



## Implementation of AI on Students' Performance in Visual Communication Design Lessons

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### Abstract

**Background and Aim:** This study investigates the use of Sea Art AI painting software in visual communication design education, focusing on its impact on students' mastery of color theory, composition, and creativity. Grounded in constructivist learning theory, it aims to assess AI's effectiveness in enhancing personalized and interactive learning experiences.

**Materials and Methods:** A quasi-experiment using mixed methods assessed the impact of AI-assisted learning on design students' creativity and efficiency by comparing outcomes between AI and traditional instruction groups.

**Results:** The results showed that the experimental group's post-test scores were significantly higher than the control group's in all evaluated areas. AI tools explained 29.8% to 46.4% of the variance, showing a moderate to substantial impact on learning outcomes. The greatest improvements were seen in creativity ( $F = 24.314$ ,  $p < 0.001$ ), visual effects ( $F = 11.050$ ,  $p = 0.002$ ), and font design ( $F = 17.996$ ,  $p < 0.001$ ). Color comprehension ( $F = 5.658$ ,  $p = 0.021$ ) and typography ( $F = 5.769$ ,  $p = 0.020$ ) showed smaller effects but were still statistically significant.

**Conclusion:** The study confirms AI's effectiveness in enhancing students' design skills and creative thinking, supporting its integration into design education. Future research should examine its long-term impact and broader applicability in personalized learning contexts.

**Keywords:** Artificial Intelligence; Visual Communication Design; Painting

### Introduction

Artificial Intelligence (AI) transformed from a mere computational novelty into an essential educational tool, particularly influential in creative fields such as Visual Communication Design. AI integration into educational settings stems from its ability to tailor learning experiences, provide automated feedback mechanisms, and improve the delivery of educational content. Design education benefits greatly from AI capabilities because it requires students to engage in iterative practice alongside visual experimentation and subjective critique, which AI can effectively support at scale (He et al., 2021). The increasing reliance on data and technology in creative fields makes AI-enhanced learning tools essential for preparing students to meet modern professional requirements.

Students excel in design because AI delivers real-time formative feedback that helps them improve their work continuously. In design education, traditional feedback systems suffer from limited instructor time and personal bias. AI tools break through these limitations by delivering steady, prompt feedback based on data analysis about student submissions (Wang et al., 2021). Students receive timely feedback, which enables rapid design iteration and a deeper understanding of their mistakes while leading to more effective application of design principles that accelerate skill development and enhance project results.

Students studying Visual Communication Design demonstrate a wide range of abilities and creative approaches alongside diverse cognitive styles. AI systems accommodate varying user needs by tailoring learning paths through complexity adjustments and resource suggestions based on user data and past performance. Self-paced learning and improved motivation through customization establish critical foundations for sustained engagement and performance during open-ended creative assignments, according to Hettiarachchi et al. (2021). AI functions to close knowledge gaps while simultaneously cultivating the creative identities of individuals.

AI tools help build student knowledge by prompting them to consider their choices while enabling them to compare different options and evaluate design results. Visual Communication Design uses visual messages rather than written words, which enables this essential reflection to develop visual literacy, the skill to understand and create meaningful visual information. AI provides design critiques, simulation, and





aesthetic evaluations, which help students make knowledgeable design choices and enhance higher-order thinking abilities that show a direct relationship with academic success (Lee et al., 2022).

When AI becomes part of Visual Communication Design education, it leads to major changes in teaching methods and how students perform. The integration of AI creates new teaching dynamics between educators and students while transforming classrooms into joint learning spaces supported by technological advances. The most crucial benefit of this innovation is its ability to provide equal access to superior design education through dependable support, which remains unaffected by institutional resources or location differences (He et al., 2021). AI's ongoing evolution establishes it as a fundamental component for future educational practice by enhancing creativity and precision alongside critical engagement in design learning.

Researchers investigate how Sea Art AI technology integrates into visual communication design educational programs. The study utilizes a quasi-experimental design to compare AI-assisted instruction with traditional teaching methods across multiple design domains, including creativity and color theory, as well as visual effects and font design. This research seeks to examine how AI affects student performance levels and their satisfaction with learning outcomes.

