REPRODUCTION OF ARTIST'S UNIQUE VISUAL STYLE. ARTIFICIAL INTELLIGENCE (AI) – TOOL FOR THE OPTIMIZATION OF CREATIVE PROCESSES

Mg. art. **Līga Vēliņa**
Art Academy of Latvia, Latvia

Abstract

This study is dedicated to examination of the ways how generative AI, specifically trained open-source models by *Stable Diffusion,* can support reproducing an artist's unique visual style. Conducted across four semesters (2023–2025) at the Art Academy of Latvia, the research investigates the pedagogical and creative outcomes of teaching students to train personalized AI models using their artworks as datasets, further combining other tools with the trained models during the study process.

A mixed-method approach – combining surveys, AI image recognition tests, semi-structured interviews, practical assignments, and qualitative observation – was applied to assess the effectiveness of AI-assisted style reproduction. The study evaluates challenges related to further combining models and learned tools, dataset preparation, authorship, and the discussion and research about cognitive differences between human and machine creativity.

Findings show that personalized model training can enhance creative autonomy, enabling results closer to an artist's unique visual style than generic AI tools. However, the process also reveals ethical and conceptual tensions regarding authorship, randomness, and control. The study concludes that, when applied critically and reflectively, generative AI can serve as a powerful tool for both creative exploration and pedagogical development.

Keywords: *generative AI, Stable Diffusion, artistic style, authorship, cognitive processes.*

Culture Crossroads
Volume 33, 2026, https://doi.org/10.55877/cc.vol33.600

ISSN 2500-9974

Introduction

In a shifting cultural paradigm, contemporary creative industries are increasingly shaped by the rise of generative artificial intelligence (AI). The oversaturation of image production, design tools, and automated workflows has introduced a new urgency to redefine the artist's role within a technological environment. AI applications – from language assistants to text-to-image generation platforms – have become commonplace. However, while most commercial tools offer rapid visual output, they often constrain artists within stylistic defaults shaped by generalized training data. This narrows artistic expression and raises ethical questions regarding imitation, originality, and authorship, as reflected in surveys conducted among art and culture students and teachers. Not all companies offer AI services, clear information about the data used, and often retain copyright in creating the work. [Midjourney 2024][1] Most available AI tools are limited in style (often referred to as "synthetic"), are designed to satisfy the tastes of the majority of consumer society, and are necessary for a beautified image. However, the saturation of these tools has already contributed to the automation of creative work, replacing photographers, designers, and representatives of other creative fields. Alongside commercial tools, however, a growing community of developers provides open-source AI models and desktop-based systems. These platforms offer opportunities for deeper understanding and enable artists to train generative models using their own datasets. Such practices allow for the creation of AI-assisted sketches, prototypes, and visualizations that reflect the artist's style.

This study responds to these developments by examining the potential of **open-source diffusion models** – specifically ***Stable Diffusion*** – for professional and emerging artists to develop customized generative tools capable of replicating their artistic style. Such an approach enables greater control over creative outputs and a critical re-engagement with **technology as a co-creative partner rather than a passive generator**.

The research draws on a four-semester pedagogical experiment conducted at the Art Academy of Latvia (2023–2025), where undergraduate bachelor's students in the Faculty of Audiovisual and Media Arts (2nd and 3rd year) were introduced to model training techniques using their visual material as data input. This article explores how generative AI can be meaningfully integrated into arts education

1 For example, one of the most widely used applications, Midjourney, will still not disclose the data used until September 2024. Also, although the results created in the respective program are allowed to be used with a paid subscription commercial, it does not provide copyright and newly created content. Available: https://docs.midjourney.com/docs/terms-of-service (viewed 15.12.2024.)

and whether it fosters deeper reflection on artistic style, authorship, and creative autonomy.

The theoretical framework combines concepts of cognitive science and AI studies, with particular attention to the distinction between human creativity and algorithmic reproduction. Neuroscientific insights into the default mode network (DMN) are discussed in parallel with early AI art systems such as Harold Cohen's AARON. The study situates machine-generated imagery within a broader discourse on aesthetic identity, authorship, and randomness.

This article contributes to the discourse on cultural production in the age of automation by proposing that artists can reclaim agency through the critical and individualized use of generative technologies. The research questions addressed here are, as follows:

1) What happens when artists train machines to imitate their thinking?
2) How do students' attitudes towards creativity, authorship, and optimization of creative work transform during the study process, while working with their data?
3) Do students build independent workflows with AI tools?
4) Do students recognize the benefits and limitations of personalized models?
5) How do attitudes toward authorship and creativity differ between students who participated in the course "Speciality and Practice: Generative Technology Studies" and those with no prior experience with model training?
6) How do students apply AI knowledge in later creative work?

Theoretical framework

This study is situated at the intersection of human cognition and machine-based generativity, focusing on how artistic style may be understood, replicated, and transformed within artificial intelligence systems. It draws on a comparison between human creative thinking and the operational logic of central point of contrast lies in how humans and machines process spontaneity, memory, and intention. While humans rely on emotion, intuition, and accumulated embodied experience, AI operates within probabilistic frameworks guided by large-scale training data.

The Default Mode Network (DMN)[2] is at the core of human creativity, a neural system active during introspection, imagination, and non-linear thought[3].

[2] The Default Mode Network (DMN) is a brain network that is activated when a person is not engaged in a purposeful thought process, such as solving a task or processing external stimuli. This network is active when our minds are "resting" or we are engaged in internal thinking, such as daydreaming, introspection, memory recall, or creative thinking. [Baroli 2014]

[3] The authors of the aforementioned study made equal contributions to the study in its creation: Authors: Eleonora Bartoli, Ethan Devara, Huy Q Dang, Rikki Rabinovich,

Recently published research by Oxford University Press *Default mode network electrophysiological dynamics and causal role in creative thinking* shows that DMN activity correlates with associative thinking and inner visualization, often associated with artistic practice and spontaneous idea generation [Bartoli et al. 2024]. The DMN allows for random, subconscious flows of thought that are not task-directed – a feature not native to AI systems, which require prompts and responses within defined algorithmic parameters.

