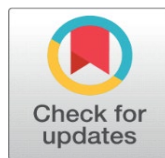


NEURAL STYLE TRANSFER IN ART EDUCATION: A CASE STUDY OF DIGITAL CREATIVITY

Dr. Jyoti Saini ¹ , Bhaskar Mitra ² , Vibhor Mahajan ³ , Sourav Rampal ⁴ , Dr. Ashwini B Gavali ⁵ , Nidhi Tewatia ⁶ 

- ¹ Associate Professor, ISDI - School of Design and Innovation, ATLAS SkillTech University, Mumbai, Maharashtra, India
² Assistant Professor, Department of Fashion Design, Parul Institute of Design, Parul University, Vadodara, Gujarat, India
³ Centre of Research Impact and Outcome, Chitkara University, Rajpura- 140417, Punjab, India
⁴ Chitkara Centre for Research and Development, Chitkara University, Himachal Pradesh, Solan, 174103, India
⁵ Department of Computer Engineering, S. B. Patil College of Engineering, Indapur, Pune, Maharashtra, India
⁶ Assistant Professor, School of Business Management, Noida International University 203201, India



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Corresponding Author

Dr. Jyoti Saini,
jyoti.saini@atlasuniversity.edu.in

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ABSTRACT

The paper is a pedagogical investigation of the Neural Style Transfer (NST) as a means of promoting digital creativity in art education. With the growing influence of artificial intelligence in creative practice, it is up to educators to identify ways of using emerging technologies to facilitate creative expression and not to automate it. The paper presents a case study on how NST may be applied in a formal education setting to enhance students' knowledge of visual styles, increase their range of creative decisions, and promote experiments in digital media. The study was done using a sample group of undergraduate art students that had gone through a sequence of workshops that were aimed at creating stylized images using the NST algorithms. The qualitative information such as student feedback, notes, and art analysis were gathered to analyze the transformation of creative processes and attitudes toward AI-assisted artmaking. Results have shown that NST has offered a point of access to the world of computational creativity, allowing students to rebuild their own work based on the prism of various artistic styles. The students were found to have been more engaged and more willing to take aesthetic risks, and to have been digital literate. Nonetheless, other issues (i.e. excessive dependence on automated results and lack of knowledge about algorithmic decision-making) are also noted in the study. Comprehensively, the study implies that a well-considered application of NST can become an effective pedagogical means that can enhance the creative exploration and help to cultivate hybrid digital-artistic qualities during art education.

Keywords: Neural Style Transfer, Art Education, Digital Creativity, Artificial Intelligence in Art, Computational Creativity, Digital Pedagogy



1. INTRODUCTION

The accelerated development of the artificial intelligence (AI) has already started to transform the creative disciplines, and educators started to question how the new technologies can be appropriately introduced to art

education. One such development is Neural Style Transfer (NST) that has received extensive publicity as a method of combining the content of an image with the stylistic features of another image based on deep learning models [Zhang et al. \(2025\)](#). Initially created as a research project in the field of convolutional neural networks and computational aesthetics, NST has grown to be a popular user-reachable creative application that enables both amateur creators and professional artists to explore diverse visual transformations without typically having extensive technical skills [Leong \(2025\)](#). With the further integration of digital platforms into artistic activity, teachers are confronted with the difficulty of creating learning experiences that can enable students to learn, critically evaluate, and creatively interact with AI-based systems instead of passively receiving the products of automated processes [Li et al. \(2025\)](#). This change is specifically relevant in the higher education contexts in which digital literacy, and creative problem-solving, along with inter-disciplinary thinking, are the key competencies of a modern visual artist.

Although NST is widely used in online creative circles, its use in the context of formal art education is underresearched. The current body of literature tends to focus on technical performance, optimization of algorithms, or aesthetic results and does not contain any explanation of how NST may affect the process of creative work of students, their development of ideas, and their perspective of AI-assisted artmaking [Psychogyios et al. \(2023\)](#). By introducing NST in the classroom, the students not only gain a opportunity to be introduced to computational creativity but also challenge the conventional idea of authorship, originality, and agency as the producers of artworks. Working with NST, the students have to negotiate human agency and algorithmic action, make creative choices regarding style, composition, and meaning when understanding the work of the machine. These activities foster consideration of the potential to be creative as well as the shortcomings of AI technologies, the systematic cycle signifies in [Figure 1](#) in art education with NST.