## Objectives

1. Compare art performance between AI and non-AI students
2. Identify learning factors in the AI group.
3. Assess skill development under AI and traditional methods.
4. Explore differences in learning experiences across groups.

## Literature Review

Artificial Intelligence (AI) is becoming an integral tool in design education, playing a transformative role in enhancing both learning outcomes and creative exploration. With its ability to provide rapid, adaptive, and data-driven responses, AI facilitates a deeper interaction between learners and design content. This shift supports personalized learning experiences that align with the diverse needs and skill levels of students, thus promoting a more inclusive and effective educational environment (He et al., 2021).

### 1. Sea Art AI as a Design Learning Tool

Among the various AI tools applied in creative education, Sea Art AI stands out due to its interactive capabilities, including real-time feedback, style transfer, and intuitive user interfaces. These features allow students to iterate on their designs swiftly, receive immediate critique, and visualize alternative artistic styles. Such functionalities promote continuous learning and help bridge the gap between theoretical concepts and practical design execution (Lee et al., 2022).

### 2. Enhancing Creativity and Overcoming Barriers

AI's capacity to generate variations and suggest novel compositions can stimulate creative thinking and reduce the intimidation students often face when starting new projects. This is particularly valuable in overcoming creative blocks, where Sea Art AI serves as a digital collaborator rather than a mere tool. Through this collaboration, students are encouraged to take risks and explore unconventional ideas without fear of failure (Wang et al., 2021).

### 3. Deepening Understanding of Color Theory

Sea Art AI also facilitates a deeper understanding of complex visual concepts such as color theory. By enabling real-time manipulation of color schemes and providing visual feedback on contrast, harmony, and mood, AI helps students concretely grasp abstract concepts. This interactivity supports constructivist approaches to learning, where knowledge is actively built through hands-on experimentation and reflection (Hettiarachchi et al., 2021).

### 4. Supporting Constructivist Learning Models

The integration of AI in design education aligns closely with constructivist principles, which emphasize learning as an active, student-centered process. Sea Art AI enhances this by enabling learners to construct knowledge through trial, iteration, and problem-solving. When used alongside Design Thinking frameworks, which prioritize empathy, ideation, and prototyping, AI contributes to a more holistic and engaging learning experience (He et al., 2021).



## 5. Promoting Self-Efficacy and Motivation

AI tools like Sea Art AI can enhance learners' self-efficacy by giving them a sense of control and immediate validation of their creative decisions. According to Wang et al. (2021), increased self-efficacy is positively correlated with sustained engagement and willingness to tackle complex design challenges. The encouragement provided by AI's supportive feedback loop helps maintain motivation, even when learners face setbacks.

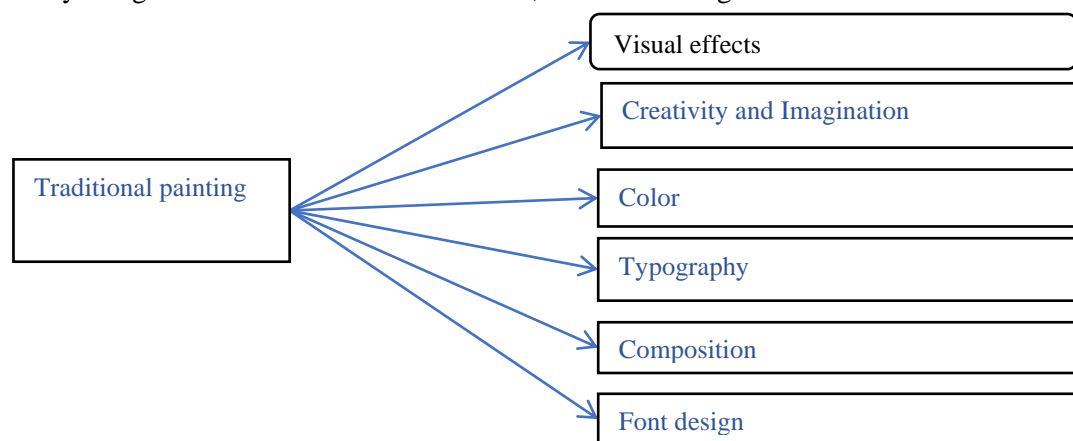
## 6. Encouraging Engagement and Cross-Disciplinary Thinking

AI's interdisciplinary nature encourages students to think beyond traditional design boundaries and engage with technology, data analysis, and algorithmic logic. This not only fosters engagement but also cultivates cross-disciplinary skills critical for modern design practice. Lee et al. (2022) argue that such hybrid learning environments prepare students to work in diverse, collaborative contexts and to view problems from multiple perspectives.