This distinction is significant when considering how an artist's style is formed. Style emerges from years of material exploration, emotional development, and sensory learning in human practice. By contrast, generative models approximate this process through data input and pattern extraction. This research used the open-source AI model *Stable Diffusion* with ***LoRA (Low-Rank Adaptation)*** **methods,** allowing students to fine-tune the model on their personal illustration data. These models were trained with 30–100 images per student, enabling a simulation of their aesthetic handwriting. By experimenting with training parameters, students obtained *LoRA* models (in a .safetensors file) during training, with which it was possible to operate in the interfac*e Automatic1111*,[4] creating frame plans for animations, idea sketches, and prototypes.

The theoretical backdrop also references Harold Cohen's early AI art system, *AARON*, which operated as a rule-based drawing program. Cohen's work raised foundational questions around authorship and agency in machine-generated art, and he maintained that AARON was not an artist but a system co-authored by a human creator [Cohen 1995]. This historical perspective helps frame current approaches to generative art as acts of procedural co-creation rather than autonomous machine authorship. It should be noted that Harold Cohen's early AI art system was based on other algorithmic structures. Still, Harold Cohen's approach is essential: controlling the algorithms as much as possible and giving them specific tasks so that the AI approaches the artist's needs.

Media artist and researcher Heidi Boisvert offers a related and contemporary perspective that integrates neuroscience, biometric data, and machine learning in developing what she calls "embodied algorithms". In her work with students, Boisvert explores how AI can be trained not only on aesthetic features but also on the emotional and neurological responses of the human body. Her approach redefines model training as a process of empathetic extension, where the machine

---

Raissa K Mathura, Adrish Anand, Bailey R. Pascuzzi, Joshua Adkinson, Yoed N. Kenett, Kelly R. Bijanki, Sameer A. Sheth, Ben Shofty. https://doi.org/10.1093/brain/awae199

[4] *Automatic1111* is a user interface (UI), open source tool for working with *Stable Diffusion* models. Thanks to its intuitive interface, no programming knowledge is required to work with AI models.

becomes attuned to the affective and cognitive dimensions of human experience. Boisvert argues that AI systems, "rather than replacing creativity, can catalyse deep reflection, empathy, and cultural transformation when integrated as co-creative tools" [Boisvert 2023].

This framework supports a critical examination of authorship, randomness, and artistic control by comparing human cognitive mechanisms with generative AI outputs. It also establishes the premise for understanding AI model training as a technical act and a conceptual strategy to control aesthetic aspects within automated environments.

Methodology

This study applies a mixed-methods approach, combining quantitative and qualitative research methods to investigate the reproducibility of artistic style using generative AI tools. The empirical component was implemented over four semesters (Autumn 2023 to Spring 2025) through the course "Speciality and Practice: Generative Technology Studies" (developed and led by Līga Vēliņa) at the Art Academy of Latvia, Department of Audiovisual-Media Arts.

The study involved parallel observations, structured surveys, and semi-structured discussions conducted within the course environment, alongside contributions from representatives of the broader cultural field and uninvolved focus groups. The course introduced second and third-year bachelor's students to open-source AI systems, particularly Stability AI's Stable Diffusion model, focusing on the fine-tuning of personalized *LoRA* (*Low-Rank Adaptation*) models using their works of art as training data. The primary objective was to investigate how artists' unique visual styles could be simulated and reused for sketching, animation, and ideation through model training. The methodological foundation was based on constructivist pedagogy, emphasizing student-centred learning, experimentation, and the adaptation of AI tools to individual artistic identities. The lecturer acted as a mediator, regularly updating content in response to emerging technologies. Learning was approached as both a technical and conceptual process, in which students explored authorship and creative control while developing their workflows with generative tools.

Quantitative methods included testing generative tools and administering two structured student surveys (Survey 1 and Survey 2) to assess prior knowledge, the perceived effectiveness of AI tools, and understanding of authorship in AI-assisted collaboration.

Quantitative data were obtained through surveys of students outside the course, including bachelor's students from the Latvian Academy of Culture and master's students from the Art Academy of Latvia, to compare perspectives. To objectively test the ability to recognize machine-generated content, Image Recognition Tests were conducted among scholars, students, and educators in the arts and culture field and general education, as well as among secondary school students from Alūksne.

Participants were divided into two primary categories: experimental groups (Focus Groups 1 and 2), who completed the full study module "Speciality and Practice: Generative Technology Studies" and engaged in training personalized AI models using their own artwork; and control groups (Focus Groups 3 to 9), who either participated in pre-course surveys or took part in image recognition tests but had no prior experience with model training. Within the control category, participants were further differentiated based on their engagement in courses and guest lectures led by Līga Vēliņa, identifying their prior knowledge and attitude: some, such as Focus Group 3, had limited familiarity with textual AI tools (e.g., ChatGPT) but lacked experience in training visual models; others (Focus Groups 4, 6–9) with wide spectre of represented age groups and represented fields participated solely in recognition tests to assess their ability to identify AI-generated content. In addition, Focus Groups 3 and 5 offered a disciplinary contrast – students from the Latvian Academy of Culture and the Art Academy of Latvia, respectively – allowing for comparison of perceptions between cultural management and visual arts education contexts. This layered design enabled a more nuanced analysis of how familiarity with generative AI tools, participants' educational background, and disciplinary identity shape perceptions of authorship, creative autonomy, and the perceived value of AI in artistic practice.

Qualitative methods comprised literature analysis, direct observation, unstructured classroom discussions, pre- and post-course surveys, and visual analysis of students' outputs.

To ensure a diverse sample, a purposive sampling strategy was employed. Participants were selected based on their involvement in AI-focused study modules, courses, and guest lectures (all led by the author L. Vēliņa). The sample included students and other focus groups (educators) with and without prior experience in generative AI workflows, aiming to capture a broad range of educational contexts and familiarity with digital tools. Surveys and recognition tests were administered in-class or via institutional platforms, either before or after course modules or guest lectures, to ensure voluntary and informed participation.

In total, six structured surveys (Survey 1 (Focus Groups 1, 2, 3, 5) and Survey 2 (Focus Groups 1, 2)), six image recognition tests (Focus Groups 3, 4, 6, 7, 8, 9), and two semi-structured interviews (Focus Groups 1, 2) were conducted. All participants provided informed consent and were informed about the purpose of the research and the use of their data.

Table 1.

