AI Art and its Impact on Artists

Harry Jiang
Independent Researcher
Canada
hhj@alumni.cmu.edu

Lauren Brown
Artist
USA
labillustration@gmail.com

Jessica Cheng
Artist
Canada
chengelingart@gmail.com

Anonymous Artist
Artist
USA

Mehtab Khan
Yale Law
USA
mehtab.khan@yale.edu

Abhishek Gupta
Montréal AI Ethics Institute
Canada
abhishek@montrealethics.ai

Deja Workman
Penn State University
USA
dqw5409@psu.edu

Alex Hanna
The Distributed AI Research Institute
USA
alex@dair-institute.org

Jonathan Flowers
California State University, Northridge
USA
johnathan.flowers@csun.edu

Timnit Gebru
The Distributed AI Research Institute
USA
timnit@dair-institute.org

ABSTRACT

The last 3 years have resulted in machine learning (ML)-based image generators with the ability to output consistently higher quality images based on natural language prompts as inputs. As a result, many popular commercial "generative AI Art" products have entered the market, making generative AI an estimated $48B industry [125]. However, many professional artists have spoken up about the harms they have experienced due to the proliferation of large scale image generators trained on image/text pairs from the Internet. In this paper, we review some of these harms which include reputational damage, economic loss, plagiarism and copyright infringement. To guard against these issues while reaping the potential benefits of image generators, we provide recommendations such as regulation that forces organizations to disclose their training data, and tools that help artists prevent using their content as training data without their consent.

ACM Reference Format:
Harry Jiang, Lauren Brown, Jessica Cheng, Anonymous Artist, Mehtab Khan, Abhishek Gupta, Deja Workman, Alex Hanna, Jonathan Flowers, and Timnit Gebru. 2023. AI Art and its Impact on Artists. In *AAAI/ACM Conference on AI, Ethics, and Society (AIES '23), August 08–10, 2023, Montréal, QC, Canada.* ACM, New York, NY, USA, 12 pages. https://doi.org/10.1145/3600211.3604681

AIES '23, August 08–10, 2023, Montréal, QC, Canada

ACM ISBN 979-8-4007-0231-0/23/08.
https://doi.org/10.1145/3600211.3604681

1 INTRODUCTION

In the two years since the publication of [18] which outlines the dangers of large language models (LLMs), multimodal generative artificial intelligence (AI) systems with text, images, videos, voice, and music as inputs and/or outputs have quickly proliferated into the mainstream, making the generative AI industry valued at an estimated $48B [125]. Tools like Midjourney [78], Stable Diffusion [5], and DALL-E [91] that take in text as input and output images, as well as image-to-image based tools like Lensa [97] which output altered versions of the input images, have tens of millions of daily users [47, 127]. However, while these products have captured the public's imagination, arguably to a much larger extent than any prior AI system, they have also resulted in tangible harm, with more to come if the ethical concerns they posit are not addressed now. In this paper, we outline some of these concerns, focusing our discussion on the impact of image based generative AI systems, i.e. tools that take text, images, or a combination of both text and images as inputs, and output images. While other works have summarized some of the potential harms of generative AI systems more generally [18, 28, 29], we focus our discussion on the impacts of these systems on the art community, which has arguably been one of the biggest casualties (Section 4) [40, 138].

As we argue in Section 3, image based generative AI systems, which we call **image generators** throughout this paper, are not artists. We make this argument by first establishing that art is a uniquely human endeavor, using perspectives from philosophies of art and aesthetics. We further discuss how anthropomorphizing image generators and describing them as merely being "inspired" by their training data, like artists are inspired by other artists, is not only misguided but also harmful. Ascribing agency to image generators diminishes the complexity of human creativity, robs artists of credit (and in many cases compensation), and transfers accountability from the organizations creating image generators, and the practices of these organizations which should be scrutinized, to the image generators themselves.

While companies like Midjourney, Stability AI and Open AI who produce image generators are valued at billions of dollars and are raising hundreds of millions of dollars[1], their products are flooding the market with content that is being used to compete with and displace artists. In section 4, we discuss the impact of these products on working artists, including the chilling effect on cultural production and consumption as a whole. Merely open sourcing image generators does not solve these problems as they would still enable people to plagiarize artists' works, and impersonate their style for uses that the artists have not consented to.

In Section 5, we provide a summary of the relevant legal questions pertaining to image generators. While there have been legal developments around the world, we focus our analysis on the US where a number of lawsuits have been filed by artists challenging the use of image generators [129]. Given that copyright has been the most frequently invoked law in such cases [28], we provide an overview discussing the relevance of US copyright law in protecting artists, and conclude that it is largely unequipped to tackle many of the types of harms posed by these systems to content creators. As we discuss in Section 6, the AI research community has enabled the aforementioned harms through data laundering, with for-profit corporations partnering with academic institutions that help them gather training data for commercial purposes while increasing their chances of courts finding these uses to be "fair use".

We end our discussion with proposals for new tools and regulations that tackle some of the harms discussed in this paper, as well as encouraging the AI community to align themselves with those harmed by these systems rather than powerful entities driving the proliferation of generative AI models trained on the free labor of content creators.

2 LITERATURE REVIEW

2.1 Background on Image Generation

We define "generative artificial intelligence (AI)" to encompass machine learning products that feature models whose output spaces overlap in part or in full with their input spaces during training, though not necessarily inference. While generative AI systems are based on generative models which statistically aim to model the joint distribution between a feature space and output space $p(x, y)$ [85], we distinguish between "generative AI" systems and generative models as the latter can be used in classification systems. This paper focuses on products whose stated output space composes, in part or in full, of visual data (i.e. images), which will be referred to as **image generators**; similarly, the scope of art discussed within this work is largely limited to the fields of visual art. We consider two different applications in the context of inference, text-to-image and image-to-image, though more recent multimodal pretrained model architectures usually are capable of both (and often necessitate both).

Early approaches to image synthesis such as [38, 95, 120], aimed to achieve texture synthesis, i.e. modifying an existing image to copy the texture of another image [38, 95, 120]. In the deep learning era of computer vision (2012 until now), Convolutional Neural Networks (CNNs) enabled the ability to recognize a large amount of latent attributes that do not conform to arbitrary statistical forms, unlike early works in texture synthesis [69].

In addition to CNNs, another architectural element of note is the variational autoencoder (VAE), like the one used in Yan et al. [135]; VAEs, which use two mirrored neural network components to map the input space to a latent space (encoder) and vice versa (decoder) [68], set the stage for the development of generative models, which significantly widened the capacity of image synthesis. A key element of VAEs is the reconstructive loss function which allows an ML system to explicitly define its training objective as the re-creation of input features, with the expectation that the model can generalize beyond the training set during inference. VAEs enabled the creation of image generation models such as VQ-VAE-2 [104] and are components of many subsequent models.

The next major breakthrough is the generative adversarial network (GAN), which employs the use of two models trained simultaneously [58]. Unlike conventional neural networks such as VAEs which directly and asymmetrically measure the divergence between a distribution known to be a reference and one known to be a hypothesis, GANs indirectly measure the divergence between two distributions of masked origin through the intermediary of the discriminator. The introduction of conditional losses in [82] made GANs the dominant architecture in image generation due to the ability to now inform outputs with text tags as auxiliary information; the paper itself used a handwriting generator trained on the MNIST dataset [35] as a demonstration. With GANs came the first large-scale image generating models, allowing for output sizes of up to 512×512 [24, 61, 65].

The adaptation of approaches from natural language processing (NLP) such as transformers further enabled having complex text as input for text-to-image models [42]. In [30], OpenAI adapted the architecture of GPT-2, a large language model (LLM), to output a series of pixel values that could be rearranged into a recognizable image. This research led to the original DALL-E [103], a tool that outputs a 256×256 RGB image based on natural language prompts, this time using the GPT-3 architecture [25].

In the last 3 years, the use of GANs for image generation has been overtaken by diffusion models which take inspiration from fluid dynamics [37, 86, 116, 118]. These models work by repeatedly applying gaussian noise on an image (imitating the diffusion process of fluids or heat), and then denoising the result in equally many steps [118]. In a departure from GANs' implicit modeling, diffusion models return to using a reconstruction loss.

In 2022, Rombach et al. released the Stable Diffusion model [4, 106], which uses a conditional latent space based on text and images: in this case a pretrained model by OpenAI called CLIP [99]. This allowed for models that are not confined to natural language understanding (NLU)-based architectures, and can generate high-quality images based on natural language prompts. In the same year, OpenAI released DALL-E 2 [91] which has a similar model architecture [102] but with a training dataset that is opaque to the public.

[1] https://www.nytimes.com/2023/01/23/business/microsoft-chatgpt-artificial-intelligence.html

In addition to different model architectures, massive image datasets such as JFT-300M (300M images) [124] have helped improve image generation performance. The current crop of image generators, primarily those based on Stable Diffusion, are pretrained on LAION [109], or its variants which are subsets of the original 5B dataset. The dataset consists of 5.85 billion CLIP-filtered image-text pairs, of which 2.32B contain English language text. An exploration of a subset of LAION can be found at [11].

