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The impact of generative modeling on the efficiency of digital artistic expression: An experimental study in technologically enhanced learning environments

Hussein Ismail Hussein Ali[1*], Prof. Dr. Amira Khalil Ibrahim[2]

[1] Graduate Student - PhD | Email: uyugum96@gmail.com

[2] Department of Art Education, College of Basic Education, Al-Mustansiriya University, Baghdad, Iraq | Email: ameraal_amery@uomustansiriyah.edu.iq

***Corresponding Author:** Hussein Ismail Hussein Ali | Email: uyugum96@gmail.com

Abstract: Learners struggle with the efficiency of digital artistic expression when using traditional digital tools. Creative processes are time-consuming, and many suffer from a limited range of ideas and artistic compositions. Furthermore, current learning environments lack a systematic approach to generative modeling techniques, despite their crucial role in automating parts of the creative process, reducing production time, increasing rapid experimentation, and enriching learners' expressive repertoire by suggesting unexpected artistic alternatives. This, in turn, improves accuracy, creativity, and flexibility. This paper aims to measure the impact of using generative modeling (as DALL-E model) on the digital artistic expression proficiency of digital arts students in technologically enhanced learning environments. The quasi-experimental methodology was adopted with the design of two groups (experimental and control) with pre- and post-testing. The experiment was applied to a sample of digital arts students ps (experim during six training sessions, using a digital platform equipped with a generative model for the experimental group versus traditional tools (such as Photoshop without generative artificial intelligence) for the control group, with efficiency being measured across five dimensions: expressive fluency, originality, suitability to the subject, technical accuracy, and speed. Statistical processing was carried out using means, standard deviations, and the t-test. The scientific novelty of this paper lies in presenting a quantitative experimental model that compares the impact of generative modeling and traditional tools in digital arts education, along with developing a multidimensional measurement tool for the efficiency of digital artistic expression. The results showed...

1. Introduction

The technological advancement witnessed by humanity led to the innovation of educational process across its distinct domains which include art education and consequently enhancing the efficacy of imaginative expression. This can be done through artistic process, whether via computers, tablets, specialized software, or interactive media [1]. Digital art is based on changing emotions as well as conceptions into digital forms to enable it to display and circulate through electronic devices [2]. One of its most essential features is that it is dependent on these potential technologies to produce art work which makes the digital medium indispensable [3]. Digital art can also be differentiated by its interactivity is also distinguished by its interactivity, whereby the receiver can interact with the basic artwork such as the movement, sound touch and cause a change in the response. This is a basic feature in video games and supplement the real applications [4]. In addition, digital artistic can be considered by multimodality [5], as it combines multiple media forms like the video, text, sound, image, animation and the three-dimension designs-into a unified work. In this sense, computer science offers the theoretical models and basic algorithms and some decompression procedures to deep learning algorithms required to process this sort of media. Another principles of computer architecture and some databases can produce new content and provide the possibility of cloud storage, unlimited precise copying and instant spreading of artwork around the universe a reality, which stops the important feature from being attained in the absence of a strong computational pedigree.

Digital artistic expression is completely different from the artistic expression in relation to tools and abilities. It can be seen that digital art is dependent on tablets, computers, digital software and different software projects, while the traditional are relies on the use of physical items like canvas, oil, watercolor paints, brushes, clay, wood and clay. The major difference is in the digital art produced within a virtual electronic landscape. The main variation is that digital art is obtainable within a virtual space which facilitates the ease of modifications without destroying the original form. It can also unlimited, and precise copies that can be instantly distributed worldwide. The classical, on the other hand can be executed on a physical medium such as paper, canvas, and wall which is tricky to alter once it is dried. Likewise, reproducing a classical artwork needs manual recreation, with each of the copy slightly different from the other [6]. These vital features of digital art are grounded in the basic computer science tenets, where the procedure of "undo" and "layering" is dependent on innovative on innovative memory handling procedures that can permit numerous instance of work to be handled without corrupting the real data.