Overview of focus groups, survey themes, and test specifics

Group	Institution / Programme	Timeframe	Participants, average age	Survey focus
1	2nd-year bachelor's students (Art Academy of Latvia, Department of Motion. Image. Sound, participants of the course "Speciality and Practice: Generative Technology Studies"), autumn and spring semesters	From September 2023 to March 2024	8 (average age, M = 21.5)	**Survey 1.** Prior knowledge, authorship, and creativity.
1	3rd-year bachelor's students (Art Academy of Latvia, Department of Motion. Image. Sound, participants of the course "Speciality and Practice: Generative Technology Studies"), autumn and spring semesters	From September 2024 to March 2025	8 (average age, M = 22.5)	**Survey 2.** Course reflection, authorship, and creativity. **Unstructured classroom discussions.**
2	2nd-year bachelor's students (Art Academy of Latvia, Department of Motion. Image. Sound, participants of the course "Speciality and Practice: Generative Technology Studies"), autumn and spring semesters	Septem-ber,2024	5 (average age, M = 26)	**Survey 1.** Prior knowledge, authorship, and creative process.
2	2nd-year bachelor's students (Art Academy of Latvia, Department of Motion. Image. Sound, participants of the course "Speciality and Practice: Generative Technology Studies"), autumn and spring semesters	March, 2025	5 (average age, M = 26)	**Survey 2.** Course reflection, authorship, and creativity. **Unstructured classroom discussions.**
3	BA students (Latvian Academy of Culture. Department of Sociology and Management of Culture, bachelor's programme "Creative Industries" (Survey before the course, "The Introduction of Using Artificial Intelligence Tools for the Creative Industries", led by L. Vēliņa)	September, 2024	10 (average age, M = 22)	**Survey 1.** Pre-course survey on AI knowledge, authorship, and creativity. **Image Recognition Test.** Recognition of AI-generated artwork.

Group	Institution / Programme	Timeframe	Participants, average age	Survey focus
4	Participants of the Professional Competence Improvement Program (led by Liga Vēliņa), Generative Artificial Intelligence. AI Tools for Optimizing Creative Processes for General Education and Art Education Teachers	March, 2024	16 (average age, M = 53)	**Image Recognition Test.** Recognition of AI-generated artwork.
5	MA students (Art Academy of Latvia)	April, 2025	57 (average age: M = 34)	**Survey 1**. Prior knowledge. authorship, and creative process.
6	MA students (Art Academy of Latvia)	March, 2025	40 (average age: M = 27)	**Image Recognition Test.** Recognition of AI-generated artworks.
7	Students & educators, Liepāja Music, Art and Design School	March, 2025	16 (average age: M = 22.5. Average age of students: M = 18)	**Image Recognition Test.** Recognition of AI-generated artworks
8	Students from Visual Communication & Environment, 2nd-year bachelor's students at the Art Academy of Latvia in the sub-programmes "Environmental Art" and "Visual Communication"	January, 2025	8 (average age: M = 22)	**Image Recognition Test.** Recognition of AI-generated artworks.
9	Lower and upper-secondary school pupils (grades 8–12) from Alūksne Secondary School	April, 2024	14 (average age, M = 15)	**Image Recognition Test.** Recognition of AI-generated artworks.

The research evaluated the effectiveness of model training based on three key dimensions: aesthetic fidelity, student self-assessment, and third-party recognition of AI-generated outputs. To further assess this, additional tests were conducted by presenting both original and AI-generated artworks to educators and students, measuring their ability to distinguish between them and assess the perceived authenticity. These tests provided insight not only into the visual accuracy of generative results but also into broader questions of authorship, creativity, and machine agency.

The primary research questions guiding this study were, as follows:

1. Can training AI models successfully reproduce an artistic style?
2. Does the study process through the course "Speciality and Practice: Generative Technology Studies" foster a more profound, critical understanding of the principles underlying AI tools?
3. To what extent does this enable artists and students to operate, understand, and apply such tools more effectively to their own creative needs?

Course context and implementation

The rapid technological development of artificial intelligence requires a quick response from educational institutions (including art and culture universities) and teachers, integrating generative AI tools into studies, with the teacher becoming a mediator between technologies and students. In the fall semester of 2023, at the Art Academy of Latvia (Riga), in the subprogramme "Audiovisual media arts", department of Image. Movement. Sound, with the initiative of Professor Ojārs Pētersons, a new mandatory subject, "Speciality and Practice. Generative Technology Studies", which was created and led by Mg. Art. Līga Vēliņa.

The first module was designed for two semesters and targeted 2nd-year bachelor's students. Following the successful implementation of the module, it was further developed and implemented over two additional semesters in September 2024, targeting third-year undergraduate students. When studying the artificial intelligence systems and applications offered at a particular time, *Stability AI* emerged as a notable presence, offering a series of open-access AI diffusion models that enabled the operation of stationary, loadable applications with various interfaces (*Automatic1111, Comfy UI, Kohya*, and others (see Figure A1, A2, A3)). Used models by *Stable Diffusion* are based on the open-access LAION-5B[5] database. By choosing it as the central technology for learning in the developed study module, the work with students expanded in this study to focus on the reproducibility of

[5] LAION-5B (Large-scale Artificial Intelligence Open Network) is one of the largest, open-source databases, consisting of 5 billion image-text pairs. Most of the data is obtained from websites where public content access is available. Available: https://laion.ai/blog/laion-5b/ (viewed 15.12.2024.)

the artist's visual language, while simultaneously studying not only the potential of the existing tool but also students' attitudes and opinions about the potential of the tool, the concepts of creativity and copyright.

The methodology was rooted in constructivist pedagogy, focusing on student-centred learning, experimentation, and adaptation of AI tools to individual artistic identities. The lecturer served as a mediator, frequently updating the content in response to new technologies. Learning was understood as a technical and conceptual practice, wherein students explored authorship and creative control while developing personal workflows with generative tools.

This section will discuss the study process of the module "Speciality and Practice. Generative Technology Studies", which is divided into four semesters.

The first two semesters emphasized the experimentation and training process of open-source AI models, primarily *Stability AI's Stable Diffusion* deep learning models, accessed via *Automatic1111* and *Kohya* interfaces. The first semester **introduces** students (Focus Groups: 1, 2) to generative tools and AI fundamentals through tasks such as *deepfake* video creation, character model training, and art style training using the fine-tuning process of models using the *LoRA (Low-Rank Adaptation)* training technique in the *Kohya* interface.