2.2 Products for Image Generation

The advent of Stable Diffusion and related models has resulted in a proliferation of commercial and non commercial image generation tools that use them. Stability AI's Stable Diffusion [5] and its commercial product Dream Studio[2], OpenAI's DALL-E 2 [91], and Midjourney [78] are the most popular systems built on diffusion models, with StarryAI [122], Hotpot.ai [94], NightCafe [123], and Imagen [108] being a few others. Established art software company Adobe has also released its image generator product, Adobe Firefly [3], which the company says is trained on Adobe Stock images, images in the public domain, and those under open licensing. The ecosystem is large and expanding, including organizations like Fotor [45], Dream by WOMBO [133], Images.AI [128], Craiyon [71], ArtBreeder [9], Photosonic [134], Deep Dream Generator [55], Runway ML [107], CFSpark [46], MyHeritage Time Machine [73], and Lensa [97]. While some advertise the model architectures they use, such as StableCog [121] using diffusion-based techniques, others provide little to no detail. For example, while the CEO of Stability AI has written that Midjourney used Stable Diffusion in past releases [3], Midjourney does not disclose underlying model information for its current releases, only mentioning "a brand-new AI architecture designed by Midjourney" in describing its releases since November 2022 [79].

Most of the products identified above emerged as specific commercial offerings for users to generate images by providing text prompts. There are other services that have been introduced as features in existing products, such as synthetic images in Canva [26], Shutterstock [113], and Adobe Stock Images [2], which seek to augment their stock image offerings with synthetic images. On the other hand, companies like Getty Images took a stance against including synthetic images in their portfolio of offerings in 2022 [130], although NVIDIA announced a collaboration with them in 2023 to develop image generators [76]. Open source efforts in the space have focused on using Stable Diffusion and other open-source variants to create plugins for Photoshop [7], Unreal Engine [43], and GIMP [20]. Some groups, such as Unstable Diffusion, are explicitly focused on generating not-safe-for-work (NSFW) content [59].

3 IMAGE GENERATORS ARE NOT ARTISTS

Many researchers have pointed out the issues that arise from the anthropomorphization of AI systems, including shifting responsibility from the people and organizations that build these systems, to the artifacts they build as if those artifacts have agency on their own [13, 16, 39]. This anthropomorphization is readily apparent in descriptions of image generators as if they are artists [39], even going as far as to claim that the image generators are "inspired" by the data they are trained on, similar to how artists are inspired by other artists' works [66]. In this section, we discuss why such arguments are misguided and harmful.

Following philosophers of art and aesthetics from varied disciplines (e.g. Chinese and Japanese Philosophy, American Pragmatism, and Africana Philosophy), we define art as a uniquely human endeavor connected specifically to human culture and experience [6, 36, 62, 74, 75, 88, 93]. Most philosophers of art and aesthetics argue that while non-human entities can have aesthetic experiences and express affect, a work of art is a cultural product that uses the resources of a culture to embody that experience in a form that all who stand before it can see. On this view, art refers to a process that makes use of external materials or the body to make present experience in an intensified form. Further, this process must be controlled by a sensitivity to the attitude of the perceiver insofar as the product is intended to be enjoyed by an audience. The artwork, therefore, is the result of a process that is controlled for some end and is not simply the result of a spontaneous activity ([36] pp. 54, 55). This control over the process of production is what marks the unique contribution of humanity: while art is grounded in the very activities of living, it is the human recognition of cause and effect that transforms activities once performed under organic pressures into activities done for the sake of eliciting some response from a viewer. As an example, a robin might sing, a peacock might dance, but these things are performed under the organic pressures of seeking a mate. In humans, song and dance are disconnected from the organic pressures of life and serve purposes beyond the mere satisfaction and expression of organic pressures, and serve cultural purposes. In brief, art is a form of communication: it communicates.

In contrast, the outputs of artifacts like image generators are not framed for enjoyment because they merely imitate the technical process, and then only those technical processes embodied in the works that make up the training dataset. The image generator has no understanding of the perspective of the audience or the experience that the output is intended to communicate to this audience. At best, the output of image generators is aesthetic, in that it can be appreciated or enjoyed, but it is not artistic or art itself. Thus, "Mere perfection in execution, judged in its own terms in isolation, can probably be attained better by a machine than by human art. By itself, it is at most technique… To be truly artistic, a work must also be esthetic—that is, framed for enjoyed receptive perception." ([36] pp. 54).

Thus, art is a uniquely human activity, as opposed to something that can be done by an artifact. While image generators have to be trained by repeatedly being shown the "right" output, using many examples of the desired target, and explicitly defining an objective function over which to optimize, humans do not have such rigid instructions. In fact, while image generators have been shown to even memorize their data and can output almost exact replicas of images from their training set under certain conditions [27, 117], as artist Karla Ortiz writes, artists' styles are so unique to them, that it is very difficult for one artist to copy another's work [92]. The very few artists who are able to do this copying are known for this skill [92]. An artists' 'personal style' is like their handwriting, authentic to them, and they develop this style (their personal voice

[2]https://dreamstudio.com

[3]https://web.archive.org/web/20220823032632/https://twitter.com/EMostaque/status/1561917541743841280, referring to V3

and unique visual language) over years and through their lived experiences [92].

The adoption of any particular style of art, personal or otherwise, is a result of the ways in which the individual is in transaction with their cultural environment such that they take up the customs, beliefs, meanings, and habits, including those habits of aesthetic production, supplied by the larger culture. As philosopher John Dewey argues, an artistic style is developed through interaction with a cultural environment rather than bare mimicry or extrapolation from direct examples supplied by a data set [23]. Steven Zapata argues, "our art 'creates' us as artists as much as we create it" [138]. This experience is unique to each human being by virtue of the different cultural environments that furnish the broader set of habits, dispositions towards action, that enabled the development of anything called a personal style through how an individual took up those habits and deployed them intelligently.

Finally, an image generator is trained to generate images from prompts by mapping images and texts into a lower dimensional representation in a latent space [58, 68, 106]. This latent space is learned during the model's training process. Once the model is trained, this latent space is fixed and can only change through training from scratch or fine-tuning on additional examples of image-text pairs [57]. In contrast, human inspiration changes continuously with new experiences, and a human's relationship with their lived experiences evolves over time. Most importantly, these experiences are not limited to additional artistic training or viewing of images. Rather, humans perform abstract interpretations between representational and imaginary subjects, topics, and of course, personal feelings and experiences that an artifact cannot have.

Let's look at Katsuhiro Otomo's seminal *Akira* as an example. Otomo notes that he created these images by drawing inspiration from his own teenage years, thinking about a rebuilding world, foreign political influence, and an uncertain future after World War II [12]. Similarly, Claude Monet created his defining *Nymphéas [Water Lilies]* series during the last 30 years of his life, after the loss of his son in 1914 [63]. As shown by both these artists, and many other artists, the human experience both defines and inspires creation across an artist's personal lifetime. Each individual's art is unique to their life experiences. Otomo's *Akira* is a fundamentally different form of artwork than Monet's *Nymphéas [Water Lilies]* series not simply due to their different stylistic and pictorial media, but due to the way in which each artists' work was an expression of a cultural inheritance that shaped the unique experiences that gave rise to their particular art forms. While image generators can imitate the stylistic habits, the "unique voices" of a given artist, they cannot develop their own particular styles because they lack the kinds of experiences and cultural inheritances that structure every creative act. Even when provided with a human-written prompt, the sampling of a probability distribution conditional on a string of text does not present a synthesis of concepts, emotion, and experience.

In conclusion, image generators are not artists: they require human aims and purposes to direct their "production" or "reproduction," and it is these human aims and purposes that shape the directions to which their outputs are produced. However, many people describe image generators as if these artifacts themselves are artists, which devalues artists' works, robs them of credit and compensation, and ascribes accountability to the image generators rather than holding the entities that create them accountable. In [39], Epstein et al. performed a study with participants on Amazon Mechanical Turk to assess the impact of anthropomorphization of image generators, finding a relationship between the manner in which participants assign credit and accountability to stakeholders involved in training and producing image generators, and the level of anthropomorphization. They advise "artists, computer scientists, and the media at large to be aware of the power of their words, and for the public to be discerning in the narratives they consume."

4 IMPACT ON ARTISTS

The proliferation of image generators poses a number of harms to artists, chief among them being economic loss due to corporations aiming to automate them away. In this section, we summarize some of these harms, including the impact of artists' styles being mimicked without their consent, and in some cases, used for nefarious purposes. We close with a discussion of how image generators stand to perpetuate hegemonic views and stereotyping in the creative world, and the chilling effects of these technologies on artists as well as overall cultural production and consumption.

4.1 Economic Loss

While artists hone their craft over years of practice, observation, and schooling, having to spend time and resources to pay for supplies, books, and tutorials, companies like Stability AI are using their works without compensation while raising billions from venture capitalists to compete with them in the same market[4]. Leaders of companies like Open AI and Stability AI have openly stated that they expect generative AI systems to replace creatives imminently[5][6]. Stability AI CEO Emad Mosque has even accused artists of wanting to have a "monopoly on visual communications" and "skill segregation"[7]. To the contrary, current image generation business models like those of Midjourney, Open AI and Stability AI, stand to centralize power in the hands of a few corporations located in Western nations, while disenfranchising artists around the world.

It is now possible for anyone to create hundreds of images in minutes, compile a children's book in an hour[8], and a project for a successful Kickstarter campaign in a fraction of the time it takes for an actual artist[9]. Although many of these images do not have the full depth of expression of a human, commercial image generators flood the market with acceptable imagery that can supplant the demand for artists in practice. This has already resulted in job losses for artists, with companies like Netflix Japan using image generators for animation, blaming "labor shortage" in the anime industry for not hiring artists [32].