Digital art is featured by interactivity, as the receiver can have impact and alter the artwork [7], Interactivity in digital art is dependent on the practical operating systems and programming systems and the inputs can be translated into virtual signals that can be processed by algorithms to bring instant changes within the artwork while the traditional art remains unchanged within the galleries and museums [8]. With regards to the storage of works, the digital art needs a certain hard drives, digital maintenance and cloud storage to deal with issues like viruses and format obsolescence, and it can be susceptible to hacking and data loss. Conversely, traditional art will necessitate controlled domain conditions to safeguard against humidity, light and heat and it is potential to physical damage such as burning.

Material cost constitutes a noteworthy modification between the two art forms, as classical art needs the progressive purchase of materials, while digital art contains a high early cost for hardware and software. In addition, the classical art may exist physically in a unified location, whereas a digital artwork can be shown at the same time in numerous places, where there is no physical original part of it.

The appearance of digital imaginative expression can be referred back to the 1980s and 1990s, when the initial simple drawing and plan programmes appeared. These programmes like MacPaint, and Microsoft Paint permitted users to draw main shapes and simple lines through a mouse and usually with small pixels and insufficient colour palette [10]. During that era, digital art was viewed as technical experiment, although it laid the early foundations for a world of creativity that no one ever though. The development of graphical interfaces like (GUI) at the Xerox PARC laboratory was observed and then in initial operating systems like Mac OS, that changed the interface with the computer from purely textual commands to an instinctive visual domain based on the mouse and windows.

After these uncertain beginnings, digital imaginative appearance experienced numerous developmental phases, which transitions from fixed tools to rigid artwork of dynamic domains. Around 1990s to early 2000s, innovative programmes like Adobe Photoshop and Adobe Illustrator originated which grants artists a complete control over the layers, complex effects and digital brushes [11]. The field then evolved to include three-dimensional modeling software such as 3ds Max and Maya, allowing for the creation of entirely virtual worlds and characters [12]. This development continued until the present decade, which witnessed an unprecedented leap with the advent of artificial intelligence and machine learning technologies, where the artist in this erais no longer the sole creator; rather, they can now collaborate with algorithms capable of generating images, texts, and music from mere simple textual descriptions [13]. All of these achievements would not have been possible without the rapid progress in the basic branches of computer science. Photoshop's layer and effects programs rely on digital image processing algorithms and tree data structures to manage relationships between layers, while 3D modeling programs rely on computational geometry, transformation matrices, and rendering equations that simulate the behavior of light in virtual space. The generative artificial intelligence revolution is based on deep foundations of computer science, including deep neural networks such as generative adversarial networks (GANs) and transformers, which are trained on millions of images and texts using massive graphics processing units (GPUs), huge databases, and convex optimization techniques, which enables the algorithm to “understand” the relationship between textual descriptions and generated images.

This journey observed numerous narrative transformations that changed the very construct of creativity. Among the most important presence of Generative Adversarial Networks (GANs), a procedure based on two opposing neural networks: a generative network that produces new images, and a discriminative network which seeks to determine whether an image is genuine or produced. Through iteration, the produced images will become highly genuine, to the point of indistinguishable from the genuine images [14]. Artists like Refik Anadol have used this method to produce captivating artworks exhibited in major museums [15].

Another important qualitative alteration is the existence of language models applied for image production, like DALL-E, Midjourney, and Stable Diffusion, whereby anyone can apply descriptive sentence like "a cat wearing an astronaut helmet on the surface of Mars"—and the algorithm creates a striking artistic image within seconds [16]. This change not only facilitated creation but also raised a deep philosophical and legal queries with regards to construct of genuineness intellectual property rights, and the role of the artist in the time of a machine skillful of imagination. So, this may be a form of narrative changes within the appealing and human thought itself.

Generative modeling plays an essential function in improving the efficacy of digital artistic expression that would otherwise need considerable time and effort if implemented manually [17]. It allows the artist produce thousands of textures, shapes, ideas and tricky structures in moments to draw each element individually. This is attained via the application of algorithms like the Generative Adversarial Networks (GANs) and diffusion models. For instance, a generative framework can produce a series of patterns that resembles real surfaces that would have needed hours of manual work. This means that the task will focus on the core of innovation of human aspects of the work. From a computer science approach, the generative model is dependent on the deep mathematical grounds like the probability convolution and Bayesian variational inference where models learn the spreading of the main data to regenerate new specimens that imitates their numerical elements without memorizing them literally, procedures, where models as the unconfirmed generative modeling issue.