The following tasks had to be completed as part of the practical work:

1. Creating *Deepfake* images and video using the *Stable Diffusion Automatic111* interface, *Reactor add-on*. The task is designed to promote understanding of deepfake content and its creation and the ability to identify it.
2. Learning to train two models and summarizing the results. (Training a model with *Hypernetwork*[6] and *LoRA (Low-Rank Adaptation)*[7] model training – in the open-access interface *Kohya*). Setting – training a person (human being) model using *the Stable Diffusion stable-diffusion-xl-base-1.0* base model, training it with portrait photos, using an average of 50 training images and an average of 100 regularization images in .jpg or .png format. The task is designed to create an understanding of the possibilities of training a person model and further manipulation – placing it in different environments, situations, and roles.

[6] *Hypernetwork* training is a technique that allows you to train an additional layer of a model to adjust the behavior of the model without having to change the entire model. The layer created by the hypernetwork adapts by learning to generate images that match the training data while maintaining the general capabilities of the original model (for example, the stable-diffusion-xl-base-1.0 model used).

[7] *LORA (Low-Rank Adaptation)* is a technique that allows training AI models efficiently using relatively small data sets and requiring less computing power. The technique offers many opportunities to optimize model parameters to achieve higher quality of generated content.

3. Training art style *LoRA* model in the open-access *Kohya*[8] interface, using the stable-diffusion-xl-base-1.0 base model, using illustrations as data – an average of 100–150 images in .jpg or .png format. One of the primary settings and tasks is to focus specifically on the training art style, allowing students to prototype ideas further to create sketches using text input and the interface parameters used to control the plot in the form of an image or animation.

Focusing on the reproducibility of the art style and the students' results, the process yielded stylistically different outcomes, depending on each student's handwriting characteristics. The most successful results in the context of animation were for students who had trained models with illustrations or used their work of art as a reference in which specific characters and objects were readable), whose data was well-thought-out and uniform, and in which stylistics were not diversified (there was no variation with different methods and stylistics; the data was uniform, clearly defined).

Since the central issue in the study is the optimization of creative work by training an AI model with your data, the following will describe the method of training the model with the *Kohya* utility, using the stable-diffusion-xl-base-1.0 diffusion model developed by Stability AI as a base, which is adjusted according to the new data, training a new *LoRA* model. *LoRA (Low-Rank Adaptation)* is a technique that trains large models, such as Stable Diffusion, more efficiently and with fewer resources. When trained with *Kohya*, *LoRA* allows you to adjust only specific model parameters, which reduces training time and required resources. *LoRA Hypernetwork* is a training technique that trains additional layers in the *Stable Diffusion* model to generate specific styles or adjust images. When trained with the *Kohya* utility, it is a faster and more resource-efficient method for adapting the *Stable Diffusion* model, keeping the primary model unchanged and training only the necessary parameters.

To better understand the principles of artificial intelligence training, students initially learned how to train a person model (Figure 1) in the *Kohya* interface with their portrait photos. In training an object or person *LoRA* model, it is necessary to prepare 25–50 images as a basis for training the model. To improve the quality of the model, it is additionally possible to use regularization images that determine the type of object or character. Accordingly, if the image contains a person who identifies as a woman or a man, it is necessary to prepare images using *Stable Diffusion Automatic111* with the help of text input, which represents a woman in various poses, situations, and roles. This method allows the character to be trained in a specific style (3D, illustration, etc.) or to utilize a realistic person model for further work in various styles chosen by the student.

---

[8] *Kohya* is a *Stable Diffusion* tool designed for model training and manipulation, focusing on individual, specific needs. The easy-to-use interface allows you to train and customize models with your own datasets, including training AI models with your own artwork photos or illustrations.

Figure 1. Author: Dagnis Stikāns. Results of the trained model in the Kohja interface with the *stable-diffusion-xl-base-1.0 diffusion* model as the base model, 2023.

Training an artistic style is similar to training a character AI model. Instead of portrait photographs, it is necessary to prepare an average of 50–100 images representing the artist's handwriting in a similar style. Care should be taken to ensure that the data represents a specific artistic style, paying attention to the relationships of lines, areas, colours, and line thickness, choosing one type of technique, and the images depicted in illustrations. In training in an artistic style, it is also possible to use photographs, images of spatial objects, and other images representing an artistic style. The training process takes from half an hour to several hours, depending on the power of the computer hardware, the data amount, and the parameters set. For example, using the computer hardware available at the Latvian Academy of Arts with an *AMD Ryzen 9 7950X 16-Core 4.50 GHz* processor and *Nvidia 4090 24 GB VRAM* video cards, training an art-style model using > 100 images takes up to 1 hour. The training result is an AI model in *.safetensors* format, which is then inserted into the *Automatic1111* interface (allowing for use in other applications such as *Comfy UI,* or in combination with other programs), further, with text input and parameters controlling sketches and prototypes in the style of a particular artist.

In the case of Katrīna Kate Kucina-Arbidāne (Figure 2), a highly successful imitation of imagery and stylistics was observed, particularly in replicating the characters' facial expressions, emotions, types, and colour tonality. hen conducting a test within the framework of the Teacher Professional Competence Improvement Program *Generative Artificial Intelligence. AI Tools for Optimizing Creative Processes* for general education and art education teachers *(Program coordinated with the Alūksne Municipality Education Board on 4 March 2024, protocol No. 2, coordination No. 2)*,

Figure 2. Author: Katrīne Kate Kucina-Arbidāne. Image 1 from the left – original work, hand-drawn digital illustration. Image 2 from the left: artificial intelligence-generated interpretation.

Katrīna's (Figure 2) – image created by artificial intelligence from the original work was recognized by 7 out of 16 respondents.

Another successful, yet stylistically distinct, example is the model trained by Katrīna Kovaļuka, featuring hand-drawn illustrations. The explicit imagery and stylistics allowed the trained dataset to consist of fewer images (on average around 50) than recommended. The trained artificial intelligence *LoRA* model successfully imitated the images, varying them in various scenes invented by the artist with a combination of text input and numerical parameters while preserving the specificity and peculiarities of artist's visual language. (Figure 3)

The second-semester course program used trained models for creating plots, sketches, and animations – moving images. Being aware that video tools in the specific period are incomplete, students were instructed to use existing models for creating animation frames (allowing the use of the *Chat GPT* language model for plot development). Along with the rapid technological development, various animation tools and programs became available in parallel with the course, which opened up opportunities to focus on experiments with moving images – and animation in the spring semester. Tools such as *RunwayMl, Pica Labs,* and derived Stable Diffusion tools and techniques provided opportunities to animate the frame plan generated by students, further manipulating and editing the video to realize the 2nd semester assignment – a short film, animation, or animation application or trailer.