[4]https://techcrunch.com/2022/10/17/stability-ai-the-startup-behind-stable-diffusion-raises-101m/

[5]https://web.archive.org/web/20220912045000/https://twitter.com/sama/status/1484950632331034625, https://web.archive.org/web/20220122181741/https://twitter.com/sama/status/1484952151222722562

[6]https://web.archive.org/web/20230811193157/https://twitter.com/emostaque/status/1591436813750906882

[7]https://web.archive.org/web/20230224175654/https://twitter.com/mollycrabapple/status/1606148326814089217

[8]https://www.youtube.com/watch?app=desktop&v=ZbVRYqsntDY

[9]https://web.archive.org/web/20230124003305/https://twitter.com/spiridude/status/1616476006444826625

One of the more high profile cases of the labor impact can be seen in the title sequence of Marvel Studio's 2023 TV series *Secret Invasion*, which uses a montage of generated imagery [81]. While prior movies from the studio feature between 5 (*The She-Hulk: Attorney at Law*[10]) and 9 (*Hawkeye*[11]) artists and illustrators for their title sequences, *Secret Invasion* has only one "Sagans Carle" credited as "AI Technical Director"[12]. This labor displacement is evident across creative industries. For instance, according to an article on Rest of World, a Chinese gaming industry recruiter has noticed a 70% drop in illustrator jobs, in part due to the widespread use of image generators [139]; another studio in China is reported to have laid off a third of its character design illustrators [139].

In addition to displacing the jobs of studio artists, the noise caused by the amount of AI-generated content will likely be devastating for self-employed artists in particular. This has become evident in the literary world with the advent of LLM based tools like ChatGPT[13]. Recently, Clarkesworld, a popular science fiction magazine, temporarily closed open submissions after being overwhelmed by the number of ChatGPT generated submissions they received [31]. They announced that they will instead only solicit works from known authors, which disadvantages writers who are not already well known. It is not difficult to extrapolate such a result with visual art venues that receive too many AI-generated images. Contrary to "democratizing art," this reduces the number of artists who can share their works and receive recognition.

Regardless of their objections, some working artists have started to report having to use image generators to avoid losing their jobs, further normalizing its commercial use [139]. Artists have also reported being approached by companies producing image generators to work on modifying the outputs of their systems [14]. This type of work reduces hard earned years of skill and artistic eye to simple cleanup work, with no agency for creative decisions. In spite of these issues, creatives in executive roles who can be isolated from the realities of most working artists, may gravitate towards using these tools without considering the effects on the industry at large, such as a reduction in the economic earning power of many working artists. For instance, the director of *Secret Invasion* had editorial control in deciding whether to use image generators[15], and chose to replace illustrators' works with image generated content.

With the increasing barriers and job losses for creatives because of image generators, the pursuit of art could be relegated to the independently wealthy and those who can afford to develop their artistic skills while working a full-time job. This will disproportionately harm the development of artists from marginalized communities, like disabled artists, and artists with dependents.

4.2 Digital Artwork Forgery

As discussed in Section 2, image generators are trained using billions of image-text pairs obtained from the Internet. Stable Diffusion V2, for instance, is trained using the publicly available LAION-5B dataset [106, 109]. Although the creators of LAION-5B have not provided a way for people to browse the dataset, various artists have reported finding their works in the training data without their consent or attribution [11]. Open AI has not shared the dataset that its image generator, DALL-E, was trained on, making it impossible to know the extent to which their training data contains copyright protected images. Using a tool[16] built by Simon Willison which allowed people to search 0.5% of the training data for Stable Diffusion V1.1, i.e. 12 million of 2.3 billion instances from LAION 2B [109], artists like Karen Hallion[17] [18] found out that their copyrighted images were used as training data without their consent [11]. And as noted in Section 3, image generators like Stable Diffusion have been shown to memorize images, outputting replicas of iconic photographs and paintings by artists [27, 92].

This type of digital forgery causes a number of harms to artists, many of whom are already struggling to support themselves and can only perform their artistic work while having other "day" jobs [70]. First, as discussed in Section 4.1, using artists' works without compensation adds to the already precarious positions that the majority of professional artists are in [70, 92, 138]. In addition to the lack of compensation, using artists' works without their consent can cause them reputational damage and trauma. Users of image generated art can mimic an artist's style by finetuning models like Stable Diffusion on specific artists' images, with companies like Wombo even offering services to generate art in the style tied to specific groups of artists like Studio Ghibli [133]. A number of artists have described this practice as "invasive" and noted the manner in which it causes them reputational damage. After a Reddit user posted images generated using artist Hollie Mengert's name as a prompt, Mengert mentioned that "it felt invasive that my name was on this tool, I didn't know anything about it and wasn't asked about it."[19] She further noted her frustration with having her name associated with images that do not represent her style except at "the most surface-level."

This type of invasive style mimicry can have more severe consequences if an artist's style is mimicked for nefarious purposes such as harassment, hate speech and genocide denial. In her New York Times Op-ed [8], artist Sarah Andersen writes about how even before the advent of image generators people edited her work "to reflect violently racist messages advocating genocide and Holocaust denial, complete with swastikas and the introduction of people getting pushed into ovens. The images proliferated online, with sites like Twitter and Reddit rarely taking them down." She adds that "Through the bombardment of my social media with these images, the alt-right created a shadow version of me, a version that advocated neo-Nazi ideology…I received outraged messages and had to contact my publisher to make my stance against this ultraclear." She underscores how this issue is exacerbated by the advent of image generators, writing "The notion that someone could type my name into a generator and produce an image in my style immediately disturbed me…I felt violated" [8]. As we discussed in Section 3, an

[10]https://ondisneyplus.disney.com/show/she-hulk
[11]https://ondisneyplus.disney.com/show/hawkeye
[12]https://www.disneyplus.com/series/invasion-secreta/3iHQtD1BDpgN
[13]https://openai.com/blog/chatgpt
[14]https://www.facebook.com/story.php?story_fbid=pfbid02L9Qkj6Bnidy6zL7hRjvQ9MuYLQF3jSUXcGLRjjgZhxH1LysnV4DZRUgMyhLMvKxGl&id=882110175
[15]https://www.polygon.com/23767640/ai-mcu-secret-invasion-opening-credits
[16]https://laion-aesthetic.datasette.io/laion-aesthetic-6pls/images
[17]https://web.archive.org/web/20230811043246/https://twitter.com/Khallion/status/1615464905565429760
[18]https://web.archive.org/web/20230117153958/https://twitter.com/shoomlah/status/1615215285526757381
[19]https://waxy.org/2022/11/invasive-diffusion-how-one-unwilling-illustrator-found-herself-turned-into-an-ai-model/

artist's style is their unique voice, formed through their life experiences. Echoing Hollie Mengert's point about the invasive nature of style mimicry, Andersen adds: "The way I draw is the complex culmination of my education, the comics I devoured as a child and the many small choices that make up the sum of my life. The details are often more personal than people realise." Thus, tools trained on artists' works and which allow users to mimic their style without their consent or compensation, can cause significant reputational damage by impersonating artists and spreading messages that they do not endorse.

4.3 Hegemonic Views and Stereotyping

Beyond the appropriation of individual identities, image generators have been shown to appropriate and distort identities of groups, encode biases, and reinforce stereotypes [87, 98, 119]. Introducing In/Visible, an exhibition exploring the intersection of AI and art, Senegalese artist Linda Dounia Rebeiz writes: "Any Black person using AI today can confidently attest that it doesn't actually know them, that its conceptualization of their reality is a fragmentary, perhaps even violent, picture…Black people are accustomed to being unseen. When we are seen, we are accustomed to being misrepresented. Too often, we have seen our realities ignored, distorted, or fabricated. These warped realities, often political instruments of exclusion, follow us around like shadows that we can never quite shake off" [64]. In an interview, the artist gives examples of stereotypes perpetuated through image generators. For instance, she notes that the images generated by Dall-E 2 pertaining to her hometown Dakar were wildly inaccurate, depicting ruins and desert instead of a growing coastal city [114]. Similarly, US-based artist Stephanie Dinkins discusses encountering significant distortions when prompting image generators to generate images of Black women [114].

There are already cases of people producing images embodying their view of other populations. In a 2018 New Yorker article, Lauren Michelle Jackson writes about a white British photographer, Cameron-James Wilson, who created a dark skinned synthetic model which he called "Shudu Gram," and the "World's first Digital Supermodel" [77]. The synthetic model, which he created using a free 3D modeling software called DAZ3D[20], first appeared on Instagram wearing "iindzila, the neck rings associated with the Ndebele people of South Africa" [77]. Jackson licensed the image to various entities such as Balmain[21] and Ellesse, [22] many of whom were criticized for their lack of diversity in hiring [96]. Now, without compensation to any Ndebele people, magazines like Vogue[23] profit off of an idealized conception of someone from that community, imagined in the mind of a white man who is compensated for creating that image. Writer Francesca Sobande writes that this is another iteration of "the objectification of Black people, and the commodification of Blackness" [115]. Five years later, on March 6 2023, entrepreneur Danny Postma announced the launch of a company, Deep Agency, that rents image generated synthetic models as a service[24], making the type of practice described by Jackson more likely to occur at scale.