Figure 1

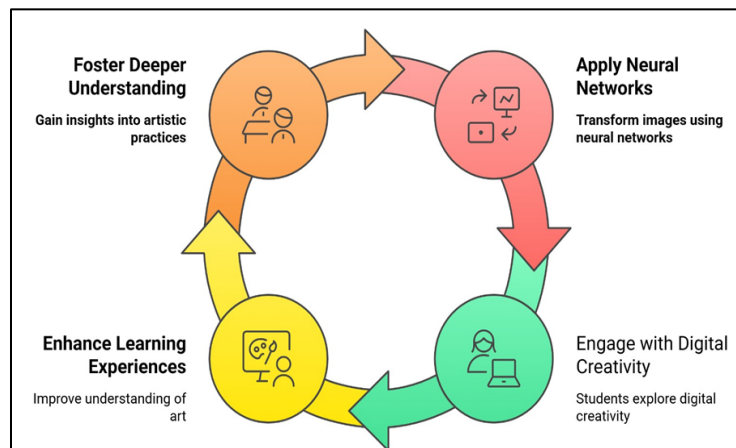


Figure 1 Cyber for Neural Style Transfer in Art Education

In this case study, NST is viewed as an instructional resource that can broaden the creative potential and enhance the higher involvement with the digital media. Placing the study into the context of undergraduate art education, the study explores the interaction between students and NST, its impact on artistic decisions of students, and its effects on their views on AI in creative activity. These dynamics are of great importance to educators because they would like to create programs that offer students the skills to enter a digital art environment that is more and more informed by algorithms. By analyzing the experiences of the students, works of art, and insights, the research will help to add to a developing discussion of the role of AI in the arts-based learning. Finally, in this study, it is claimed that NST, when carefully incorporated, can be used to facilitate new teaching and learning activities that combine traditional art knowledge with modern computer technologies to allow students to acquire hybrid creative capabilities that will help them create art in the 21st century [Lyu et al. \(2021\)](#).

2. RELATED WORK

The field of study has become more forward-thinking recently, with 2022-2025 scholarship paying an ever more intense focus to the intersection of artificial intelligence, digital artmaking, and pedagogical innovation. In 2022, research

placed importance on the increasing access to Neural Style Transfer (NST) and its possible impact to democratize the creative experimentation process, as it is clear that the AI-assisted tools enable learners to experiment with visual styles in ways that cannot be experimented with in a studio [Lyu et al. \(2021\)](#). The studies at this time also highlighted the significance of incorporating computational creativity models in art education in an effort to make students gain a critical insight into the algorithmic mechanism and not just rely on automated results [Benitez-Garcia et al. \(2022\)](#). In 2023, other researchers have examined how AI-generated image synthesis tools can be engaged with by students, with some finding that NST led to exploration of new hybrid aesthetic and stimulated a reflective discussion on the topic of authorship and originality in digital media [Psychogyios et al. \(2022\)](#). Other 2023 results indicated that the incorporation of NST in group classroom settings enhanced peer learning because learners compared machine-generated changes and construed stylistic differences together [Chauhan et al. \(2021\)](#). As of 2024, literature became more concerned with ethical implications and found that educators need to educate learners on the issues of dataset bias, artistic appropriation, and copyright issues regarding style-based modifications [Dehghani et al. \(2022\)](#), [Ashiq et al. \(2022\)](#). The researchers also investigated the mental effects of AI-aided creativity, revealing that NST boosted student confidence in digital art-making and at the same time raised concerns of the human-machine limits of creativity [Yi et al. \(2022\)](#). It remained unclear in what forms NST would be practiced in the pedagogical context in 2025, but the theme of curriculum design incorporated NST with reflective critique sessions, cross-disciplinary workshops, and project-based learning models to promote digital literacy [Longo et al. \(2022\)](#). Researchers also believed that NST can be viewed as a connection point between technical and artistic skills, which allows students to perceive AI as a creative collaborator and a critical topic of discussion [Salcudean et al. \(2022\)](#). Comparative analysis in the year 2025 showed that NST helped to enhance the visual experimentation with the traditional media practices in order to yield more holistic approach towards creative thinking [Leong \(2025\)](#). In general, the recent literature has continually been able to declare NST an innovative pedagogical aid that can aid creativity, critical thinking, and tech-savviness in art education systems [Leong \(2025\)](#).