Figure 3. Author: Katrīna Kovaļuka. Image 1 from the left – original work, hand-drawn illustration. Image 2 from the left: artificial intelligence-generated interpretation.

After learning the complexities and strategies of the AI training process, 2nd year and 3rd year undergraduate students in the third semester were invited to research specific AI instruments of their interest to learn in-depth usage and **strategy** of their chosen tool. The task was to use the explored tools to create an individual artistic project. Projects resulted in a diverse range of topics and technical methods. **Students' projects revealed diverse directions – some developed speculative animation scenes, and others created visual narratives embedded with emotional tone, surrealism, or symbolic language.** Two students turned their attention to a new tool called AI videogrammetry (by *Pica Labs*) that allowed video to turn into a three-dimensional point cloud object (*Gaussian splatting technique*), later processed and animated in 3D software *Blender* (see Figure A4). One of the students also chose to use this technique in other modules during the autumn semester of 2024 and the spring semester of 2025. The specific student was amazed by the artistic appearance of scanned material, which resembled painting values while creating cinematic scenes. During the semi-structured interview and discussions, the student admitted that this discovered AI tool has become interesting in creating works of art lately. It should be noted that the student deliberately chose a more complex method of solving the course tasks in order to get closer to the desired aesthetics. During the interview, the student says:

> "It is interesting to research specific techniques in depth. [...] Now I find it very interesting to combine handmade objects with digital technologies (scanning them using the Gaussian splatting technique)."

Figure 4. Author: Lūcija Dzenīte. Image 1 from the left: frame of animation. Image 2 from the left: Sketch later turned into 3D objects.

In the spring semester of 2025, second-year and third-year students, using their gained knowledge, were tasked with creating a short film (1–10 minutes short) for the AIFF 2025 – *Runway's third annual AI Film Festival (Screenings for finalists planned to be on 5 June in NYC at Alice Tully Hall in Lincoln Center at 7 pm ET and on 12 June in Los Angeles at the Eli and Edythe Broad Stage at 6 pm PT.).* The lecturer's task was to thematically reflect an individual or collective experience with a deeper meaning, using any AI tools, The Festival allows the use of any AI tool while allowing the combination of classical methods. Students' projects revealed diverse directions – some developed speculative animation scenes, and others created visual narratives embedded with emotional tone, surrealism, or symbolic language. Students chose different technical methods; some used their work as a base, emphasizing originality, and later manipulated and animated original drawings with AI tools. For instance, one of the 3rd-year students drew frames with a hand and used *Runway Ml* to animate them. The animation was based on a student's own fictional story about a selfish artist who tries to achieve perfection by creating his self-portraits. Another student used sketches to create 3D objects using AI instruments; later, they rendered frames from different viewing angles in *Blender* and experimented with lighting and atmosphere (Figure 3 and Figure 4). Later, prepared frames were animated in *RunwayMl*. The student turned the story to exploring parallel worlds, creating abstract, moving beings with consciousness.

Another interesting technique employed by one of the students involves using the felting method to create handmade objects, which are then scanned with AI tools to produce a painterly animation. Another student used her trained model and an open-access plasticine open-source *LoRA* model to create a story about social

Figure 5. Author: Betija Jakaite. Image 1 from the left – a character made with *Stable Diffusion* in *Automatic1111* interface. Image 2 from the left: trained *LoRA* character model combined with plasticine opensource *LoRA* model.

media identities (Figure 5). Further operating with the *Stable Diffusion* interface *Automatic1111*, rich, expressive scenes were created with various characters invented by the artist.

While creating an animation for the film festival, students applied their acquired knowledge of training artificial intelligence models and utilizing and combining other tools to bring their ideas to life. Within this framework, students explored ways to better control AI tools, planning the framing plot and animating them, understanding how artificial intelligence tools function, and discovering new strategies and techniques. Animation ideas differed, depending on the interests and stylistics of the students. Although not all of them utilized their trained models, it was noticeable how the students considered logical solutions to control the AI tools and achieve the desired result to the maximum extent.

The course "Speciality and Practice: Generative Technology Studies" functioned as a pedagogical experiment and a cultural inquiry into emerging forms of co-creation between humans and machines. It encouraged students to critically evaluate their role as authors and curators of their visual language.

Results and discussion

The results of the four-semester experiment, conducted during the course "Speciality and Practice: Generative Technology Studies", reflect a diverse range of student experiences and learning outcomes. Based on qualitative observation and thematic analysis of student reflections, it became evident that participants developed a heightened sensitivity to the influence of dataset composition on visual outputs. Students shifted their perception of AI **from a passive image generator to a co-creative partner**, capable of extending and mirroring their stylistic thinking. In critique sessions, several students referred to AI-generated "hallucinations" – unexpected or surreal outcomes – as either aesthetic surprises or training errors, depending on the context. While some students sought to achieve the cleanest, most controllable results in completing the tasks, others used AI-generated hallucinations as an artistic effect.

Several individual projects demonstrated strong stylistic fidelity. One student trained a *LoRA* model using narrative-based digital illustrations featuring emotionally expressive characters. The model produced new scenes that preserved both line quality and emotional tone. While temporal coherence remained a technical challenge, these experiments revealed how hybrid practices can provoke new modes of visual storytelling. During the discussion, the student described her trained model as her "baby" that must be "taught and understood". The student was truly surprised by the creative results and imagery (Figure 3). She believed that the model perfectly represented her inner world.

Between 11 March 2024, and 20 March 2025, a structured image recognition test was conducted among young scholars, students, art, culture, and general education educators, with six independent semi-structured focus groups (Focus Groups: 3, 4, 6, 7, 8, 9). Each session involved viewing 12 slides, each presenting a pair of images: one original illustration by a student and one generated by a personalized *Style Diffusion* model trained on that student's data. The total number of respondents was 104, aged between 11 and 67 (with an average age of 28.4). Results showed that participants correctly identified the AI-generated image in only **54.9%** of cases – effectively a chance result – indicating a limited ability to distinguish machine-generated reproductions from original artwork. **This suggests that stylistic imitation achieved through training was highly convincing and successful.** Although the highest recognition rate was observed in Focus Group 8 – 2nd-year bachelor's students from the sub-programmes Environmental Art and Visual Communication at the Art Academy of Latvia, who achieved a correct identification rate of 67.71%, this numerical advantage is not considered statistically significant. Given the small sample size (N = 8) and the lack of consistent trends across other groups, the result is likely coincidental rather than indicative of a meaningful correlation. Overall, no clear relationship was observed between the ability to recognize AI-generated content and participants' age, educational level, or affiliation with the arts, culture, or other professional sectors. Recognition performance appeared to be independent of demographic or disciplinary background.