Due to these questions of who gets to use (and profit from) these tools by representing which cultures in what way, participants from Pakistan, India and Bangladesh surveyed in [98] raised "concerns about artist attribution, commodification, and the consequences of separating certain art forms from their traditional roots," with some questioning which cultural products should be included in the training set of image generators. To expose these issues, Quadri et al. recommend further examination of the cultural harms posed by image generators, including perpetuating cultural hegemony, erasure or stereotyping [98].

4.4 Chilling Effects on Cultural Production and Consumption

The harms discussed in the prior sections have created a chilling effect among artists, who, as artist Steven Zapata notes, are already a traumatized community with many members struggling to make ends meet [137]. First, students who foresee image generators replacing artists have become demoralized and dissuaded from honing their craft and developing their style [138]. Second, both new and current artists are becoming increasingly reluctant to share their works and perspectives, in an attempt to protect themselves from the mass scraping and training of their life's works [92, 138]. Independent artists today share their work on social media platforms and crowdfunding campaigns, and sell tutorials, tools, and resources to other artists on various sites or at art-centric trade shows [25]. For most artists, gaining enough visibility on any of these platforms (online or in person) is extremely competitive, taking them years to build an audience and fanbase to sell their work and eventually have the ability to support themselves [26]. Thus, having less visibility in an attempt to protect themselves from unethical practices by corporations profiting from their work, further reduces their ability to receive compensation for their work.

Artists' reluctance to share their work and teach others also reduces the ability of prospective artists to learn from experienced ones, limiting the creativity of humans as a whole. Similar to the feedback loop created by next generations of large language models trained on the outputs of previous ones [18], if we, as humanity, rely solely on AI-generated works to provide us with the media we consume, the words we read, the art we see, we would be heading towards an ouroboros where nothing new is truly created, a stale perpetuation of the past. In [18], the authors warn against a similar issue with future generations of large language models trained on outputs of prior ones, and static data that does not reflect social change.

In his 1916 book titled Art, Clive Bell writes "The starting-point for all systems of aesthetics must be the personal experience of a peculiar emotion. The objects that provoke this emotion we call works of art" [15]. As Steven Zapata notes, we need to "protect

[20] https://www.daz3d.com/
[21] https://projects.balmain.com/us/balmain/balmains-new-virtual-army
[22] https://hypebae.com/2019/2/ellesse-ss19-campaign-shudu-virtual-cgi-digital-influencer-model
[23] https://www.vogue.com.au/fashion/trends/meet-shudu-the-digital-supermodel-who-is-changing-the-face-of-fashion-one-campaign-at-a-time/news-story/80a96d3d70043ed2629b5c0bc03701c1
[24] https://www.deepagency.com/
[25] https://www.muddycolors.com/2019/09/results-of-the-artist-income-goals-survey-2019/
[26] https://news.artnet.com/art-world/artist-financial-stability-survey-1300895

the creative human spirit…Making art is one of the best ways to investigate one of the ways you are influenced, and the way to send how you're influenced to other people. If we don't curb this, this influence can come from AI, AI that can't discern boundaries, and influence feelings. Let's not let it happen" [137].

5 AI ART AND US COPYRIGHT LAW

Given the speed at which image generators have been adopted and their impact, countries around the world are grappling with what policies to enact in response. In particular, there is a lot of uncertainty about whether using copyrighted materials to train image generators is copyright infringement. Some governmental bodies, like the EU, will require companies to "document and make publicly available a summary of the use of training data protected under copyright law"[27] [44], which could trigger copyright lawsuits if it becomes possible to identify specific instances of copyright infringement [72]. However, it is not clear what the scope of this law is and if it requires an itemized list of what is included in the training data, or only a summary of other key information.

While a number of artists have filed class action lawsuits in the US against companies providing commercial image generation tools [129], image generators represent a dynamic between artists and large-scale companies appropriating their work that has previously not been examined in US copyright law [56]. This is due to the unprecedented scale at which artists' works are being used to create image generators, the recent proliferation of publicly available image generators trained on that content, and the level to which the output of the image generators threatens to displace artists. Furthermore, this dynamic is distinct because of the data collection practices by which image generators are developed in the first place [67].

While some of the harms discussed in Section 4 overlap with the rights protected by US copyright law, others are not. There are also a number of unanswered legal questions when it comes to determining the ways in which copyright law applies to image generators and both the inputs and outputs that go into creating these tools. Hence, US copyright law is largely unequipped to tackle many of the types of harms posed by these systems to content creators. This lack of certainty about whether copyright applies means that the companies producing these tools can do so largely without accountability, unless they are sued for specific violations of copyright law. And waiting for court determinations on their lawsuits means that artists may not be able to get recourse until the cases are resolved. In this section, we highlight specific parts of US copyright law that may be a source of uncertainty and tension for artists and companies using their work. We conclude that there are gaps in the law that do not take into account the social and economic harm to artists.

5.1 Authorship

Thus far, no works created by an image generator have been given copyright protection, and authorship is limited to human creators. The US Copyright Office recently affirmed this position by declining to recognize the copyrightability of works that were created by an image generator [90]. In the US, the mere effort required to create a piece of art work does not, on its own, render the resulting work protected by copyright law, meaning that the number of prompts or hours poured into the creation of an image using text-to-image generators will not on its own qualify the work as copyrightable.[28] Moreover, the prompts themselves may be protectable if they are independently creative, and the resulting work may be copyrightable if the prompts were part of an active process by which the human creator exercised judgment by selecting, arranging, or designing the work [29]. US law also requires that the creator of the work be the source of the creativity and inventiveness of the work, and the Copyright Office noted that image generators produce images in an "unpredictable" way [90] and thus cannot be considered creative or inventive.

These dimensions of what it means to be an "author" under copyright law as well as how the law understands the process of creativity means that image generators on their own cannot create copyright protected works. How artists interact with these tools would determine the legal status of the output they create. Given this uncertainty about the legal status of the image generators' outputs, we can direct our policy attention to the inputs that go into creating the tools. There is an opportunity here to exercise more caution in the ex-ante processes of the tools' development such that the artists whose works are used to create the tools are not harmed, which we discuss in Section 7.

5.2 Fair Use

Fair use is a doctrine in copyright law that permits the unauthorized or unlicensed use of copyrighted works; whether it is to make copies, to distribute, or to create derivative works. Whether something constitutes fair use is determined on a case-by-case basis and the analysis is structured around four factors[30]. Most relevant for artists and generative AI systems are factors 1 and 4, which look at the purpose or character of the use and its impact on the market [14]. Part of the first factor includes the question of whether the use is commercial and "transformative". Commercial use usually weighs against finding fair use. If the use is found to be transformative, however, it can be considered fair use even for commercial purposes, but not always[31]. This is in part due to the fourth factor, which examines whether a use is a threat to the market of the original creator's work.

The question of fair use arises at two points within the image generation ecosystem. First is when the images used to train the datasets are copyrighted, and especially if the copyright holders are small-scale artists. These small scale artists could have an interest in not allowing their work to be used to create synthetic images, not only because image generators could be used to produce works resembling theirs, but because of issues around consent and misuse of their works for harassment, disinformation and hate speech as described in Section 4.2. Artists may not want to participate in the creation of an infrastructure that facilitates other informational harms, even if the image generator is not creating works resembling

[27] https://www.euaiact.com/

[28] Bellsouth Advertising & Pub. v. Donnelley Inf. Pub., 933 F. 2d 952 - Court of Appeals, 11th Circuit 1991

[29] Feist Publications, Inc. v. Rural Tel. Serv. Co., 499 U.S. 340 (1991)

[30] https://www.govinfo.gov/app/details/USCODE-2011-title17/USCODE-2011-title17-chap1-sec107

[31] Fox News Network, LLC v. TVEyes, Inc., No. 15-3885 (2d Cir. 2018)

theirs. In this case, their concerns wouldn't be ones that can be addressed through fair use.

Moreover, small-scale artists may not want to pursue copyright infringement claims because of a lack of resources to participate in prolonged legal battles against powerful companies that claim such copying is fair use. This again means that copyright law is not the most effective recourse for them and the question of fair use may not be addressed in a case involving small-scale artists. The complaint[32] filed by Getty Images (a large and well-resourced copyright holder) against Stability AI is illustrative of the resources needed to assert copyright claims against companies producing image generators and the power differential that exists between small-scale copyright holders and these companies. Copyright infringement is a concern for small-scale artists but the overall system of how image generators normalize appropriation of art at the input stages is a problem that is beyond the scope of fair use considerations.

The second point where fair use is a question is if an image generator is used to create works that are similar to a human artist, and as a result compete with the human artist's market, as we describe in Section 4.1. In such instances, the fourth factor may weigh heavily against finding fair use. If the work is being used in ways that displaces the artist's market share, or prevents them from receiving appropriate attribution and compensation, there is a clear harm in place, and may be addressed through copyright law.

5.3 Derivative Works and Moral Rights

When companies design their products around "mimicking" the style of an artist, then it becomes difficult to justify the company's use as fair use [49]. In such instances, there is a clear connection between the company's product and the intended outcome being harm to the market for the original artist's work.