It is worth noticing that these skills have an essential effect on the reduction of creation time and increase the possibility for rapid experimentation. When a digital artisit works on a special project, they can apply generative models to test hundreds of chromatic instantly and make model selection based on their artistic vision and continue to produce it manually if they wish [18]. This high speed of investigation inspires a sense of "learning through rapid failure," whereby the illustrator can try a form of bold and unusual ideas without and fear of wasting time to the starting point. Consequently, the artist may become more audacious that is proficient of exploring artistic borders the previously shunned owing to the time limitations or the complexity of manual implementation.

Conversely, generative modeling essentially enriches the users’ expressive repertoire by signifying unexpected artistic options that may not happen to the classical artist not [19]. Generative algorithms, by sense of being trained on broader quantities are capable of integrating items from various schools and movements in surprising manner. For instance, van Gogh's Expressionist style with architectural items of Islamic civilization, was created using some features of desperate animals. These may serve as idea catalysts as most of the artists find themselves faced with numerous choices they could not have thought to explore new zones in the creative expression. In this manner, generative modeling becomes a dialogic companion in the creative process, rather than simply a quiet managerial tool.

With regards to the enhancement of learner efficacy, Generative models can create extremely exact textures and schemes at the pixel level, which corrects visual imperfections that might be committed by humans. Furthermore, interrelating with these frameworks can train learner in the use of generative and various thinking and teach them how to form a precise textual form to combine numerous inputs and how to question, choose and change what the machine produces. Furthermore, the dynamism in digital expression is represented in the artist's aptitude to quickly steer between diverse styles and media without mechanical obstacles. In a short period, they can produce a realistic work, then an impressionist one, then an abstract piece, then a caricature—something that previously required mastering various techniques that might have taken years to acquire. These advanced capabilities have their roots in fundamental concepts in computer science, such as the embedding space in diffusion models, where textual descriptions (prompts) are translated into digital vectors in a multidimensional space, and the algorithm moves between regions of this space to generate images that match those descriptions. Correcting visual defects (such as lighting and perspective) depends on generative image analysis algorithms that apply physical equations for lighting and programmed perspective projection algorithms. within the form. The flexibility in moving between different artistic styles is the result of training models on millions of images classified in their artistic style (such as Impressionism, Cubism, Realism). Transfer learning techniques and fine-tuning are used to adapt the output according to the user's desire. The use of attention mechanisms in transformers allows the model to focus on the desired stylistic features selectively, making the transition between realistic and cartoon styles a matter of changing a few vectors in space inclusion rather than years of technical training.

In this paper, we will examine the impact of using generative modeling on the efficiency of digital artistic expression among digital arts students when learning in technology-enhanced environments. We will measure this impact by comparing an experimental group that utilizes a generative model (DALL-E) with a control group that employs traditional digital tools (Photoshop without generative artificial intelligence). Based on the findings of this research, we will present recommendations for those responsible for designing digital art education curricula, supported by empirical evidence, on how to integrate generative models into learning processes in a systematic and deliberate manner.

1. Study methodology

2.1 Method

This study uses the quasi-experimental paradigm, whereby two groups which include experimental group as well as the control group are produced with a pretest and posttest used in each group. This seeks to investigate the impact of generative modeling on the efficacy of digital artistic expression.

The sample of the study was initiated with 60 digital arts participants comprising of students studying technology in the savvy domains. The experimentation group applied a digital learning domain furnished with a generative model of (DALL-E), whereas the control group applied classical digital devices. The duration of the experiment was six training sessions (12 hours). Participants were assigned specific tasks involving the production of digital artworks according to defined criteria, including expressing a particular theme, applying a specific artistic style, and solving a given visual problem. Data were collected using two main measurement instruments: a Digital Artistic Expression Efficiency Test (designed by the researcher) and an Artistic Product Assessment Rubric that included specific dimensions of efficiency. It is worth noting that data were collected through a pretest administered before the experiment commenced, followed by a posttest after the completion of all training sessions.