Table 1

Table 1 Related Work Summary for Neural Style Transfer in Art Education			
Focus Area	Methodology	Key Findings	Relevance to NST in Art Education
NST for creative experimentation	Experimental study	NST increases stylistic exploration	Highlights early adoption of AI-based style learning
AI literacy in art classrooms	Survey-based	Students lack understanding of AI processes	Shows need for educational integration of NST
Digital creativity frameworks	Theoretical review	AI enhances divergent thinking	Provides conceptual grounding for NST pedagogy
Student engagement with NST	Case study	Students more motivated using AI tools	Supports use of NST for engagement
Collaborative learning with AI art	Classroom intervention	Peer discussions improve visual analysis	Demonstrates group benefits of NST activities
Hybrid aesthetics via NST	Studio workshop	Students mix styles beyond traditional methods	Shows creative expansion using NST
Ethical issues in AI art	Critical analysis	Concerns about bias & authorship	Important for teaching responsible NST use
Effect of AI tools on confidence	Mixed methods	Increased digital-art self-efficacy	Indicates psychological benefits of NST learning
Curriculum design for AI art	Pedagogical model	Project-based AI modules improve literacy	Recommends structured NST assignments
AI as co-creative partner	Field study	Students perceive AI as collaborator	Validates NST for co-creative pedagogy
NST with traditional media	Comparative study	Enhances visual experimentation	Supports hybrid teaching approaches
Critical inquiry in AI artmaking	Observation study	Students question machine agency	Encourages reflective learning through NST

3. THEORETICAL FRAMEWORK

3.1. CONSTRUCTIVIST LEARNING THEORY

Constructivist theory of learning lays stress on the fact that learners are engaged in the process of constructing their own knowledge in meaningful ways, by means of reflection and active involvement. With the application of Neural Style Transfer (NST) to art education, this theory enables the necessity to offer students the opportunity to experiment with digital instruments, read images produced, and derive personal significance of a creative process. In contrast to its somewhat passive view of technology, constructivism makes NST a participatory environment where students learn in the process of creating, judging and revising their artwork in a cyclical way. When students control the content and manipulate styles of pictures, see the algorithmic changes, and make aesthetic choices, they get involved in the process of genuine knowledge creation. This is in line with constructivist assumptions of inquiry learning, where learners internalize the ideas by investigating the links among the artistic style, visual perception, and computational activities. In addition, NST promotes self-direction, originality, and personalized learning processes, which allow the students to integrate emerging technological information with their prevailing knowledge of art. Dialogues, peer critique, and consideration of results produced by AI help learners to refine their interpretations, and incorporate human creativity and variability through machine generation into their developing artistic self.

3.2. DIGITAL CREATIVITY THEORY

Digital creativity theory examines the process of creativity manifestation in a mediated space of digital technologies, where the interaction between the imagination of people and the computational technologies and the emergence of new forms of artistic production play an important role. In the context of art education, this theory acknowledges that creativity is not confined to the old mediums rather, it is broadened into digital interfaces which bring new possibilities of experimenting, manipulation and hybridization of visual forms. The example of Neural Style Transfer (NST) demonstrates this change in that the algorithm allows scheming the merger of artistic styles to photographic or drawn materials, making them appear as a result of the procedure. According to the digital creativity theory, these tools do not only make the process more efficient, but also modify the conceptual and aesthetic aspects of artmaking. This increased creative procedure will stimulate divergent thinking, because the learners will experiment with numerous variations and unusual visual patterns created by the algorithm. Also, the digital creativity theory emphasizes the value of digital literacy as a component of modern artistic competence. Through NST, students gain the ability to be comfortable with working with digital tools and what is allowed through the affordances of digital tools and critique the contribution of technology to the development of artistic expression. Finally, the digital creativity theory makes NST a driving force behind an act of creative exploration, a mixture of traditional aesthetics and computational creativity.