Such mimicking or use of an artist's work and style may also be covered under moral rights in copyright law. Moral rights vest in "visual art", such as paintings and photographs, and protect the creator's personal and reputational interest in their work by preventing the distortion or defacement of the original work [80]. The scope of moral rights in US copyright law is narrowly constructed for various policy reasons [89], but this area of copyright law may need more attention as artists try to articulate the harms they face.

6 SHORTCOMINGS OF THE AI RESEARCH COMMUNITY

In the previous section, we provided a brief analysis of US copyright law that may be relevant to artists' fight against the harms they face due to the proliferation of image generators. In this section, we discuss how academic researchers' partnerships with corporations help the latter sidestep some of these laws aimed at protecting creators. In her paper titled The Steep Cost of Capture, whistleblower Meredith Whittaker writes about the level to which academic AI research has been captured by corporate interests [132]. In The Grey Hoodie Project: Big tobacco, big tech, and the threat on academic integrity, Mohamed and Moustafa Abdalla liken this capture to the tobacco and fossil fuel industries, noting that corporations fund academics aligned with their goals, the same way that tobacco companies funded doctors that claimed that cigarettes did not cause cancer [1]. In her article, "You are not a stochastic parrot," Liz Weil notes "The membrane between academia and industry is permeable almost everywhere; the membrane is practically nonexistent at Stanford, a school so entangled with tech that it can be hard to tell where the university ends and the businesses begin" [131]. This corporate entanglement means that the academic research agenda is increasingly being set by researchers who align themselves with powerful corporate interests [51, 52, 132].

6.1 Data Laundering

One of the results of this corporate academic partnership has been data laundering [34]. Similar to money laundering, where business fronts are created to move money around while obfuscating the source of illicit funds, researchers have argued that companies use data laundering to obtain data through nonprofits that are then used in for profit organizations [10].

The LAION dataset used to train Stability AI's Stable Diffusion model, which is also used in their commercial Dream Studio product, is one such example[33]. While LAION is a nonprofit organization, the paper announcing the LAION-5B dataset notes that Stability AI CEO Emad Mostaque "provided financial and computation support for open source datasets and models" [109]. The dataset's associated datasheet further answers the question "Who funded the creation of this dataset" with "This work was sponsored by Hugging Face and Stability AI." As we mentioned in Section 6, while US copyright law is not fully equipped to resolve disputes related to image generated content, companies are more likely to be granted fair use exceptions in US copyright law if they claim that the dataset was gathered for research purposes, even if they end up using it for commercial products. According to the US copyright office, "Courts look at how the party claiming fair use is using the copyrighted work, and are more likely to find that nonprofit educational and noncommercial uses are fair."[34] This allows corporations like Stability AI to raise $101M in funding with a $1B valuation[35], using datasets that contain artists' works without their consent or attribution. The accountability for the dataset creation and maintenance, on the other hand, including copyright or privacy issues, is shifted to the nonprofit that collected it. Thus, while there is no legal distinction at present between data laundering and the normative data mining practices in the machine learning communities, this question needs more attention when the issue of fair use discussed in Section 5.2 arises in the context of image generators.

6.2 Power, ML Fairness, and AI Ethics

In the Moral Character of Cryptographic Work, cryptographer Philip Rogaway notes that the cryptographic community bears the responsibility of failing to stop the rise of surveillance [105]. One of the main reasons for this disconnect, according to him, is that cryptographers fail to take into account how power affects their analyses, and have a "politically detached posture," writing "if power is anywhere in the picture, it is in the abstract capacities

[32] https://news.bloomberglaw.com/ip-law/getty-images-sues-stability-ai-over-art-generator-ip-violations

[33] https://stability.ai/blog/stablediffusion2-1-release7-dec-2022

[34] https://www.copyright.gov/fair-use/

[35] https://techcrunch.com/2022/10/17/stability-ai-the-startup-behind-stable-diffusion-raises-101m/

of notional adversaries or, in a different branch of our field, the power expenditure, measured in watts, for some hardware." Except for a few exceptions, the machine learning fairness and AI ethics communities have similarly failed to stop the harms caused by image generators proliferated by powerful entities, due to their disproportionate focus on abstract concepts like defining fairness metrics [84, 110, 136], rather than preventing harm to various communities. We urge the machine learning and AI ethics research communities to orient their focus towards preventing and mitigating harms caused to marginalized communities, in order to prevent further casualties of which the art community is only one.

7 RECOMMENDATIONS TO PROTECT ARTISTS

To fight back against the harms that artists have already experienced, they have filed class action lawsuits in the US against Midjourney, Stable Diffusion and DeviantArt [129], organized protests, boycotted online services like ArtStation that allowed image generated content on their platforms[36], and continue to raise awareness about the impact of image generators on their communities [92, 137, 138]. However, as discussed in Section 5, the US courts can take years to issue a decision, during which more artists would be harmed, and current US copyright law is ill equipped to protect artists. Because of this, artists themselves have suggested a number of regulations to protect them.

A letter to members of The Costume Designers Guild, Local 892, a union of professional costume designers, assistant costume designers, and illustrators working in film, television, commercials and other media[37], suggests legislation to allow "using AI derived imagery strictly for reference purposes and making it unacceptable to hand over a fully AI generated work as a finished concept" [126]. Visual artists who paint in a more representational style usually work from photo reference or build sculptures to understand how lighting works, for example, using stock/licensed photography and assets, or the artist's own work [38]. This would allow artists to use image generators to provide inspiration in the way that nature, for example, is a source of inspiration to many artists. The art collective Arte es Ética suggests having a metric to quantify the amount of human interaction with an image generator to determine whether or not a generated image is copyrightable, with a 25% or less interaction level being uncopyrightable [41].

While these proposals may address the issue of economic loss, they do not stop the use of artists' work for training image generators without their consent or compensation. Additional proposed regulations by Arte es Ética address this issue by recommending legislation that requires the explicit consent of content creators before their material is used for generative AI models [41]. In order to do this, they suggest having detection and filtering algorithms to ensure that uploaded content belongs to creators who have consented to their work being licensed or opted-in for use as training data. Similar to [18]'s recommendations to ensure that synthetic texts generated by LLMs be "watermarked and thus detectable," Arte es Ética suggests that each image carry "a digital signature" in its metadata, which is disclosed along with the generated image. Regulation that mandates that organizations disclose their training data, at the very least to specific bodies that can verify that people's images were not used without their consent, is needed in order to enforce the opt-in requirements artists are demanding. Such a mandate will likely exist outside of conventional copyright requirements. However, algorithmic accountability regimes and recently proposed laws like the Algorithmic Accountability Act of 2022 in the US [111], or the transparency requirements of the EU's AI Act that would require datasheets [54] or similar data documentation [44], may be preliminarily useful in instituting disclosure requirements for companies.

However, most of these existing measures require individuals to prove harm, rather than placing the onus on organizations to show lack of harm before proliferating their products. There need to be pathways toward better accountability of the entities and stakeholders that create the image generators in the first place, rather than placing additional burdens on artists to prove that they have been harmed. While auditing, reporting, and transparency are well-known possible proposals for regulating AI in general [17, 22, 54, 83, 100], formulating sector and industry specific proposals is essential when it comes to effective governance [100], and is what will be needed for image generators and art.

Regulation, even if successfully passed, takes a long time to be enforced however, and is by its very nature reactive. As artist Steven Zapata asks: "What are we going to do…to prevent this recurring over and over again" [137]? This is a fundamental question that requires us to understand why we are in a position where prominent machine learning researchers have used their skills to disenfranchise artists. One answer is the corporate capture of AI research that we discussed in Section 6.1. To combat this capture, computer scientist Timnit Gebru suggests having government research funding that is not tied to the military, in order to have "alternatives to the hugely concentrated power of a few large tech companies and the elite universities closely intertwined with them" [51].

A few researchers in machine learning have come to the defense of artists but they are much smaller in number than those working on image generators without attempting to mitigate their harms. For instance, University of Chicago student Shawn Shan and his collaborators, advised by security professor Ben Y. Zhao, created a tool called Glaze that allows artists to add perturbations to their images which would prevent diffusion model based generators from being used to mimic their styles [112]. The researchers collaborated with 1000 artists, going to town halls and creating surveys to understand their concerns. While building Glaze, Shawn Shan et al. measured their success by how much the tool was addressing the artists' concerns. This is an example of research that is conducted in service of specific groups, using a process that identifies stakeholders and values that should be incorporated in the work, rather than the current trend of claiming to build models with "general" capabilities that do not perform specific tasks in well defined domains [53, 101]. We echo [18]'s recommendations to use methodologies like value sensitive design and design justice [33, 48] to identify stakeholders and their values, and work on systems that meaningfully incorporate them. These processes encourage researchers and practitioners to consult with visual artists and build tools that make their lives

[36] https://www.theverge.com/2022/12/23/23523864/artstation-removing-anti-ai-protest-artwork-censorship
[37] https://www.costumedesignersguild.com/
[38] https://cynthia-sheppard.squarespace.com/#/burn-out/

easier, rather than claiming to create tools that "democratize art" without consulting them, as a number of artists have noted [40, 60].

In summary, we advocate for regulation that prevents organizations from using people's content to train image generators without their consent, funding for AI research that is not entangled with corporate interests, and task specific works in well defined domains that serve specific communities. It is much easier to accomplish these goals if machine learning researchers are trained in a manner that helps them understand how technology interacts with power, rather than the "view from nowhere" stance that has been critiqued by feminist scholars, which teaches scientists and engineers that their work is neutral [50, 105]. We thus advocate for a computer science education system that stresses the manner in which power interacts with technology [19, 105].

