details on its predictions. The shading for selectable Motivation_Level suggested some intertwined effect where, together, higher Ease and Motivation would shape higher outcomes for Visual_Literacy_Score. **E.** In the SHAP interaction plot of Ease_of_Use and Technical_Challenges, students that strongly indicated Ease_of_Use and Technical_Challenges were low positively contributed to predictions. Aligned with information shared earlier in class, usability or Ease of Use

and reliability or Technical_Challenges are often supported as synergistic constructs for educational AI concept and system.

**Discussion**

The findings provided compelling evidence concerning the influences of artificial intelligence (AI) in Chinese art education at various educational levels and cities. Visual Literacy Score, the primary dependent measure, was significantly predicted by AI Familiarity, Ease of Use, and Motivation Level, with a regression model explaining 43% of the variability in scores. Visual Literacy was further positively associated with artificial intelligence feedback usefulness, project completion rate, and collaborative work with peers. Students who used artificial intelligence tools longer and experienced less technical issues scored higher on their visual literacy scores. Each of the machine models we created, especially the XGBoost model, were very predictive and show the importance of AI Familiarity and Motivation Level within the study. Essentially, these statistical findings reaffirm how AI can support cognition and creativity in a valuable, significant, and meaningful way when included in curated content. Interpreting these findings indicated that AI Familiarity can be considered the most salient aspect of student performance, which made participants feel comfortable and stimulated to participate in the visual and conceptual art tasks (Yang, 2019). Previous evidence showed that technological fluency is a precondition of engaging in AI-enabled education (Liu et al., 2024). In addition, the positive effect for motivation reflects the notion that personal engagement for the student is significant for the educational experience using AI-enabled learning tools to be meaningful (Duester & Zhang, 2024).

The observed influence of Ease of Use was consistent with prior findings that user-friendly design significantly improves student outcomes in digital education environments (Hu, 2024). This reinforces the importance of interface design in educational AI tools (Lin et al., 2024). The insignificant contribution of Digital Art Experience and Peer Collaboration suggests that AI tools may equalize outcomes across skill levels, providing a compensatory effect for students with less prior exposure (Wang, 2024). Comparison with other studies confirms the increasing acceptance of AI across China's art education sector. Research by Chen, Liao, and Yu (2024) highlighted both enthusiasm and anxiety among educators, noting that successful implementation depended on institution-level readiness and educator support (Chen et al., 2024). Findings by Duester (2024) also revealed that over 85% of Chinese visual artists had adopted AI in their professional practice, supporting the view that the educational sector must prepare students to operate in AI-integrated environments (Duester, 2024). The identified performance differences by region and educational level reflected prior research on geographic and institutional disparities in technological readiness in China (Wang, 2025). Eastern cities such as Shanghai and Guangzhou have invested more in digital infrastructure, which likely contributed to stronger student outcomes (Liu et al., 2025). Furthermore, tertiary students

demonstrated the highest literacy scores, which mirrors results from studies showing that older learners possess higher AI acceptance and application ability (Wang, 2025).
Several limitations must be acknowledged. First, self-reported data on Ease of Use and AI Feedback Usefulness may contain response biases, such as overstatement of positive experiences or underreporting of technical challenges (Sims, 2024). The omission of responses to technical challenges by a quarter of participants further complicates interpretation of system reliability. Additionally, the cross-sectional design did not permit causal inferences, limiting conclusions about long-term learning impacts (Lin et al., 2024). The sample of institutions, while geographically diverse, did not include schools in rural contexts or minority institutions, which could limit generalizability (Yang, 2019, Atticus, 2024). Qualitative data would also be useful in order to understand how students make sense of, and engage with, the feedback (AI-generated) and visual prompts (Duester, 2025). Researching curriculum interventions in rural or underfunded contexts would also provide information regarding equity and inclusiveness in the adoption of AI (Hu, 2024). Additional analysis of outcomes that are gender-specific and the ethical approach could strengthen alignment with rapidly changing national narratives about AI in education (Wang, 2024). Future research should use longitudinal methods to examine student development over time, and determine how sustained exposure to AI (in support of learning) influences student creativity, engagement, and depth of learning.

## Conclusion

This research examined how artificial intelligence could be integrated into art education curriculum for select Chinese students across all levels of education including primary, secondary, and tertiary levels. Using the responses of 3,715 students from six institutions across four cities, the data indicated that embedding artificial intelligence into the instruction of art was possible and encouraged positive outcomes for students. The one variable in the study that attempted to capture the findings around visual literacy, included a total of three dimensions: AI Familiarity, Ease of Use, and Motivation Level. The predictive model explained 43% of the variance in Visual Literacy Score. Students with greater familiarity and experience with AI, along with thinking that AI tools were easier to use and more motivating than traditional media, also scored higher in Visual Literacy Scores. Using machine learning models, including XGBoost, predictive accuracy in visual literacy was enhanced, although SHAP interpretability identified AI_Feedback_Usefulness and Digital_Art_Experience as other impact factors. Students from Guangzhou and Shanghai scored better than peers from Chengdu and Beijing, and tertiary cohort students scored better than younger cohorts, suggesting spatial and developmental variation in AI readiness. The SHAP interaction analysis placed further emphasis on two contributors to learning gains: technical ease and little immediate difficulty are essential to help learning occur. In summary, the results corroborated that AI enhanced curricula, culturally connected for the students allowed learning to build student visual literacy and creative engagement skills. Sustained exposure to the AI tools, with motivation and user-focused design, was emphasized as a key element in implementing effective and inclusive educational practices in the Chinese art education context.