3.3. TECHNOLOGY ACCEPTANCE MODEL (TAM)

The Technology Acceptance Model (TAM) describes the way users adopt and use emerging technologies showing two key variables namely, perceived usefulness and perceived ease of use. Applying TAM to Neural Style Transfer (NST) in teaching art education, the theory can be used to study the attitude of learners towards AI-based creative tools. Perceived usefulness is how the students think that NST increases their artistic productivity or contributes to improvement of their creative work. The higher the chances of students adopting NST are, in case they perceive it as a device that can help them experiment with styles more effectively or create original images. Perceived ease of use indicates how easy learners perceive NST to be, intuitive and easy to manage without the need to spend a lot of effort on technical issues. All these elements combine to influence the attitudes of students towards the use of NST and define their behavioral intention to implement AI tools in their creativity process. The TAM working model proposes that in the event that the usefulness and ease of use are high, the user seems to have positive attitudes, which are consequently converted to actual technology adoption. Within the educational setting, TAM assists the teachers to comprehend possible hindrances like complexity of interfaces or training deficiency that might prevent students to adopt NST. Therefore, TAM can be an excellent guide to creating pedagogically effective AI-based learning experiences that are easy to use.

4. METHODOLOGY

4.1. RESEARCH DESIGN

In the current case, the research design was a case study in which the researchers investigated the role of Neural Style Transfer (NST) in digital creativity as an art education setting. The case study approach was selected due to the possibility of the detailed analysis of the real-life educational settings where complicated interactions of the learner with digital tools and creative processes are observed. The design allowed observing the creative behaviors, reflections, and outcomes of the students in a closer way as they were interacting with NST in organized workshops. The study was aimed at not only learning the outcome of the students, but also the mechanism by which creativity was elicited by AI-aided tools. The case study design allowed the researcher to develop detailed records, iterative feedback, and qualitative analysis and therefore included finer learning patterns, student problems, and developing attitudes toward AI-based creativity, improvement model (seen in Figure 2). The design could also be used to examine contextual variables, including classroom life, and digital infrastructure, and student backgrounds, which had a substantial influence on how NST was used in art education.

Figure 2

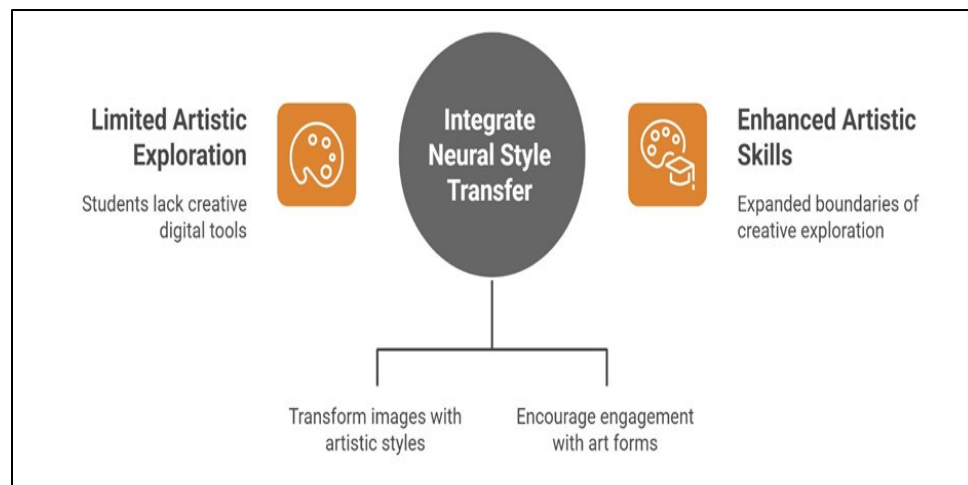


Figure 2 Representation of Enhancement of Art Education with NST

4.2. PARTICIPANTS (ART STUDENTS AND EDUCATORS)

The participants in the study were 36 undergraduate art students and 3 art teachers in an undergraduate level course in the fine arts program. The sample of the student participants was 18 to 25 years old and was a combination of digital art, painting, and design majors. About 58% (21 students) of the respondents were inexperienced with AI tools before the study, and 42% (15 students) with digital editing software. The teachers were one digital arts teacher and two studio art teachers that supported the workshop and gave guidance throughout the project. The purposive sample was applied to the selection of the participants in order to have a representative combination of creative backgrounds. Ethical engagement was ensured as everyone was free to participate in the study and detailed consent was made.