8 CONCLUSION

In this paper, we have reviewed the chilling impact of image generators on the art community, ranging from economic loss, to reputational damage and stereotyping. We summarized recommendations to protect artists, including new regulation that prohibits training image generators on artists' works without opt-in consent, and specific tools that help artists protect against style mimicry. Our work is rooted in our argument that art is a uniquely human endeavor. And we question who its further commodification will benefit. As artist Steven Zapata asks, "How can we get clear on the things we do not want to forfeit to automation?" [137]

Image generators can still be a medium of artistic expression when their training data is not created from artists' unpaid labor, their proliferation is not meant to supplant humans, and when the speed of content creation is not what is prioritized. One such example is the work of artist Anna Ridler, who created a piece called Mosaic Virus in 2019[39], generating her own training data by taking photos of 10, 000 Tulips, which itself is a work of art she titled Myriad (Tulips). She then trained a GAN based image generator with this data, creating a video where the appearance of a tulip is controlled by the price of bitcoin, "becoming more striped as the price of bitcoin goes up—it was these same coveted stripes that once triggered tulip mania...a 17th-century phenomenon which saw the price of tulip bulbs rise and crash...It is often held up as one of the first recorded instances of a speculative bubble" [21]. If we orient the goal of image generation tools to enhance human creativity rather than attempt to supplant it, we can have works of art like those of Anna Ridler that explore its use as a new medium, and not those that appropriate artists' work without their consent or compensation.

ACKNOWLEDGMENTS

Thank you to Emily Denton, Énora Mercier, Jessie Lam, Karla Ortiz, Neil Turkewitz, Steven Zapata, and the anonymous peer reviewers for giving us invaluable feedback.

REFERENCES

[1] Mohamed Abdalla and Moustafa Abdalla. 2021. The Grey Hoodie Project: Big Tobacco, Big Tech, and the Threat on Academic Integrity. In *Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society* (Virtual Event, USA) *(AIES '21)*. Association for Computing Machinery, New York, NY, USA, 287–297. https://doi.org/10.1145/3461702.3462563

[2] Adobe. 2022. Generative AI Content. Retrieved March 13, 2023 from https://helpx.adobe.com/ca/stock/contributor/help/generative-ai-content.html

[3] Adobe. 2023. Generative AI for creatives - Adobe Firefly. Retrieved July 6, 2023 from https://www.adobe.com/sensei/generative-ai/firefly.html

[4] Stability AI. 2022. Stable Diffusion Launch Announcement. Retrieved March 13, 2023 from https://stability.ai/blog/stable-diffusion-announcement

[5] Stability AI. 2022. Stable Diffusion Public Release. https://stability.ai/blog/stable-diffusion-public-release/

[6] Thomas M Alexander. 2013. *The human eros: Eco-ontology and the aesthetics of existence.* Fordham University Press.

[7] Abdullah Alfaraj. 2023. Auto-Photoshop-StableDiffusion-Plugin. Retrieved March 13, 2023 from https://github.com/AbdullahAlfaraj/Auto-Photoshop-StableDiffusion-Plugin

[8] Sarah Andersen. 2022. The Alt-Right Manipulated My Comic. Then A.I. Claimed It. *New York Times* (Dec. 31, 2022). https://www.nytimes.com/2022/12/31/opinion/sarah-andersen-how-algorithim-took-my-work.html

[9] Artbreeder. 2022. artbreeder. Retrieved March 13, 2023 from https://www.artbreeder.com/

[10] Andy Baio. 2021. AI Data Laundering: How Academic and Nonprofit Researchers Shield Tech Companies from Accountability. *Waxy* (2021).

[11] Andy Baio. 2022. Exploring 12 Million of the 2.3 Billion Images Used to Train Stable Diffusion's Image Generator. Retrieved July 6, 2023 from https://waxy.org/2022/08/exploring-12-million-of-the-images-used-to-train-stable-diffusions-image-generator/

[12] Ollie Barder. 2017. Katsuhiro Otomo On Creating 'Akira' And Designing The Coolest Bike In All Of Manga And Anime. *Forbes* (2017).

[13] Alexis T Baria and Keith Cross. 2021. The brain is a computer is a brain: neuroscience's internal debate and the social significance of the Computational Metaphor. *arXiv preprint arXiv:2107.14042* (2021).

[14] Barton Beebe. 2008. An Empirical Study of U.S. Copyright Fair Use Opinions, 1978-2005. *University of Pennsylvania Law Review* 156, 3 (2008). https://scholarship.law.upenn.edu/penn_law_review/vol156/iss3/1/

[15] Clive Bell. 1916. *Art.* Chatto & Windus.

[16] Emily M Bender. 2022. Resisting Dehumanization in the Age of "AI". (2022).

[17] Emily M Bender and Batya Friedman. 2018. Data statements for natural language processing: Toward mitigating system bias and enabling better science. *Transactions of the Association for Computational Linguistics* 6 (2018), 587–604.

[18] Emily M. Bender, Timnit Gebru, Angelina McMillan-Major, and Shmargaret Shmitchell. 2021. On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?. In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* (Virtual Event, Canada) *(FAccT '21)*. Association for Computing Machinery, New York, NY, USA, 610–623. https://doi.org/10.1145/3442188.3445922

[19] Ruha Benjamin. 2020. Race after technology: Abolitionist tools for the new jim code.

[20] blueturtleai. 2023. gimp-stable-diffusion. Retrieved March 13, 2023 from https://github.com/blueturtleai/gimp-stable-diffusion

[21] Ruby Boddington. 2019. Anna Ridler uses AI to turn 10,000 tulips into a video controlled by bitcoin. *It's Nice That* (2019).

[22] Karen L Boyd. 2021. Datasheets for datasets help ml engineers notice and understand ethical issues in training data. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW2 (2021), 1–27.

[23] Jo Ann Boydston. 2008. *The Middle Works of John Dewey, Volume 9, 1899-1924: Democracy and Education 1916.* Southern Illinois University Press.

[24] Andrew Brock, Jeff Donahue, and Karen Simonyan. 2018. Large Scale GAN Training for High Fidelity Natural Image Synthesis. https://doi.org/10.48550/ARXIV.1809.11096

[25] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *Advances in neural information processing systems* 33 (2020), 1877–1901.

[26] Canva. 2022. Text to Image - Canva Apps. Retrieved March 13, 2023 from https://www.canva.com/apps/text-to-image

[27] Nicholas Carlini, Jamie Hayes, Milad Nasr, Matthew Jagielski, Vikash Sehwag, Florian Tramèr, Borja Balle, Daphne Ippolito, and Eric Wallace. 2023. Extracting Training Data from Diffusion Models. https://doi.org/10.48550/ARXIV.2301.13188

[28] Electronic Privacy Information Center. 2023. Generating Harms. Generative AI's Impact & Paths Forward. Retrieved July 6, 2023 from https://epic.org/documents/generating-harms-generative-ais-impact-paths-forward/

[29] Chen Chen, Jie Fu, and Lingjuan Lyu. 2023. A Pathway Towards Responsible AI Generated Content. https://doi.org/10.48550/ARXIV.2303.01325

[30] Mark Chen, Alec Radford, Rewon Child, Jeffrey Wu, Heewoo Jun, David Luan, and Ilya Sutskever. 2020. Generative Pretraining From Pixels. In *Proceedings of the 37th International Conference on Machine Learning (Proceedings of Machine*