In conclusion, AI—exemplified by tools like Sea Art AI—offers significant pedagogical benefits for design education. It enhances creativity, supports conceptual understanding, and fosters critical design skills such as experimentation, reflection, and interdisciplinary thinking. Grounded in educational frameworks on creativity, engagement, motivation, and self-efficacy, the integration of AI into design education not only modernizes curriculum delivery but also prepares students for a rapidly evolving creative industry.

## Conceptual Framework

This study is based on Constructivism and Design Thinking, focusing on active, creative learning. It integrates models on creativity (He et al., 2021), self-efficacy (Wang et al., 2021), engagement (Lee et al., 2022), and motivation (Hettiarachchi et al., 2021). These frameworks guide the analysis of AI's impact on key design skills in visual communication, as shown in Figure 1.



**Figure 1** Conceptual Framework

## Study Aim and Hypotheses

This study examines the impact of Sea Art AI on visual communication design education, focusing on its effects on creativity, design quality, and efficiency. It hypothesizes that significant differences exist between the AI-based experimental group and the traditional control group in areas like visual effects, creativity, color, typography, composition, and font design.

## Methodology

A quasi-experimental mixed-methods design was used, with two groups: an experimental group using Sea Art AI and a control group using traditional methods. The study lasted eight weeks with the same instructor and curriculum for both groups.

## Participants



60 first-year visual communication design students from a Chinese university were selected, divided into high, medium, and low performance categories to ensure balanced representation.

### Data Collection

Quantitative data was gathered through pre-tests and post-tests, measuring creativity, visual effect, and other design aspects. Qualitative data were collected via semi-structured interviews with the experimental group.

## Results

Descriptive statistics were used to compare the design competencies between the two groups, supporting the integration of AI in art education.

### Demographic Information

In the first two years, there were 30 students per class. In the experimental group, 22 were female (73.33%) and 8 were male (26.67%). In the control group, 19 were female (63.33%) and 11 were male (36.67%).

**Table 1** Demographic Information of Samples

Variable	Category	Frequency	Percentage
Gender	Male	41	68.33%
	Female	19	31.67%
	<b>Total</b>	<b>60</b>	<b>100%</b>
Group	Experimental	30	50%
	Control	30	50%
	<b>Total</b>	<b>60</b>	<b>100%</b>

### Descriptive Statistics of Variables

**Table 2** Descriptive Statistics of Visual Effect

	Group	N	Mean	SD	Minimum	Maximum
PreTest_Score	Ctrl	30	14.70	3.82	8.00	20.00
	Exp	30	14.13	3.31	7.00	19.00
PostTest_Score	Ctrl	30	15.00	4.08	7.00	20.00
	Exp	30	17.00	3.01	10.00	20.00

Table 2 shows that both groups started with similar scores (Control: 16.7, Experimental: 16.3). After the intervention, scores improved in both groups, but the Experimental group improved more (20.5 vs. 18.5), suggesting the intervention was more effective.

**Table 3** Descriptive Statistics of Creativity and Imagination

	Group	N	Mean	SD	Minimum	Maximum
PreTest_Score	Ctrl	30	14.80	3.83	8.00	20.00
	Exp	30	15.03	3.30	7.00	20.00
PostTest_Score	Ctrl	30	15.27	3.14	8.00	20.00
	Exp	30	18.13	2.22	14.00	22.00



Table 3 shows that before the intervention, the Control group's mean score was 14.80, while the Experimental group's was 15.03. After the intervention, the Control group's score increased to 15.27, while the Experimental group's score rose to 18.13, showing a more significant improvement. This indicates that the Experimental group benefited more from the intervention.