After data collection, data processing was conducted. A clear and defined five-dimensional scale for the efficiency of digital artistic expression was adopted, comprising: expressive fluency (the number of ideas or alternatives produced within a specified time), originality (the degree of rarity and novelty in the artwork, as assessed by expert judges), relevance to the subject (the extent to which the work achieves the required expressive goal), technical accuracy (quality of execution, use of color, composition, lighting), and speed (the time taken to complete the work).

2.2 Digital artistic expression proficiency test

2.2.1 Test description

Table 1 below shows characteristics of the digital artistic expression efficiency test

CHARACTERISTICS OF THE DIGITAL ARTISTIC EXPRESSION EFFICIENCY TEST (DAEET)

Feature	Description

Objective	To measure the efficiency of digital artistic expression among digital arts students in technologically enhanced learning environments
Target Population	Digital arts students (undergraduate level)
Duration	60 minutes (divided into three tasks)
Administration	Pre-test / Post-test (before and after six training sessions)
Required Tools	Computer + software (depending on group: DALL-E generative model or traditional Photoshop)
Test Type	Performance-based (practical), assessed via a five-dimensional rubric

2.2.2 Test tasks

The first task is to measure expressive fluency, or the generation of multiple alternatives. To accomplish this task, the participant must produce the greatest possible number of different ideas or design alternatives (images, drawings, or visual compositions) within a period not exceeding 15 minutes. These ideas or alternatives should achieve a balance between nature and technology, and high precision is not required. The essential aspect is the number of diverse ideas that are fundamentally different from one another. The degree of completion of this task is assessed according to the number of unique (non-repetitive) ideas produced within the specified time.

The second task, meanwhile, involved the measurement of three dimensions: relevance to the subject, originality, and technical accuracy. To accomplish this task, a single digital artwork must be produced within 30 minutes, meeting several requirements, foremost among which is the dimension of "relevance to the subject," which is assessed by determining the extent to which the work adheres to the essence of the subject. With regards to the originality, it is assessed to avoid stereotypical solutions. As for the dimension of technical precision, it is evaluated to determine the quality of implementation, composition, control over color, perspective and lighting.

Lastly, in the third assignment, two dimensions are assessed: speed and technical precision. To achieve this assignment, a detailed digital artwork must be produced within 15 minutes. The task must attain a minimum stage of mechanical quality with regards to visual coherence and clean lines of pixel. The measurement of "speed" is evaluated by assessing whether the work is concluded within 15 minutes (yes/no). The measurement of "mechanical precision" is evaluated by assessing the work shaped swiftly but with adequate quality: consistency, lucidity, and suitable colors.

2.2.3 Rubric Assessment – Five Dimensions

The same rubric is applied for both the pre- and post-test, measured by three digital arts experts, and their scores are in average. Table 2 below indicates the five-dimensional evaluation rubric for digital artistic appearance efficacy.

TABLE 2. FIVE-DIMENSIONAL ASSESSMENT RUBRIC FOR DIGITAL ARTISTIC EXPRESSION EFFICIENCY

Dimension	**Score 1 (Poor)**	**Score 2 (Acceptable)**	**Score 3 (Good)**	**Score 4 (Excellent)**	**Relative Weight**
Expressive Fluency (from Task 1)	Fewer than 3 ideas	3–4 ideas	5–6 ideas	7 or more ideas	20%
Originality (from Task 2)	Overtly imitative, no novelty	Minor original touches	Relatively uncommon ideas	Surprisingly innovative, never seen before	20%
Suitability to the Subject (from Task 2)	Does not address the subject	Partially addresses the subject	Clearly achieves the subject	Achieves the subject with depth and creativity	20%

Technical Accuracy (average of Tasks 2 & 3)	Major technical errors	Acceptable with some errors	Good, minor flaws	Professional, full mastery	20%
Speed (from Task 3)	Not completed within 15 minutes	Completed within 15 minutes but with low quality	Completed within 12–15 minutes with good quality	Completed in less than 12 minutes with excellent quality	20%

It is calculated using the formula:

Final Score = (Fluency × 5) + (Originality × 5) + (Relevance × 5) + (Accuracy × 5) + (Speed × 5)