[39] http://annaridler.com/mosaic-virus

Learning Research, Vol. 119), Hal Daumé III and Aarti Singh (Eds.). PMLR, 1691–1703. https://proceedings.mlr.press/v119/chen20s.html
[31] Neil Clarke. 2023. A Concerning Trend. (2023).
[32] Samantha Cole. 2023. Netflix Made an Anime Using AI Due to a ’Labor Shortage,’ and Fans Are Pissed. *Vice* (2023).
[33] Sasha Costanza-Chock. 2020. *Design justice: Community-led practices to build the worlds we need.* The MIT Press.
[34] Subhasish Dasgupta. 2005. *Encyclopedia of virtual communities and technologies.* IGI Global.
[35] Li Deng. 2012. The mnist database of handwritten digit images for machine learning research. *IEEE Signal Processing Magazine* 29, 6 (2012), 141–142.
[36] John Dewey. 1934. *Art as Experience.* Penguin Group (USA) Inc.
[37] Prafulla Dhariwal and Alex Nichol. 2021. Diffusion Models Beat GANs on Image Synthesis. https://doi.org/10.48550/ARXIV.2105.05233
[38] Alexei A. Efros and William T. Freeman. 2001. Image Quilting for Texture Synthesis and Transfer. In *Proceedings of the 28th Annual Conference on Computer Graphics and Interactive Techniques (SIGGRAPH ’01)*. Association for Computing Machinery, New York, NY, USA, 341–346. https://doi.org/10.1145/383259.383296
[39] Ziv Epstein, Sydney Levine, David G Rand, and Iyad Rahwan. 2020. Who gets credit for AI-generated art? *Iscience* 23, 9 (2020).
[40] Arte es Ética. 2023. Arte es Ética presente en la ACM FAccT Conference 2023. Retrieved July 6, 2023 from https://arteesetica.org/arte-es-etica-presente-en-la-acm-facct-conference-2023/
[41] Arte es Ética. 2023. Un manifiesto para comprender y regular la I.A. generativa. (April 2023). https://arteesetica.org
[42] Patrick Esser, Robin Rombach, and Björn Ommer. 2020. Taming Transformers for High-Resolution Image Synthesis. https://doi.org/10.48550/ARXIV.2012.09841
[43] Alberto Cerdá Estarelles. 2023. ue-stable-diffusion. Retrieved March 13, 2023 from https://github.com/albertotrunk/ue-stable-diffusion
[44] European Commission. 2021. The Artificial Intelligence Act. (2021).
[45] Everimaging. 2022. Fotor. Retrieved March 13, 2023 from https://www.fotor.com/features/ai-image-generator/
[46] Creative Fabrica. 2022. CF Spark AI Art Generator. Retrieved March 13, 2023 from https://www.creativefabrica.com/spark/ai-image-generator/
[47] Mureji Fatunde and Crystal Tse. 2022. Stability AI Raises Seed Round at $1 Billion Value. *Bloomberg* (Oct. 17, 2022). https://www.bloomberg.com/news/articles/2022-10-17/digital-media-firm-stability-ai-raises-funds-at-1-billion-value
[48] Batya Friedman. 1996. Value-sensitive design. *interactions* 3, 6 (1996), 16–23.
[49] Thania Garcia. 2023. David Guetta Replicated Eminem’s Voice in a Song Using Artificial Intelligence. *Variety* (Feb. 8, 2023). https://variety.com/2023/music/news/david-guetta-eminem-artificial-intelligence-1235516924/
[50] Timnit Gebru. 2019. Chapter on race and gender. *Oxford Handbook on AI Ethics. Available from: http://arxiv. org/abs/1908.06165 [Accessed 28th April 2020]* (2019).
[51] Timnit Gebru. 2021. For truly ethical AI, its research must be independent from big tech. *Guardian* (2021).
[52] Timnit Gebru. 2022. Effective Altruism is Pushing a Dangerous Brand of ‘AI Safety’. *Wired* (2022).
[53] Timnit Gebru. 2023. Eugenics and The Promise of Utopia through Artificial General Intelligence.
[54] Timnit Gebru, Jamie Morgenstern, Briana Vecchione, Jennifer Wortman Vaughan, Hanna Wallach, Hal Daumé Iii, and Kate Crawford. 2021. Datasheets for datasets. *Commun. ACM* 64, 12 (2021), 86–92.
[55] Deep Dream Generator. 2022. Deep Dream Generator. Retrieved March 13, 2023 from https://deepdreamgenerator.com/
[56] Jessica Gillotte. 2020. Copyright Infringement in AI-Generated Artworks. *UC Davis Law Review* 53, 5 (2020). https://ssrn.com/abstract=3657423
[57] Ian Goodfellow, Yoshua Bengio, and Aaron Courville. 2016. *Deep Learning.* MIT Press. http://www.deeplearningbook.org.
[58] Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. 2014. Generative Adversarial Networks. https://doi.org/10.48550/ARXIV.1406.2661
[59] Abhishek Gupta. 2022. Unstable Diffusion: Ethical challenges and some ways forward. Retrieved March 13, 2023 from https://montrealethics.ai/unstable-diffusion-ethical-challenges-and-some-ways-forward/
[60] The Distributed AI Research Institute. 2023. Stochastic Parrots Day: What’s Next? A Call to Action. Retrieved July 6, 2023 from https://peertube.dair-institute.org/w/a2KCCzj2nyfrq5FvJbL9jY
[61] Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, and Alexei A. Efros. 2016. Image-to-Image Translation with Conditional Adversarial Networks. https://doi.org/10.48550/ARXIV.1611.07004
[62] Philip J Ivanhoe. 2000. *Confucian moral self cultivation.* Hackett Publishing.
[63] Nina Kalitina and Nathalia Brodskaya. 2012. *Claude Monet.* Parkstone International.
[64] KALTBLUT. 2023. Feral File presents In/Visible: Where AI Meets Artistic Diversity, A Fascinating Encounter of Limitations and Storytelling. Retrieved July 6, 2023 from https://www.kaltblut-magazine.com/feral-file-presents-in-visible-where-ai-meets-artistic-diversity-a-fascinating-encounter-of-limitations-and-storytelling/
[65] Tero Karras, Samuli Laine, and Timo Aila. 2018. A Style-Based Generator Architecture for Generative Adversarial Networks. https://doi.org/10.48550/ARXIV.1812.04948
[66] Kevin Kelly. 2022. Picture Limitless Creativity at Your Fingertips. *Wired* (2022).
[67] Mehtab Khan and Alex Hanna. 2022. The Subjects and Stages of AI Dataset Development: A Framework for Dataset Accountability. (Sept. 13, 2022). https://doi.org/10.2139/ssrn.4217148
[68] Diederik P Kingma and Max Welling. 2013. Auto-Encoding Variational Bayes. https://doi.org/10.48550/ARXIV.1312.6114
[69] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. 2012. ImageNet Classification with Deep Convolutional Neural Networks. In *Advances in Neural Information Processing Systems*, F. Pereira, C.J. Burges, L. Bottou, and K.Q. Weinberger (Eds.), Vol. 25. Curran Associates, Inc. https://proceedings.neurips.cc/paper/2012/file/c399862d3b9d6b76c8436e924a68c45b-Paper.pdf
[70] Jennifer C Lena and Danielle J Lindemann. 2014. Who is an artist? New data for an old question. *Poetics* 43 (2014), 70–85.
[71] Craiyon LLC. 2022. Craiyon. Retrieved March 13, 2023 from https://www.craiyon.com/
[72] Freshfields Bruckhaus Deringer LLP. 2023. Has copyright caught up with the AI Act? Retrieved July 6, 2023 from https://www.lexology.com/library/detail.aspx?g=d9820844-8983-4aec-88d7-66e385627b4a#:~:text=Among%20the%20amendments%20to%20the,used%20for%20training%20those%20models
[73] MyHeritage Ltd. 2022. AI Time Machine. Retrieved March 13, 2023 from https://www.myheritage.com/ai-time-machine
[74] Michele Marra. 1995. Japanese Aesthetics: The construction of meaning. *Philosophy East and West* (1995), 367–386.
[75] Michael F Marra. 1999. *Modern Japanese aesthetics: a reader.* University of Hawaii Press.
[76] Rick Merritt. 2023. Getty Images bans AI-generated content over fears of legal challenges. *NVIDIA Blog* (21, 2023). https://blogs.nvidia.com/blog/2023/03/21/generative-ai-getty-images/
[77] Lauren Michele Jackson. 2018. Shudu Gram Is a White Man’s Digital Projection of Real-Life Black Womanhood. *New Yorker* (2018).
[78] Midjourney. 2022. Midjourney. Retrieved March 13, 2023 from https://www.midjourney.com/home/
[79] Midjourney. 2023. Version. Retrieved July 7, 2023 from https://docs.midjourney.com/docs/model-versions
[80] Martin Miernicki and Irene Ng (Huang Ying). 2021. Artificial intelligence and moral rights. *AI & SOCIETY* 36, 1 (March 1, 2021), 319–329. https://doi.org/10.1007/s00146-020-01027-6
[81] Zosha Millman. 2023. Yes, Secret Invasion’s opening credits scene is AI-made — here’s why. *Polygon* (June 22, 2023). https://www.polygon.com/23767640/ai-mcu-secret-invasion-opening-credits
[82] Mehdi Mirza and Simon Osindero. 2014. Conditional Generative Adversarial Nets. https://doi.org/10.48550/ARXIV.1411.1784
[83] Margaret Mitchell, Simone Wu, Andrew Zaldivar, Parker Barnes, Lucy Vasserman, Ben Hutchinson, Elena Spitzer, Inioluwa Deborah Raji, and Timnit Gebru. 2019. Model cards for model reporting. In *Proceedings of the conference on fairness, accountability, and transparency.* 220–229.
[84] Arvind Narayanan. 21. Fairness definitions and their politics. In *Tutorial presented at the Conf. on Fairness, Accountability, and Transparency.*
[85] Andrew Ng and Michael Jordan. 2001. On Discriminative vs. Generative Classifiers: A comparison of logistic regression and naive Bayes. In *Advances in Neural Information Processing Systems*, T. Dietterich, S. Becker, and Z. Ghahramani (Eds.), Vol. 14. MIT Press. https://proceedings.neurips.cc/paper/2001/file/7b7a53e239400a13bd6be6c91c4f6c4e-Paper.pdf
[86] Alex Nichol and Prafulla Dhariwal. 2021. Improved Denoising Diffusion Probabilistic Models. https://doi.org/10.48550/ARXIV.2102.09672
[87] Leonardo Nicoletti and Dina Bass. 2023. Humans Are Biased. Generative AI Is Even Worse. *Bloomberg* (2023). https://www.bloomberg.com/graphics/2023-generative-ai-bias/
[88] Nkiru Nzegwu. 2005. Art and community: A social conception of beauty and individuality. *A companion to African Philosophy* (2005), 415–424.
[89] United States Copyright Office. 2019. Authors, Attribution, and Integrity: Examining Moral Rights in the United States. https://www.copyright.gov/policy/moralrights/full-report.pdf
[90] United States Copyright Office. 2023. Re: Zarya of the Dawn (Registration # VAu001480196). https://www.copyright.gov/docs/zarya-of-the-dawn.pdf
[91] OpenAI. 2022. DALL-E 2. Retrieved March 13, 2023 from https://openai.com/product/dall-e-2
[92] Karla Ortiz. 2022. Why AI Models are not inspired like humans. (Dec.10 2022). https://www.kortizblog.com/blog/why-ai-models-are-not-inspired-like-humans
[93] Stephen Owen. 2020. *Readings in Chinese literary thought.* Vol. 30. BRILL.
[94] LLC Panabee. 2022. Hotpot. Retrieved March 13, 2023 from https://hotpot.ai/
[95] Javier Portilla and Eero P. Simoncelli. 2000. A Parametric Texture Model Based on Joint Statistics of Complex Wavelet Coefficients. *International Journal of*