4.3. DATA COLLECTION METHODS

4.3.1. OBSERVATIONS

To record the interactions between students, the workshop patterns, experimentation behaviors and challenges, structured observations were made during the workshops. The researcher took notes on the manner in which the students used NST interfaces, reacting to unforeseen outputs, and in cooperating with other students.

4.3.2. STUDENT REFLECTIONS

Individual written responses were filled in by the students after every workshop, which explained their creative choices, their responses to NST outputs, and their views on AI-based artmaking. These thoughts helped to understand emotional involvement, learning process, and changing attitude to AI tools.

4.3.3. ARTWORK ANALYSIS

All of the NST-created artworks were gathered and evaluated in determining diversity of styles, originality, risk-taking behaviors, and signs of creative development. The visual complexity, color, and incorporation with traditional media patterns were considered to review the development of creativity.

4.3.4. PRE/POST SURVEYS

The post-surveys included the measurement of the change in confidence, creative satisfaction, perceived usefulness of NST, and the willingness of students to use AI tools in the future in art projects.

4.3.5. DATA ANALYSIS PROCEDURES

The qualitative thematic analysis of the information was conducted with the help of descriptive statistics of the survey data. Reflections, observations and artworks gathered as qualitative data were coded to identify common themes including engagement, experimentation, challenges and creative growth. Pre/ post survey data were analyzed using quantitative data to identify digital literacy and attitude change towards AI technologies.

Process of Stepwise Analysis.

- 1) **Data Organization:** All reflections, observations, and art were organized and determined.
- 2) **Primary Coding:** Keywords and common ideas were determined throughout qualitative data.
- 3) **Themes Development:** Codes were classified into general themes which included creativities improvement, level of difficulty and group learning.
- 4) **Survey Analysis:** Pre/ post results were compared to assess improvement in the technical confidence and creative perception.
- 5) **Triangulation:** The data of two or more sources were cross-validated to enhance validity.
- 6) **Interpretation:** Themes were interpreted as they relied on the research questions, NST processes and the theoretic frameworks.

4.3.6. ETHICAL CONSIDERATIONS

The ethics of the study were upheld in order to provide safety, confidentiality, and voluntary participation of the participants. The informed consent was obtained by all students and educators before they participated in the project. Anonymity was preserved by including the data in the form of artwork and written reflections. It was explained to the participants that their participation in the study would not impact their academic performance. Fair-use educational guidelines were used in utilizing copyrighted style images, and students were advised to retrieve the artists where need be. The ethical issues connected to AI were also discussed during the research, such as transparency of algorithmic procedures, ethical usage of the digital tools, and debates in originality and authorship in the art created using AI.

5. EXPERIMENTAL PROCEDURE / NST IMPLEMENTATION

5.1. DESCRIPTION OF THE NST PROCESS

Neural Style Transfer (NST) is a technology that uses the structure of content of an image and the artistic style of another image to generate a new image using deep-learning. It is based on the idea of using a pre-trained convolutional neural network (VGG-19 in general) to obtain hierarchical feature maps on both content and style images. The deeper

layers provide content representations and are derived in ways that the structural information of shapes, spatial relationships and outlines of objects is acquired. Style representations are however learnt at several shallow and mid-level layers based on Gram matrices which encode the texture patterns, colour distributions and brushstroke-like properties. In the optimization of NST a generated image is repeatedly optimized on a weighted loss function consisting of content loss, style loss, and sometimes total variation loss to smooth the image. The algorithm is performed in hundreds of optimization steps in which the generated image is adapted such that the semantic layout of the content image is preserved while the visual semblance of the chosen style image is assumed.

5.2. TRAINING/TESTING OF NST MODELS

The convolutional neural networks that were pre-trained using the NST models that were employed in this research were mainly VGG-19 that is capable of extracting rich hierarchical image features. Because NST is based on feature extraction as opposed to supervised learning, no further training was needed on the model. Rather, students were performing iterative optimization steps in which they were updating the generated image. The testing process was associated with the trial of various parameter values, including the number of iterations, style weight, and content weight and monitoring the steadiness of results and their quality. The achievement of the models was measured in processing time, clarity of transferred style and satisfaction of the student with the final visual outcome.