#### Descriptive Statistics of Color

**Table 4** Descriptive Statistics of Color

	Group	N	Mean	SD	Minimum	Maximum
PreTest_Score	Ctrl	30	14.37	4.08	2.00	20.00
	Exp	30	15.07	3.83	8.00	20.00
PostTest_Score	Ctrl	30	15.60	3.08	9.00	20.00
	Exp	30	17.57	3.15	7.00	20.00

Table 4 shows that the experimental group improved more than the control group, increasing from 15.07 to 17.57, while the control group reached 15.60, indicating a stronger impact on the experimental group's color understanding.

#### Descriptive Statistics of Typography

**Table 1** Descriptive Statistics of Typography

	Group	N	Mean	SD	Minimum	Maximum
PreTest_Score	Ctrl	30	11.23	3.08	5.00	15.00
	Exp	30	11.57	2.65	7.00	15.00
PostTest_Score	Ctrl	30	11.23	3.00	5.00	15.00
	Exp	30	12.80	2.14	8.00	15.00

Table 5 shows that both groups improved in typography skills, but the experimental group increased from 11.57 to 12.80, showing a greater impact from the intervention.

#### Descriptive Statistics of Composition

**Table 2** Descriptive Statistics of Composition

	Group	N	Mean	SD	Minimum	Maximum
PreTest_Score	Ctrl	30	10.30	3.08	5.00	15.00
	Exp	30	11.10	2.87	6.00	15.00
PostTest_Score	Ctrl	30	10.30	2.71	5.00	15.00
	Exp	30	12.07	2.43	5.00	15.00

Table 6 shows that the experimental group improved in composition skills from 11.10 to 12.07, while the control group stayed at 10.30. This indicates the intervention was more effective for the experimental group.

#### Descriptive Statistics of Font Design

**Table 3** Descriptive Statistics of Font Design

	Group	N	Mean	SD	Minimum	Maximum
PreTest_Score	Ctrl	30	6.77	2.79	2.00	10.00
	Exp	30	6.37	2.48	1.00	10.00
PostTest_Score	Ctrl	30	6.70	2.29	1.00	9.00
	Exp	30	8.43	1.61	5.00	10.00



Table 7 shows that before the intervention, the control group had a mean score of 6.77, while the experimental group had a mean of 6.37. After the intervention, the control group's score slightly decreased to 6.70, while the experimental group's score increased to 8.43, indicating greater improvement in font design for the experimental group. This suggests that the intervention had a more significant impact on their font design skills.

### Summary of Interview

An interview conducted on December 28, 2024, at Beijing University of Science and Technology involved 30 first-year students from the experimental group and aimed to explore their experiences using the AI drawing software Sea AI in visual communication design courses. The findings indicated that the use of AI drawing tools significantly enhanced students' design skills, creativity, and efficiency. Participants reported improved understanding, greater confidence, and more informed decision-making, underscoring the positive impact of such tools on both learning outcomes and skill development.

### Hypothesis 1

H<sub>01</sub>: There is no difference between the treatment group and the Control group in visual effect.

H<sub>a1</sub>: There is a difference between the treatment group and the Control group in visual effect.

Table 8 shows that both Pre-test (skew = -0.053, kurtosis = -0.754) and Post-test (skew = -0.772, kurtosis = -0.290) data are nearly normal. The small changes suggest consistent visual effect assessments.

**Table 8** Normality of data visual effect

	Skewness		Kurtosis	
	Statistic.	Standard Error	Statistic.	Standard Error
Pre-test	-0.053	0.309	-1.041	0.608
Post-test	-0.772	0.309	-0.586	0.608

Table 9 shows a significant improvement in visual effect for the experimental group. The model explains 46.4% of the variance, and the group effect is significant ( $p = 0.002$ ), confirming that the experimental group outperformed the control group.

**Table 4** Analysis of Covariance (ANCOVA) Results for visual effect

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	372.749 <sup>a</sup>	2	186.374	24.634	0.000	0.464
Intercept	147.526	1	147.526	19.499	0.000	0.255
PreTest	312.749	1	312.749	41.337	0.000	0.420
Group	83.599	1	83.599	11.050	0.002	0.162
Error	431.251	57	7.566			
Total	16164.000	60				
Corrected Total	804.000	59				

a. R Squared = .464 (Adjusted R Squared = .445)

### Hypothesis 2

H<sub>02</sub>: There is no difference between the treatment group and the Control group in creativity and imagination.

H<sub>a2</sub>: There is a difference between the treatment group and the Control group in creativity and imagination.