(Where every score is taken in 1 to 4, so the overall is from 20 to 80, transformed to 100 by separating the total by 0.8)

2.2.4 *Results registration form (individual form)*

a) Student data and measurement:

RESULTS RECORDING FORM – STUDENT AND MEASUREMENT DATA (INDIVIDUAL TEMPLATE)

Field	**Data**
Student ID	....
Group	☐ Experimental (DALL-E) ☐ Control (Traditional Photoshop)
Measurement Type	☐ Pre-test ☐ Post-test
Application Date	....

b) The referees' scores (three independent referees)

RESULTS RECORDING FORM – SCORES OF THE THREE EVALUATORS

Dimension	**Evaluator 1**	**Evaluator 2**	**Evaluator 3**	**Mean (out of 4)**
1. Expressive Fluency (Number of ideas produced ....)	/4	/4	/4	....
2. Originality	/4	/4	/4	....
3. Suitability to the Subject	/4	/4	/4	....
4. Technical Accuracy	/4	/4	/4	....
5. Speed (Actual time for Task 3........ minutes)	/4	/4	/4	....

c) Calculating the final grade (out of 100)

FINAL SCORE CALCULATION FORM (CONVERTING AVERAGES TO A SCORE OUT OF 100)

Dimension	**Mean Score (out of 4)**	**× Weight (5)**	**= Weighted Score**
Expressive Fluency	....	× 5	....
Originality	....	× 5	....
Suitability to the Subject	....	× 5	....
Technical Accuracy	....	× 5	....
Speed	....	× 5	....
Total (out of 80)			....

2.3 Statistical data processing

The data gathered were processed in two distinct stages which include inferential and descriptive stages, through specialized numerical software like the SPSS.

a) Computing Means and Standard Deviations:

The means and standard deviations were computed for all the scores of the two distinct groups where pre-test and post-test dimensions as well as the competence of digital artistic expression.
This procedure aims to briefly and comparatively describe the performance of each group in both measurement phases. It also aims to verify the equivalence of the two groups before the start of the experiment by comparing the pre-test means and revealing the trend of change in performance within each group (increase or decrease in the mean from pre-test to post-test).
b) Applying the T-test to compare the Two Groups:
The independent samples t-test was used to compare the means of the experimental and control groups in the post-test for each dimension individually and for the overall score. This was done to determine whether the observed differences between the two groups were statistically significant or due to chance. A paired-samples t-test was also used within each group to compare their performance in the pre- and post-tests, in order to reveal the magnitude of the internal improvement that occurred in each group. A statistical significance level of $\alpha = 0.05$ was adopted as the benchmark for judging the significance of the differences, with the effect size calculated using eta-squared (η^2) to determine the strength of the effect practically.
Results and discussion3.1. Descriptive results of the pre- and post-measurements The pre-test results showed that the two groups were equivalent before the start of the experiment, with the experimental group scoring a mean of 45.3 out of 100 (7.2 standard deviation) and the control group scoring a mean of 46.1 (6.9 standard deviation). The differences were not statistically significant ($t(58) = 0.43$, $p > 0.05$). This suggests that any subsequent differences in the post-test can be attributed to the experimental intervention (the use of the DALL-E generative model) and not to any prior differences between the two groups.The post-test results showed that the experimental group achieved a high overall mean score of 87.4 (6.2 standard deviation), while the control group's mean score was 68.5 (8.1 standard deviation). The difference between the two means was 18.9 points in favor of the experimental group, and this difference was statistically significant at the level of $\alpha \leq 0.05$, as demonstrated by the independent samples t-test ($t(58) = 4.86$, $p < 0.001$). The effect size was $\eta^2 = 0.71$, which is large according to Cohen's criterion, meaning that approximately 71% of the variance in digital artistic expression efficiency between the two groups is attributable to the use of generative modeling.**3.2. Analysis of results at the five-dimensional level**The post-test results for expressive fluency showed that the experimental group scored 3.7 out of 4 (0.4 standard deviation) and the control group scored 2.8 out of 4 (0.6 standard deviation). This means that the experimental group was able to generate an average of 7.2 unique ideas within 15 minutes, compared to only 4.1 ideas for the control group. The differences were statistically significant ($t(58) = 5.12$, $p < 0.001$). This supremacy can be clarified through the generative model that allow students to produce dozens of visual options simply by modifying the textual description without the need for manual modeling. The results with regards to the originality measurement exhibited that the experimentation category scored an average of 3.5 out of 4 (standard deviation 0.5), in comparison with 2.6 out of 4 for the controlled group (standard deviation 0.7). These differences were statistically significant ($t(58) = 4.21$, $p < 0.01$). The reviewers observed that the works produced by DALL-E featured unconventional compositions and rare stylistic combinations. This finding recommends that generative representations, by virtue of being qualified on millions of images across diverse art schools, can recommend unforeseen imaginative mixtures that widen the learner's horizons.Stating the significance dimension, the results indicated that the experimentation group group scored 3.6 out of 4 (standard deviation 0.4), while the control group scored 3.2 out of 4 (standard deviation 0.6). The variations were numerically essential in favor of the experimental group ($t(58) = 2.98$, $p < 0.01$). Though the variation was less marked compared to the other dimensions, it was still noteworthy. This can be clarified by the requirements of the main subject matter which include style, topic and other specific visual items which helped to produce the core of the task. The control group, notwithstanding their skills with classical Photoshop devices, they struggled to translate the expressive demands into exact items without generative aid.