Despite technical successes during the studies in the course "Speciality and Practice: Generative Technology Studies", students (Focus Groups: 1, 2) faced recurring challenges, including overfitting due to limited training data, inconsistent output resolution, and sensitivity to prompts. These limitations led to valuable troubleshooting processes, during which students adopted iterative testing strategies and began to treat model training as a form of visual scripting and aesthetic inquiry.

Furthermore, emotional and cognitive responses to AI interaction were varied. Some students (Focus Groups: 1, 2) expressed frustration when the model failed to capture the nuances of their style, describing a sense of alienation. Others experienced a sense of empowerment and discovery, particularly when seeing their visual language articulated algorithmically. These responses underscore that the creative use of AI tools is not neutral – it reshapes the artist's role, prompting reconsideration of authorship, intention, and aesthetic control. Some students expressed that the training helped define and understand their artistic style in semi-structured discussions. Most students agreed that it was interesting to watch how the algorithms interpreted their artistic style or character models. Students confirmed that although it was sometimes difficult to control the models, the training process helped them better understand AI systems and find new ways to control them. One of the students confirms that training a model (especially a person model) is like a mental process where you get to know yourself and learn how the algorithms see you. To the question of whether model training can be considered a reflective experience, one of the students answered:

> "As a person who didn't succeed at first, and... seeing that others succeeded, you look at your model differently when it succeeds. [...] Then there's that uncanny valley moment; it's your face, but it's still not yours."

Students (Focus Groups: 1, 2) describe embellished versions, frightening feelings, and dark undertones, which some perceive as valuable, while others experience them as an alienating experience.

Both groups of students are aware of shared authorship. There is talk about the moral dilemma: you don't feel complete authorship. One of the students during the discussion commented:

> "I have to choose from the options **it** offers, which one I work with next. It's not exactly what I want, but I choose the best option."

At the same time, both groups of students (Focus Groups: 1, 2) that were interviewed raised the question of digital art and conventional digital tools: Why should AI tools be distinguished from tools like *Adobe Photoshop*, which offer effects or other capabilities?

The findings indicate personalized AI model training can catalyse technical growth and critical reflection among emerging artists. When embedded in a supportive pedagogical framework, generative tools become not just instruments of replication but arenas for experimentation, self-definition, and conceptual exploration.

Conclusion

A. Insights from pedagogical practice

This study demonstrates that when embedded in a reflective educational framework, personalized generative AI training can be a valuable strategy for supporting emerging artists in navigating their visual language. Through empirical observation and student feedback across four semesters, it became evident that teaching machines to imitate one's artistic style also becomes a process of rediscovery and refinement of that style.

Stable Diffusion open-source latent diffusion model, (implemented in *PyTorch*) developed by *Stability AI* offers several interfaces for content generation with ready-made or one's own, improved models with their database, offering training of a person, object, image model, or training of one's handwriting, artistic style. Stable Diffusion models, which utilize generative artificial intelligence (*GenAI*) technologies, can generate new content, such as images, using large datasets and previously learned structures. For example, the *LoRA* training method allows you to adapt models to specific stylistic or visual tasks. However, unlike the DMN in the human brain, *Stable Diffusion* creativity is algorithmic and based on data and predetermined patterns. It cannot form intuitive associations on its own or use emotions like a human. *Stable Diffusion* models generate content by building on the structure of previous data and synthesizing it in new ways. Still, they do not have the consciousness, imagination, or self-reflection capabilities essential for human creativity. The DMN in the human brain and *Stable Diffusion* models can generate new ideas or visualizations using previously accumulated knowledge or data. A person spontaneously combines ideas, much like *Stable Diffusion* models generate new visual compositions using previous datasets. This "creative process" uses existing information to create something new in both cases, but their operating principles differ. Although *Stable Diffusion* models and the DMN in the human brain can generate new solutions, they operate on fundamentally different principles. The DMN in the human brain is associated with spontaneous, emotional, and intuitive thinking. At the same time, *Stable Diffusion* is based on data and statistical models that create a mechanical simulation of creativity. Creativity in the human brain is deeply subjective, whereas creativity generated by artificial intelligence is based on algorithms and training datasets, such as the *LoRA* model training technique.

While students (Focus Groups: 1, 2) gained practical skills in dataset preparation and AI model training during the module "Generative Technology Studies", the greater value lay in their increased critical awareness of authorship, randomness, and control. The generative tools introduced were not treated as final solutions but as media through which students explored identity, aesthetic intention, **and the tension between automation and originality**. In this respect, AI became not a substitute for the artist but a mirror – a reflective system that required careful calibration, interpretation, and ethical engagement.

In discussions and surveys, students (Focus Groups: 1, 2) know shared authorship with AI systems and indicate that authorship depends on the type of AI applications. Students expressed the opinion that, when used correctly, AI tools can be considered auxiliary tools, just like any other digital content creation program. AI remains an imperfect but generative collaborator. Students learned to treat training as both a technical task and a curatorial and conceptual one, positioning themselves as active co-authors of algorithmic processes.

Most students who participated in the course "Speciality and Practice: Generative Technology Studies" (Focus Groups: 1, 2) see the potential for further using the AI model of style in artistic processes, sketching, and process creation. Emphasis is placed on prototyping, less on creating an autonomous work of art.

B. Broader implications for AI in art education

The research also highlights a broader need within art education to incorporate AI literacy – not only in terms of software use, but also in developing the philosophical, ethical, and cognitive understanding necessary to engage with intelligent systems critically. This entails integrating AI-related content directly into both existing and newly developed study modules across higher education institutions.