Table 10 shows that the pre-test skewness (-0.390) and post-test skewness (-0.664) are within the normal range. The pre-test kurtosis (-0.691) and post-test kurtosis (-0.022) indicate nearly normal distributions, with minimal changes from the intervention.

**Table 10** Normality of data creativity and imagination

	Skewness		Kurtosis	
	Statistic.	Standard Error	Statistic.	Standard Error
Pre-test	-0.390	0.309	-0.691	0.608
Post-test	-0.664	0.309	-0.022	0.608

Table 11 shows that the ANCOVA model is significant ( $F = 30.471$ ,  $p < 0.001$ ), explaining 51.7% of the variance ( $\eta^2 = 0.517$ ). Both pre-test scores ( $F = 34.632$ ,  $p < 0.001$ ;  $\eta^2 = 0.378$ ) and group membership ( $F = 24.314$ ,  $p < 0.001$ ;  $\eta^2 = 0.299$ ) are significant predictors of creativity and imagination outcomes, with the treatment group outperforming the control group, confirming the intervention's effectiveness.

**Table 5** Analysis of Covariance (ANCOVA) Results for creativity and imagination

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	285.533 <sup>a</sup>	2	142.766	30.471	0.000	0.517
Intercept	297.243	1	297.243	63.440	0.000	0.527
PreTest	162.266	1	162.266	34.632	0.000	0.378
Group	113.922	1	113.922	24.314	0.000	0.299
Error	267.067	57	4.685			
Total	17286.000	60				
Corrected Total	552.600	59				

a.  $R^2 = 0.517$  (Adjusted  $R^2 = 0.500$ )

### Hypothesis 3

$H_{03}$ : There is no difference between the treatment group and the Control group in Color.

$H_{a3}$ : There is a difference between the treatment group and the Control group in Color.

Table 12 shows that both pre-test and post-test data for "color" are nearly normal, with pre-test skewness (-0.497) and kurtosis (0.160) close to zero. The post-test skewness (-0.956) is mildly negative, and kurtosis (0.484) is near zero, confirming normality and supporting the use of parametric tests.

**Table 12** Normality of data Color

	Skewness		Kurtosis	
	Statistic.	Standard Error	Statistic.	Standard Error
Pre-test	-0.497	0.309	0.160	0.608
Post-test	-0.956	0.309	0.484	0.608

Table 13 shows that the ANCOVA model for "color" is significant ( $F = 12.073$ ,  $p < 0.001$ ), with pre-test scores ( $F = 16.560$ ,  $p < 0.001$ ) and the intercept ( $F = 63.068$ ,  $p < 0.001$ ) having the strongest effects. The group variable also has a smaller but significant impact ( $F = 5.658$ ,  $p = 0.021$ ). Overall, pre-test scores and baseline differences are the most influential factors in post-test color results.



**Table 13** Analysis of Covariance (ANCOVA) Results for Color

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	184.665 <sup>a</sup>	2	92.332	12.073	0.000	0.298
Intercept	482.325	1	482.325	63.068	0.000	0.525
PreTest	126.648	1	126.648	16.560	0.000	0.225
Group	43.274	1	43.274	5.658	0.021	0.090
Error	435.919	57	7.648			
Total	17121.000	60				
Corrected Total	620.583	59				

a.  $R^2 = 0.298$  (Adjusted  $R^2 = 0.273$ )

#### Hypothesis 4

H<sub>0</sub>4: There is no difference between the treatment group and the Control group in Typography.

H<sub>a</sub>4: There is a difference between the treatment group and the Control group in Typography.

Table 14 shows that the pre-test skewness is -0.343, and the kurtosis is -1.026, indicating a nearly normal distribution. The post-test skewness is -0.738, and the kurtosis is -0.427, which still fall within acceptable normality ranges. Both sets of data meet the assumption of normality for hypothesis testing.

**Table 14** Normality of data Typography

	Skewness		Kurtosis	
	Statistic.	Standard Error	Statistic.	Standard Error
Pre-test	-0.343	0.309	-1.026	0.608
Post-test	-0.738	0.309	-0.427	0.608

Table 15 shows that the ANCOVA model is significant ( $F = 12.994$ ,  $p = 0.000$ ), explaining 31.3% of the variance. Baseline differences ( $F = 31.402$ ,  $p = 0.000$ ) account for 35.5%, and pre-test scores ( $F = 18.900$ ,  $p = 0.000$ ) explain 24.9%. The group factor ( $F = 5.769$ ,  $p = 0.020$ ) explains 9.2%. The most influence comes from baseline differences and pre-test scores.