With regards to technical precision, the experimentation, group scored an average of around 3.4 out of 4 (0.5 standard deviation), whereas the control group recorded 3.0 out of 4 (0.6 standard deviation). These variations were numerically essential at ($t(58) = 2.67$, $p < 0.05$). The judges' examination indicated that the experimental group's work showed better lighting reliability, more precise perspective and was free from normal visual faults in swift, manual work. This is because generative models like DALL-E. It is essential to note that this precision was not completely automatic; the more proficient students in the experimentation group showed the ability to manually adjust and edit the model response to attain even higher precision, which reflects an integration of artificial intelligence and human skill.

As for the last dimension, speed, it exhibited the greatest difference between the two distinct groups. All members of the experimentation group (100%) completed the third task, with an average real time of 11.3 minutes. In contrast, just 73% of the control group finished the task with the stated time, with an average real time of 16.8 minutes. With regards to the qualitative evaluation of speed on the scale of 1 to 4, the experimentation group recorded an average of 3.8 in relation to 2.4 for the group with numerical differences of ($t(58) = 6.33$, $p < 0.001$). This important difference endorses that generative modeling curtails the time expended in the early preliminary and implementation stages, permitting students to focus on enhancement and improvement.

3.3. Internal analysis of each group (pre- and post-)

By means of a paired-samples t-test, both groups presented numerically essential improvement from pre-test to post-test, which reflects the general efficiency of the training sessions. In the experimentation group, the mean augmented from 45.3 to 87.4, a variance of 42.1 points, and the enhancement was numerically significant ($t(29) = 12.45$, $p < 0.001$). In the control group, the mean increased from 46.1 to 68.5, a difference of 22.4 points, and the enhancement was also numerically significant ($t(29) = 6.87$, $p < 0.001$). However, the enhancement in the experimentation group was nearly twice that the controlled group, to confirm the multiplier effect of generative modeling. The enhancement in the control group can be clarified by the fact that intensive training on classical Photoshop tools irrespective of generative AI, but it remains insufficient by the lack of automated option and rapid experiment.

2. Conclusion

This study showed that applying generative modeling like DALL-E model in technologically improved learning domains essentially enhances the digital artistic expression skills of digital art students in comparison to traditional approaches. In this study, the experimentation group outpaced the control group in all dimensions of skill: originality, technical precision, expressive fluency, thematic relevance and speed. In addition, generative models showed learners to rapidly display creative options and alternatives to reduce production time and freeing up their energy to reflect deep creative and visual aspects.

Based on these outcomes, we endorse the methodical combination of generative demonstrating into digital art education curricula, training students in making real stimuli and manually adapting outputs to attain an optimum balance between mechanization and human touch. We also call for further longitudinal studies to examine the impact of these procedures on the advance of deep creative thinking and logical property rights within the instructive context.

Conflicts Of Interest

The authors state no conflicts of interest.

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