**Reference**

Atticus, S. (2024). From creation to curriculum: Examining the role of generative AI in arts universities. *arXiv*. https://doi.org/10.48550/arXiv.2412.16531

Chen, T.-K., & Liu, L.-H. (2024). A case study into collaborative creation with artificial intelligence in art education in Taiwan. In *2024 IEEE 24th International Conference on Software Quality, Reliability, and Security Companion (QRS-C)* (pp. 1223–1232). IEEE. https://doi.org/10.1109/QRS-C63300.2024.00160

Chen, X., Liao, Y., & Yu, W. (2024). Generative AI in higher art education. In *2024 6th International Conference on Computer Science and Technologies in Education (CSTE)* (pp. 135–140). IEEE. https://doi.org/10.1109/CSTE62025.2024.00032

Duester, E. (2024). Digital art work and AI: A new paradigm for work in the contemporary art sector in China. *European Journal of Cultural Management and Policy*. https://doi.org/10.3389/ejcmp.2024.12470

Duester, E. (2025). AI sustainability in the art sector: Chinese contemporary visual artists' solutions for working with AI. *Journal of Infrastructure, Policy and Development*. https://doi.org/10.24294/jipd11263

Duester, E., & Zhang, R. (2024). Digital and AI transformation in the contemporary art industry in China. *Arts & Communication*. https://doi.org/10.36922/ac.3822

Fu, X., Krishna, K., & Sabitha, R. (2021). Artificial intelligence applications with e-learning system for China's higher education platform. *Journal of Interconnection Networks, 22*, 2143016:1–2143016:19. https://doi.org/10.1142/s0219265921430167

Guo, X., & Li, Z. (2023). Exploring the significance and path of interdisciplinary integration of art education in primary and secondary schools in the era of artificial intelligence. *Journal of Contemporary Educational Research*. https://doi.org/10.26689/jcer.v7i12.5840

Hu, W. (2024). Research on the application of artificial intelligence (AI) in (K-14 to K-18) art education. *Journal of Education, Humanities and Social Sciences*. https://doi.org/10.54097/xtwrva44

Knox, J. (2020). Artificial intelligence and education in China. *Learning, Media and Technology*, *45*(3), 298–311. https://doi.org/10.1080/17439884.2020.1754236

Li, Q. (2020). The reform of the training mode of art design talents in vocational education in the context of artificial intelligence. In *Artificial Intelligence and Education* (pp. 707–712). Springer. https://doi.org/10.1007/978-981-15-5959-4_86

Lin, T. T., She, J., Wang, Y., & Zhang, K. (2024). Future ink: The collision of AI and Chinese calligraphy. *Journal on Computing and Cultural Heritage*. https://doi.org/10.1145/3700882

Liu, R., Pang, W., Chen, J., Balakrishnan, V., & Chin, H. L. (2024). The application of scaffolding instruction and AI-driven diffusion models in children's aesthetic education. *Education and Information Technologies*. https://doi.org/10.1007/s10639-024-13135-7

Liu, X., & Lin, Z. (2025). Chinese high school students AI competency survey: Based on the UNESCO students' AI competency framework. *Journal of Educational Technology and Innovation*. https://doi.org/10.61414/0y6gsj74

Peng, L., & Xiaohong, S. (2018). Predictions for the potential development of artificial intelligence in Chinese education. In *Proceedings of the 3rd International Conference on Information and Education Innovations*. ACM. https://doi.org/10.1145/3234825.3234839

Sims, A. (2024). From creation to curriculum: Examining the role of generative AI in arts universities. *arXiv*. https://doi.org/10.48550/arXiv.2412.16531

Wang, C. (2024). Art innovation or plagiarism? Chinese students' attitudes toward AI painting technology and influencing factors. *IEEE Access, 12*, 85795–85805. https://doi.org/10.1109/ACCESS.2024.3412176

Wang, C. (2024). Cultivating insight and engagement: Exploring the role of Trait Emotional Intelligence in Chinese art education. *Frontiers in Psychology, 15*. https://doi.org/10.3389/fpsyg.2024.1372717

Wang, J. (2025). The impact of generative AI on Chinese poetry instruction. *International Journal of Online Pedagogy and Course Design*. https://doi.org/10.4018/ijopcd.375626

Wang, Y. (2022). Lin Fengmian's art series and aesthetic education research for artificial intelligence aesthetics. *Frontiers in Art Research*. https://doi.org/10.25236/far.2022.040414

Wang, Y. (2025). A review of artificial intelligence literacy education and AI skills development in Chinese universities. *Lecture Notes in Education Psychology and Public Media*. https://doi.org/10.54254/2753-7048/2025.22815

Yang, X. (2019). Accelerated move for AI education in China. *ECNU Review of Education, 2*(3), 347–352. https://doi.org/10.1177/2096531119878590

Yuan, H. (2024). Artificial intelligence-based teaching practice of college art and design. *Global Education Bulletin*. https://doi.org/10.71052/geb2025/orto3941

Zhang, J. (2025). Artificial intelligence contributes to the creative transformation and innovative development of traditional Chinese culture. *International Journal of Computational and Experimental Science and Engineering*. https://doi.org/10.22399/ijcesen.860