**Table 6** Analysis of Covariance (ANCOVA) Results for Typography

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	134.967 <sup>a</sup>	2	67.483	12.994	0.000	0.313
Intercept	163.080	1	163.080	31.402	0.000	0.355
PreTest	98.150	1	98.150	18.900	0.000	0.249
Group	29.960	1	29.960	5.769	0.020	0.092
Error	296.016	57	5.193			
Total	9095.000	60				
Corrected Total	430.983	59				

a.  $R^2 = 0.313$  (Adjusted  $R^2 = 0.289$ )



### Hypothesis 5

H<sub>05</sub>: There is no difference between the treatment group and the Control group in Composition.

H<sub>a5</sub>: There is a difference between the treatment group and the Control group in Composition

Table 16 shows that both the pre-test and post-test data for "Composition" are approximately normally distributed. The pre-test skewness is -0.005, and kurtosis is -1.171, indicating a symmetrical distribution with no significant outliers. These values support the assumption of normality, allowing for reliable hypothesis testing.

**Table 7** Normality of data Composition

	Skewness		Kurtosis	
	Statistic	Standard Error	Statistic	Standard Error
Pre-test	-0.005	0.309	-1.171	0.608
Post-test	-0.510	0.309	-0.382	0.608

Table 17 shows that the ANCOVA model for "Composition" is significant ( $F = 18.692$ ,  $p = 0.000$ ), explaining 39.6% of the variance. The biggest influences are baseline differences (36.0%) and pre-test scores (32.2%). Group membership also has a smaller but significant effect ( $F = 6.083$ ,  $p = 0.017$ ), explaining 9.6%. Overall, baseline differences and pre-test scores are the main factors.

**Table 17** Analysis of Covariance (ANCOVA) Results of Composition

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	170.704 <sup>a</sup>	2	85.352	18.692	0.000	0.396
Intercept	146.374	1	146.374	32.055	0.000	0.360
PreTest	123.888	1	123.888	27.131	0.000	0.322
Group	27.779	1	27.779	6.083	0.017	0.096
Error	260.279	57	4.566			
Total	7935.000	60				
Corrected Total	430.983	59				

a.  $R^2 = 0.396$  (Adjusted  $R^2 = 0.375$ )

### Hypothesis 6

H<sub>06</sub>: There is no difference between the treatment group and the Control group in Font design.

H<sub>a6</sub>: There is a difference between the treatment group and the Control group in Font design.

Table 18 shows that both pre-test and post-test data for "Font design" are approximately normal. The pre-test has a skewness of -0.188 and kurtosis of -1.105, while the post-test has a skewness of -1.063 and kurtosis of 0.875, confirming the normality assumption for hypothesis testing.

**Table 8** Normality of data Font design

	Skewness		Kurtosis	
	Statistic.	Standard Error	Statistic.	Standard Error
Pre-test	-0.188	0.309	-1.105	0.608
Post-test	-1.063	0.309	0.875	0.608

Table 19 shows that the ANCOVA model for "Font design" is significant ( $F = 17.727$ ,  $p < 0.001$ ), explaining 38.3% of the variance. Baseline differences account for 55.1%, pre-test scores for 26.1%, and group membership for 24.0%.



**Table 19** Analysis of Covariance (ANCOVA) Results for Font design

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	104.588 <sup>a</sup>	2	52.294	17.727	0.000	0.383
Intercept	206.579	1	206.579	70.029	0.000	0.551
PreTest	59.521	1	59.521	20.177	0.000	0.261
Group	53.085	1	53.085	17.996	0.000	0.240
Error	168.146	57	2.950			
Total	3708.000	60				
Corrected Total	272.733	59				

a.  $R^2 = 0.383$  (Adjusted  $R^2 = 0.362$ )

Table 20 shows the summary of the results of the hypothesis testing in the study.