Surveys conducted among students (Focus Groups 3 and 5), who were familiar with textual AI tools (e.g., *ChatGPT*) but unfamiliar with AI model training and its creative potential, revealed a narrower conceptualization of artificial intelligence. Their responses reflected limited awareness of how generative AI can be adapted for personalized or stylistic output. Interestingly, a notable divergence in attitudes emerged between the two groups. Bachelor's students from the Latvian Academy of Culture (Focus Group 3), surveyed prior to participating in the course "Introduction to AI Tools for Creative Industries", generally held more open and optimistic views toward AI's potential in artistic fields. Conversely, master's students at the Art Academy of Latvia, who also had no experience with training AI models, or other more in-depth knowledge (Focus Group 5), despite their higher proficiency, expressed more cautious, critical, and sometimes sceptical positions, particularly concerning the role of AI in artistic authorship and cultural production. Furthermore, the comparison between multiple groups, ranging from general education participants to postgraduate art students, revealed that neither age nor professional background alone determines AI recognition accuracy or openness to its integration in creative practice. Instead, the findings suggest that structured exposure to AI tools within a critical pedagogical framework plays a crucial role in shaping understanding and engagement.

In contrast, students from Focus Groups 1 and 2, who had hands-on experience training AI models, demonstrated deeper insight and more nuanced critical thinking, particularly regarding authorship, the interpretation of their individual style, "artistic handwriting", and the potential for optimizing creative processes through AI tools.

By integrating creative AI tools and critical thinking into the study process, students can develop a nuanced understanding of the potential and limitations of these technologies. This ensures emerging artists are tool users and informed, adaptive thinkers in a rapidly evolving cultural and technological environment. As generative technologies continue to grow, such literacy becomes essential for sustaining artistic autonomy.

Ultimately, this study suggests that AI can enrich creative practices when thoughtfully implemented by provoking questions about **representation, authorship, and meaning.** Rather than replacing creativity, it can extend it – offering new frames to see, question, and shape artistic futures. Students (Focus Groups: 1, 2) confirm that working with AI tools requires cognitive effort to control the system. For some students, creating art by hand can be more straightforward than training and using AI models. Here, we can link the idea of meta-cognitive abilities to stimulate and develop our cognitive abilities, enabling us to work skilfully with artificial intelligence tools.

Acknowledgments

This research is funded by the project "Cultural and Creative Ecosystem of Latvia as a Resource of Resilience and Sustainability" / CERS (No. VPP-MM-LKRVA-2023/1-0001) (2023–2026) and Culture Capital Foundation (KKF).

CERS
Cultural and creative ecosystem of Latvia as a resource of resilience and sustainability
No. VPP-MM-LKRVA-2023/1-0001

VALSTS KULTŪRKAPITĀLA FONDS

Bibliography

Bartoli, E., Smith, J., and Lee, A. (2024). *Default Mode Network Electrophysiological Dynamics and Causal Role in Creative Thinking*. Oxford: Oxford University Press. https://doi.org/10.1093/brain/awae199

Boisvert, H. (2024). *AI Creativity: Genius or Gimmick?* World Science Festival. Video, 40:00. Filmed on 27 September 2024. Available: https://www.youtube.com/watch?v=wU49MKIhMRU (viewed 06.09.2024.)

Cohen, H. (1995). *The Art of AARON, and the AARON of Art*. Stanford: Stanford University Press.

Guerrero Guerrero, M. (2024). *Midjourney and Its Future Implications for Intellectual Property regarding Content Generated by AI.* Available: https://chambers.com/articles/midjourney-and-its-future-implications-for-intellectual-property-regarding-content-generated-by-arti (viewed 02.08.2024.)

Grunert, P. F., Craglia, M., Gómez, E., and Thielen-del Pozo, J. (eds.). (2022). *HumaniTies and Artificial Intelligence*. Noema Media Publishing. Available: https://noemalab.eu/wp-content/uploads/2022/11/HumaniTies-and-Artificial-Intelligence-v1.1.pdf (viewed 16.05.2024.)

Magdy, H. (2023). The Use of Artificial Intelligence Art Generator 'Midjourney' in Artistic and Advertising Creativity. *Journal of Design Sciences and Applied Arts*, 4(2), 42–58. https://www.researchgate.net/publication/371377778_The_Use_of_Artificial_Intelligence_Art_Generator_Midjourney_in_Artistic_and_Advertising_Creativity Available: https://doi.org/10.21608/jdsaa.2023.169144.1231 (viewed 01.08.2024.)

Haynes, G. (2024). *Human or AI?: The Nuances of Intelligence.* Available: https://www.kornferry.com/content/dam/kornferry-v2/pdf/institute/kfi-human-or-ai-series-part-1.pdf (viewed 15.07.2024.)

Kelomees, R., Guljajeva, V., Laas, O. (2022). *The Meaning of Creativity in the Age of AI*. Tallinn: Estonian Academy of Arts. Available: https://www.researchgate.net/publication/375696443_The_Meaning_of_Creativity_in_the_Age_of_AI (viewed 11.05.2024.)

Kahneman D. (2011). *Thinking, Fast and Slow*. New York: Farrar, Straus, and Giroux.

Harvard, P. S. (2013). Two Hs from Harvard to Habsburg or Creative Semantics About Creativity: A Prelude to Creativity. In: Carayannis, E. G. (ed.), *Encyclopedia of Creativity, Invention, Innovation and Entrepreneurship*, New York, NY: Springer. https://doi.org/10.1007/978-1-4614-3858-8_2

Manovich, L. (2021–2024). *Artificial Aesthetics: Generative AI, Art, and Visual Media*. Available: http://manovich.net/index.php/projects/artificial-aesthetics (viewed 10.06.2024.)

Manovich, L. (2023/2024). *Memory, Draw. In Exhibition Catalog.* Available: http://manovich.net/index.php/projects/memory-draw (viewed 01.06.2024.)

Marquis, E., Vajoczki, S. (2012). Creative Differences: Teaching Creativity Across the Disciplines. *International Journal for the Scholarship of Teaching and Learning*, 6(1), article 6. https://doi.org/10.20429/ijsotl.2012.060106

Midjourney (2024). *Terms of Service.* Available: https://docs.midjourney.com/docs/terms-of-service (viewed 10.08.2024.)

Mirzoeff, N. (2006). *An Introduction to Visual Culture*. London: Routledge.