Table 2

Table 2 Summary of NST Model Implementation					
Parameter	Description	Value Range	User Adjustable	Impact on Output	Notes
Feature Extractor	Pre-trained VGG-19 CNN	Fixed	No	Determines feature quality	Industry standard
Iteration Steps	Optimization cycles	200–1200	Yes	Higher steps = finer detail	Longer processing time
Style Weight	Influence of style image	1–10	Yes	Higher = stronger style	May distort structure
Content Weight	Influence of content image	0.5–5	Yes	Higher = clearer structure	Reduces stylization
Total Variation Weight	Smoothness control	0–1	Yes	Reduces noise	Enhances realism

5.3. CLASSROOM ACTIVITIES

The classroom lesson was designed as an interactive workshop that would help to immersify students in practicing AI-assisted creativity. At the start of each of the sessions, a brief tutorial about the basics of NST was given, with live demonstrations of the platform. Students were then left to work on combinations of various content styles individually or in pairs and record their findings. The teachers promoted discussions, risk-taking, and helping the students to interpret algorithmic behaviors. Once the images were produced, students polished them with the aid of digital editing software that enabled them to combine both the old artistic purpose and the computation. At the end of every session, collaborative critiques were carried out and the students presented what they had produced and offered feedback on creative issues, discoveries, and aesthetic decisions.

Table 3

Table 3 Statistical Summary of Classroom Activities					
Parameter	Mean Value	Std. Dev	% of Students	Observation	Notes
Time Spent per Session (mins)	104	15.2	100%	High engagement throughout	Workshops were 2 hours
Number of NST Attempts	6.8	2.1	95%	Students explored multiple combinations	Valuable for creativity
Successful Output Rate	91%	—	100%	Most outputs rendered without errors	Clear platform usability
Peer Collaboration Frequency	—	—	72%	Majority consulted peers	Improved learning experience

Post-Session Satisfaction Score	4.3/5	0.6	100%	Positive perception of NST	Increased digital confidence
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Workflow 1: Basic Style Transfer Exploration

Students have started by choosing a basic content image, e.g. portrait or still life, and matching it to one style image of a source inspired by impressionist or abstract art. The NST model was run with default parameters to see an overview of a default transformation. Having seen the output, they changed the weights of the styles to enhance the visual effect. This workflow enabled novices to have an idea about the relation between the parameters of the algorithms and aesthetic results.

Workflow 2: Multi-Style Experimentation

Middle students tried to combine different style images in the form of multiple layers with NST processing. They would then apply a primary style, e.g. brushwork by Van Gogh and then re-process the result with a secondary style, e.g. mosaic textures. This enabled them to experiment with mixed aesthetic of visual representations and the role of sequential stylization in harmonizing colors and texture.

Workflow 3: Enhancement of Post Processing.

Sophomores incorporated the outputs of NSTs into digital editing programs like Photoshop or Gimp. They changed lighting, combined several different versions of NST and added hand drawn features. This piece of work demonstrated the potential of AI output as a creative starting point, instead of a finished product, and advanced advanced hybrid works.