**Table 20** Summary of Hypothesis testing and results

Hypotheses	Statement	Result after Analysis
H <sub>01</sub>	There is no difference between the treatment group and the Control group in visual effect.	Rejected
H <sub>02</sub>	There is no difference between the treatment group and the Control group in creativity and imagination.	Rejected
H <sub>03</sub>	There is no difference between the treatment group and the Control group in Color.	Rejected
H <sub>04</sub>	There is no difference between the treatment group and the Control group in Typography.	Rejected
H <sub>05</sub>	There is no difference between the treatment group and the Control group in Composition.	Rejected
H <sub>06</sub>	There is no difference between the treatment group and the Control group in Font design.	Rejected

## Conclusion

This study demonstrates that the SEA ART AI platform has a significant and positive impact on visual communication design education. Students who engaged with the AI platform outperformed their peers in key areas such as creativity, color theory, typography, and composition. The platform's real-time feedback and personalized learning support accelerated the learning process and enhanced instructional effectiveness. Additionally, it fostered greater student engagement, innovation, adaptability, and creative confidence, highlighting the broad pedagogical advantages of AI-assisted design education.

## Discussion

The research demonstrates that student performance in visual communication design education improves substantially when they use AI tools such as Sea Art AI. The group that used AI assistance demonstrated better performance than the control group in multiple areas, such as creativity and understanding of color and typography, alongside composition. The study demonstrates AI technology functions as both a supportive educational tool and a transformative agent that develops design talent through immediate feedback and ongoing learning processes combined with active participation in visual content tasks (Lee et al., 2022).



The ANCOVA results ( $F = 24.314$ ,  $p < 0.001$ ) show that AI tools enhance creativity and imagination by promoting divergent thinking and artistic risk-taking. Sea Art AI offers features like instant visual options and interactive tools, which probably decrease cognitive load while increasing students' readiness to experiment. Our results match up with the findings reported by Wang et al. Wang et al. (2021) showed how AI feedback systems help sustain student engagement and build self-efficacy within creative subject areas.

The statistical results demonstrate that AI-supported tools lead to better design understanding through enhanced visual elements such as color ( $F = 5.658$ ,  $p = 0.021$ ) and typography ( $F = 5.769$ ,  $p = 0.020$ ). The real-time simulation of color harmony and contrast, along with typographic alignment, lets students visualize the direct relationships between their design selections and resulting visual effects. As Hettiarachchi et al. AI environments help students learn through experience by providing ongoing opportunities to experiment and correct mistakes without high risk.

The research framework of constructivism receives strong validation from the learning results observed during this study. Through active engagement with AI-driven tools, students constructed knowledge during a hands-on iterative learning experience. Bada and Olusegun's (2015) research finds that constructivist learning develops learner autonomy along with reflection and critical thinking, which must be present in artistic and design education. Through its application, AI strengthens educational principles by developing an environment that adapts to and focuses on the needs of students.

The field of font design ( $F = 17.996$ ,  $p < 0.001$ ) shows significant progress despite its reputation for technical difficulty and creative restrictions. The platform provided support that made complex typographic elements easier to understand for users of the AI-assisted group, as shown by their enhanced post-test results. New research from Bai et al. validates these findings. Bai et al. (2024) demonstrate how AI-powered interfaces make typographic design easier for beginners through the systematic division of style elements into simple design choices.

The successful influence of Sea Art AI on visual communication design performance demonstrates the necessity of broader integration of AI technologies in art education systems. The use of AI to connect theoretical design principles with practical applications results in higher student engagement while promoting innovative thinking and building confidence. Educational strategies should integrate AI into curriculum development and teacher training over an extended period to develop designers who are both technologically skilled and creatively empowered through changes in educational policy.

## Recommendations

To maximize educational outcomes, AI tools like SEA ART should be systematically integrated into design curricula to support the development of both technical proficiency and creative capability. Future research should examine the long-term effects of AI-assisted learning and expand the participant base to include diverse student populations for more comprehensive insights. It is also recommended to explore the application of AI in other design domains, such as animation and product design. For successful implementation, attention must be given to the development of personalized learning pathways, adequate teacher training, cost-effectiveness, and scalability. Furthermore, ethical considerations—including algorithmic bias, data privacy, and intellectual property—must be addressed to ensure that students emerge as both competent and ethically responsible designers.

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