Shawn, S., Ding, W., Passananti, J., Wu, S., Zheng, H., Zhao, Y. B. (2023). *Nightshade: Prompt-Specific Poisoning Attacks on Text-to-Image Generative Models*. https://doi.org/10.48550/arXiv.2310.13828

Stability AI (2024). *Stable Diffusion XL Base 1.0 – Technical Overview.* Available: https://huggingface.co/stabilityai/stable-diffusion-xl-base-1.0 (viewed 04.06.2024.)

Appendix

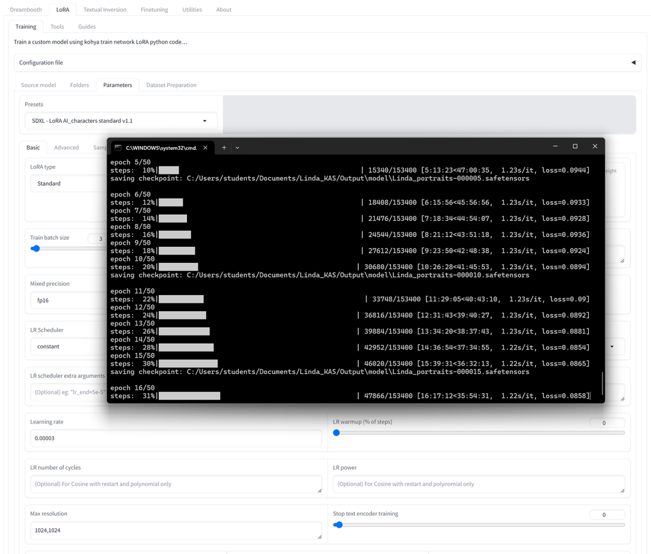

Figure A1. Training process in the *Kohya* interface using the *Stable Diffusion XL* base model. This figure illustrates the workflow of training a personalized *LoRA* (*Low-Rank Adaptation*) model, based on a dataset of student-created artworks.

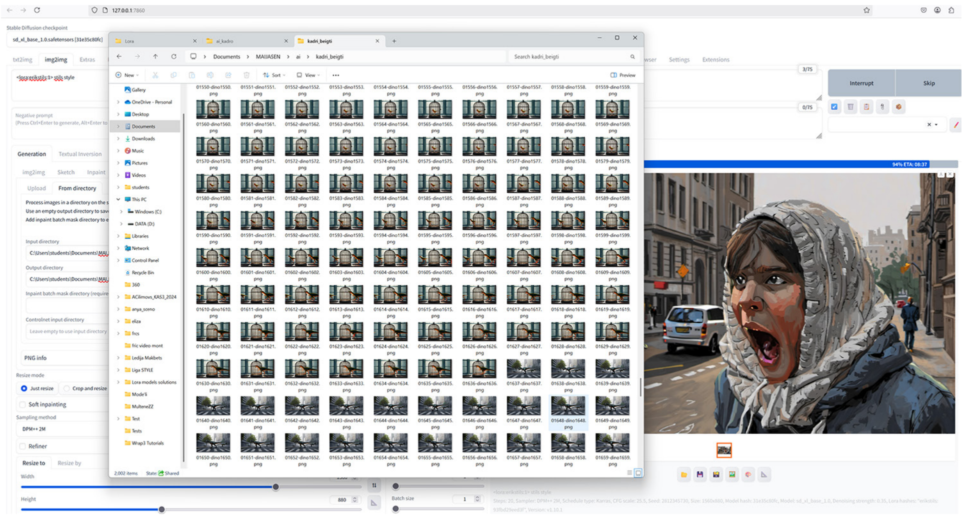

Figure A2. Example of the *Automatic1111* interface – frame-by-frame video processing using the Batch animation option. This figure illustrates the use of the *Automatic1111 Stable Diffusion* interface for transforming video sequences into a consistent artistic style through batch processing. The workflow involves importing an input directory of sequential video frames (shown in the file explorer window), applying a selected *LoRA* model and diffusion parameters, and exporting the processed frames in an output directory.

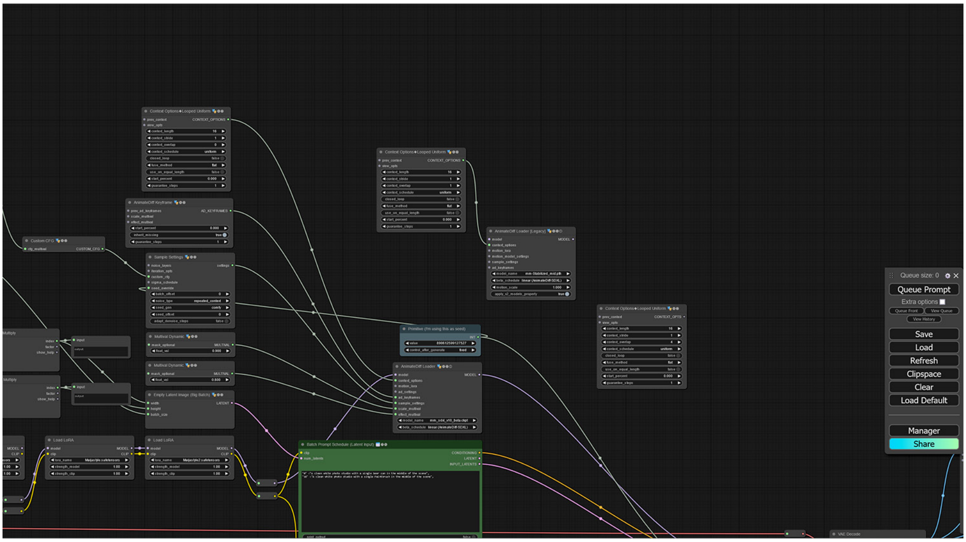

Figure A3. Example of an alternative interface – *ComfyUI* workflow. This figure demonstrates the use of the *ComfyUI* node-based interface for controlling and customizing generative processes in Stable Diffusion. Unlike text-prompt-driven environments such as *Automatic1111*, *ComfyUI* allows users to build complex visual pipelines by connecting modular nodes that define prompts, *LoRA* models, latent image initialization, and sampling parameters.

Figure A4. Gaussian splatting technique – animation still by Ance Dalmane, 2024. This figure presents a frame from an experimental animation created by student Ance Dalmane using the Gaussian splatting technique. The method transforms video material into a three-dimensional point cloud structure, where spatial information is represented through dense clusters of "splats" (2D Gaussian primitives).