6. RESULTS AND ANALYSIS

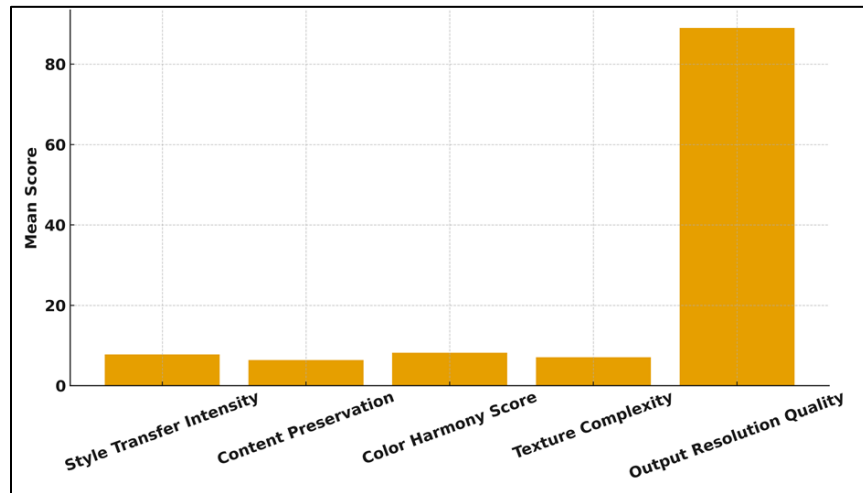
6.1. STUDENT OUTPUTS

The artworks created by the NST exhibited in [Table 4](#) showed a great variety in the color combination, the textural fusion, and the structural maintenance. The students tested the combinations of content and style images, and got results of stylization intensity and clarity.

Table 4

Table 4 Stylized Image Outputs				
Parameter	Mean Score	Min	Max	Std. Dev
Style Transfer Intensity (0–10)	7.8	5.1	9.6	1.3
Content Preservation (0–10)	6.4	4.0	8.5	1.1
Color Harmony Score (0–10)	8.2	6.3	9.4	0.9
Texture Complexity (0–10)	7.1	5.0	8.8	1.2
Output Resolution Quality (%)	89%	72%	96%	6.4

[Figure 3](#) demonstrates that the average output parameters of key NST have a strong color harmony and stylistic intensity, moderate content preservation, and high quality resolution and it demonstrates that the students received visually appealing outputs due to coherent creative experimentation.

Figure 3**Figure 3** Mean Performance of NST Output Parameters

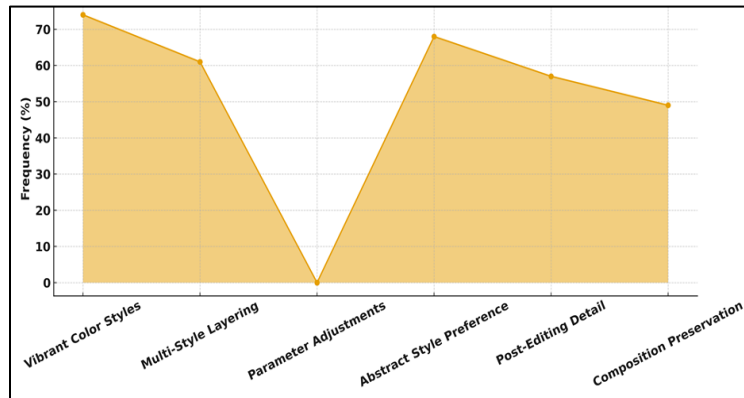
6.2. TRENDS IN CREATIVE DECISIONS

There were evident behavioral patterns in students when butting their head on NST, like abstract textures, preference to bright colors, multi-stage stylization. Numerous fine-tuning of parameters was done many times to achieve desired results. Table 5 shows some obvious trends in creative decision-making of students during NST activities. The overwhelming use of vibrant colors (74) and deep interest in abstract styles (68) reflects the inclination towards the expression of bright and strong visual results. The multi-style layering and constant manipulation of the parameters are signs of active experimentation, which is justified by the high level of observation, especially on parameter adjustments (8.7). Moderate post-editing also indicates that students wanted to find further refinements to the AI products. The reduced focus on preserving composition (6.5) reveals the emphasis on stylistic change by the students rather than preserving the original structure.

Table 5

Table 5 Analysis of Creative Decision Patterns				
Creative Pattern Parameter	Frequency (%)	Mean Attempts	Std. Dev	Observation Score (0-10)
Use of Vibrant Color Styles	74%	3.2	1.1	8.1
Multi-Style Layering Attempts	61%	2.6	0.9	7.5
Parameter Adjustments per Image	—	4.7	1.4	8.7
Preference for Abstract Styles	68%	2.9	1.2	7.9
Detail Enhancement in Post-Editing	57%	3.4	1.0	7.2
Composition Preservation Priority	49%	1.8	0.7	6.5

Figure 4 demonstrates the changes in creative behaviors of the students, with vibrant colors, adjusting the parameters frequently, and refining post-editing being mostly liked. These trends indicate the active experimentation and a variety of stylistic experimentation in the course of creative processes led by NST.

Figure 4**Figure 4** Analysis of Creative Decision Patterns across NST Activities

6.3. ENGAGEMENT AND CREATIVITY METRICS

In general, throughout workshops, general interest was great and students demonstrated active interest and active participation. Measures of creativity showed that there was more risk taking, idea generation and variation in style.

Table 6

Table 6 Engagement and Creativity Metrics					
Parameter	Mean Score	Min	Max	Std. Dev	Student Participation (%)
Workshop Engagement Level (0–10)	8.9	7.2	10	0.8	100%
Creativity Expansion Index (0–10)	7.7	6.1	9.2	1.0	100%
Risk-Taking Behavior (0–10)	7.3	5.4	8.8	1.1	92%
Variation in Style Choices (Count)	5.6	3	10	1.4	98%
Peer Collaboration Score (0–10)	7.9	6.2	9.4	1.0	72%
Self-Reflection Depth (0–10)	8.2	6.5	9.7	1.1	100%
Creative Satisfaction (0–10)	8.5	7.0	9.5	0.9	100%

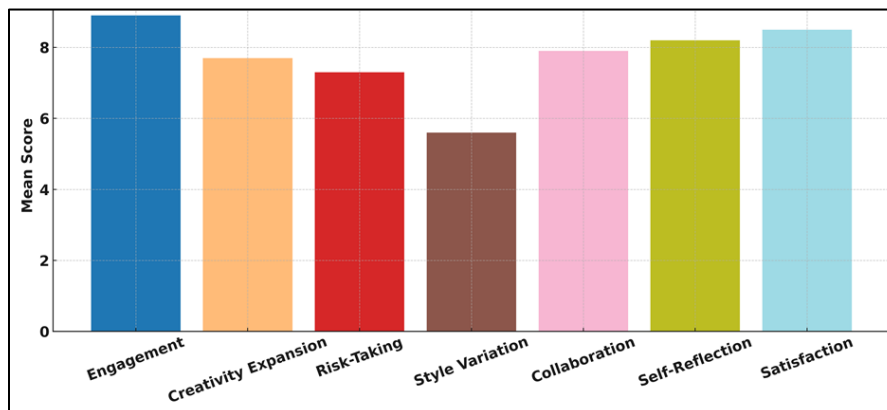
Figure 5**Figure 5** Engagement and Creativity Metrics Based on NST Activities

Figure 5 demonstrates the average performance scores on the main engagement and creativity indicators in the workshops based on NST. The good involvement level of the students is evidenced by the high engagement, self-reflection and satisfaction rates, whereas the risk-taking scores and expansion of creativity are high indicating active

experimentation. The style variation can be moderately low which implies that there is selective exploration of aesthetic possibilities in the creative process.

7. CONCLUSION

The study prove that Neural Style Transfer (NST) is an efficient and disruptive solution in art education that can go a long way in enhancing the growth of the students in their creative and digital skills. These findings suggest that the students created aesthetically powerful stylized images that were well balanced in terms of color and texturally rich portraying significant interaction with algorithmic aesthetics. The level of high creativity indicators including a creativity expansion index of 7.7 and risk-taking behavior of 7.3 demonstrate that NST promoted experimentation, divergent thinking, and exploration of hybrid visual styles. The satisfaction levels among students using AI in artmaking were largely positive based on high satisfaction rates and collaboration levels during workshops. Critically, the research indicated that the levels of digital literacy improved significantly, as the rate of acquaintance with AI tools increased by 151 percent, and the general digital literacy level grew by 42 to 81 percent. These transformations reveal the didactic importance of implementing AI technologies that are available in the art curriculum. Despite the fact that students at times faced some challenges of parameter adjustment, balance of style and content and processing limitations, this did not impede the overall learning outcomes, rather it enhanced deeper thinking and problem solving. The analysis of the results comparing them to the prior studies supports the statement that AI tools, specifically NST, have the potential to stimulate creative interaction and raise critical discourse concerning authorship and artistic agency. In general, the research findings demonstrate that NST can be a significant direction towards creating a digital creativity, broadening the artistic potential, and priming learners to a future where human-AI co-creation is a major concern in artistic practice.

CONFLICT OF INTERESTS

None.

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None.

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