Computer Vision 40, 1 (Oct. 1, 2000), 49–70. https://doi.org/10.1023/A:1026553619983
[96] Anshuman Prasad, Pushkala Prasad, and Raza Mir. 2011. 'One mirror in another': Managing diversity and the discourse of fashion. *Human Relations* 64, 5 (2011), 703–724.
[97] Inc. Prisma Labs. 2022. Lensa. Retrieved March 13, 2023 from https://prisma-ai.com/lensa
[98] Rida Qadri, Renee Shelby, Cynthia L. Bennett, and Emily Denton. 2023. AI's Regimes of Representation: A Community-centered Study of Text-to-Image Models in South Asia. In *2023 ACM Conference on Fairness, Accountability, and Transparency*. ACM. https://doi.org/10.1145/3593013.3594016
[99] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. 2021. Learning Transferable Visual Models From Natural Language Supervision. https://doi.org/10.48550/ARXIV.2103.00020
[100] Inioluwa Deborah Raji. 2022. From Algorithmic Audits to Actual Accountability: Overcoming Practical Roadblocks on the Path to Meaningful Audit Interventions for AI Governance. In *Proceedings of the 2022 AAAI/ACM Conference on AI, Ethics, and Society*. 5–5.
[101] Inioluwa Deborah Raji, Emily M Bender, Amandalynne Paullada, Emily Denton, and Alex Hanna. 2021. AI and the everything in the whole wide world benchmark. *arXiv preprint arXiv:2111.15366* (2021).
[102] Aditya Ramesh, Prafulla Dhariwal, Alex Nichol, Casey Chu, and Mark Chen. 2022. Hierarchical Text-Conditional Image Generation with CLIP Latents. https://doi.org/10.48550/ARXIV.2204.06125
[103] Aditya Ramesh, Mikhail Pavlov, Gabriel Goh, Scott Gray, Chelsea Voss, Alec Radford, Mark Chen, and Ilya Sutskever. 2021. Zero-Shot Text-to-Image Generation. https://doi.org/10.48550/ARXIV.2102.12092
[104] Ali Razavi, Aaron van den Oord, and Oriol Vinyals. 2019. Generating Diverse High-Fidelity Images with VQ-VAE-2. https://doi.org/10.48550/ARXIV.1906.00446
[105] Phillip Rogaway. 2015. The moral character of cryptographic work. *Cryptology ePrint Archive* (2015).
[106] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. 2021. High-Resolution Image Synthesis with Latent Diffusion Models. https://doi.org/10.48550/ARXIV.2112.10752
[107] Inc. Runway AI. 2022. Runway. Retrieved March 13, 2023 from https://runwayml.com/
[108] Chitwan Saharia, William Chan, Saurabh Saxena, Lala Li, Jay Whang, Emily Denton, Seyed Kamyar Seyed Ghasemipour, Burcu Karagol Ayan, S. Sara Mahdavi, Rapha Gontijo Lopes, Tim Salimans, Jonathan Ho, David J Fleet, and Mohammad Norouzi. 2022. Photorealistic Text-to-Image Diffusion Models with Deep Language Understanding. https://doi.org/10.48550/ARXIV.2205.11487
[109] Christoph Schuhmann, Romain Beaumont, Richard Vencu, Cade Gordon, Ross Wightman, Mehdi Cherti, Theo Coombes, Aarush Katta, Clayton Mullis, Mitchell Wortsman, Patrick Schramowski, Srivatsa Kundurthy, Katherine Crowson, Ludwig Schmidt, Robert Kaczmarczyk, and Jenia Jitsev. 2022. LAION-5B: An open large-scale dataset for training next generation image-text models. https://doi.org/10.48550/ARXIV.2210.08402
[110] Andrew D Selbst, Danah Boyd, Sorelle A Friedler, Suresh Venkatasubramanian, and Janet Vertesi. 2019. Fairness and abstraction in sociotechnical systems. In *Proceedings of the conference on fairness, accountability, and transparency*. 59–68.
[111] Ron Sen. Wyden. 2022. The Algorithmic Accountability Act of 2022. (2022).
[112] Shawn Shan, Jenna Cryan, Emily Wenger, Haitao Zheng, Rana Hanocka, and Ben Y Zhao. 2023. GLAZE: Protecting Artists from Style Mimicry by Text-to-Image Models. *arXiv preprint arXiv:2302.04222* (2023).
[113] Shutterstock. 2022. Shutterstock. Retrieved March 13, 2023 from https://www.shutterstock.com/
[114] Zachary Small. 2023. Black Artists Say A.I. Shows Bias, With Algorithms Erasing Their History. *New York Times* (July 4, 2023). https://www.nytimes.com/2023/07/04/arts/design/black-artists-bias-ai.html
[115] Francesca Sobande. 2021. CGI influencers are here. Who's profiting from them should give you pause. *Fast Company* (2021).
[116] Jascha Sohl-Dickstein, Eric A. Weiss, Niru Maheswaranathan, and Surya Ganguli. 2015. Deep Unsupervised Learning using Nonequilibrium Thermodynamics. https://doi.org/10.48550/ARXIV.1503.03585
[117] Gowthami Somepalli, Vasu Singla, Micah Goldblum, Jonas Geiping, and Tom Goldstein. 2022. Diffusion Art or Digital Forgery? Investigating Data Replication in Diffusion Models. https://doi.org/10.48550/ARXIV.2212.03860
[118] Jiaming Song, Chenlin Meng, and Stefano Ermon. 2020. Denoising Diffusion Implicit Models. https://doi.org/10.48550/ARXIV.2010.02502
[119] Ramya Srinivasan and Kanji Uchino. 2021. Biases in generative art: A causal look from the lens of art history. In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*. 41–51.
[120] A. Srivastava, A.B. Lee, E.P. Simoncelli, and S.-C. Zhu. 2003. On Advances in Statistical Modeling of Natural Images. *Journal of Mathematical Imaging and Vision* 18, 1, 17–33. https://doi.org/10.1023/A:1021889010444
[121] Inc. Stablecog. 2022. Stablecog. Retrieved March 13, 2023 from https://stablecog.com/
[122] starryai. 2022. starryai. Retrieved March 13, 2023 from https://starryai.com/
[123] NightCafe Studio. 2022. AI Art Generator. Retrieved March 13, 2023 from https://nightcafe.studio/
[124] Chen Sun, Abhinav Shrivastava, Saurabh Singh, and Abhinav Gupta. 2017. Revisiting Unreasonable Effectiveness of Data in Deep Learning Era. https://doi.org/10.48550/ARXIV.1707.02968
[125] Kentaro Takeda, Akira Oikawa, and Yukiko Une. 2023. Generative AI mania brings billions of dollars to developers. *Nikkei Asia* (March 4, 2023). https://asia.nikkei.com/Spotlight/Datawatch/Generative-AI-mania-brings-billions-of-dollars-to-developers
[126] The Costume Designers Guild, Local 892. 2022. A Letter to Membership. (2022).
[127] Nitasha Tiku. 2022. AI can now create any image in seconds, bringing wonder and danger. *Washington Post* (Sept. 28, 2022). https://www.washingtonpost.com/technology/interactive/2022/artificial-intelligence-images-dall-e/
[128] Unite.AI. 2022. Images.AI. Retrieved March 13, 2023 from https://images.ai/
[129] James Vincent. 2022. AI art tools Stable Diffusion and Midjourney targeted with copyright lawsuit. *The Verge* (2022).
[130] James Vincent. 2022. Getty Images bans AI-generated content over fears of legal challenges. *The Verge* (Sept. 21, 2022). https://www.theverge.com/2022/9/21/23364696/getty-images-ai-ban-generated-artwork-illustration-copyright
[131] Liz Weil. 2023. You are not a stochastic parrot. *New York Magazine* (2023).
[132] Meredith Whittaker. 2021. The steep cost of capture. *Interactions* 28, 6 (2021), 50–55.
[133] WOMBO. 2022. Dream by WOMBO. Retrieved March 13, 2023 from https://dream.ai/
[134] Writesonic. 2022. Photosonic. Retrieved March 13, 2023 from https://photosonic.writesonic.com/
[135] Xinchen Yan, Jimei Yang, Kihyuk Sohn, and Honglak Lee. 2015. Attribute2Image: Conditional Image Generation from Visual Attributes. https://doi.org/10.48550/ARXIV.1512.00570
[136] Meg Young, Michael Katell, and PM Krafft. 2022. Confronting Power and Corporate Capture at the FAccT Conference. In *2022 ACM Conference on Fairness, Accountability, and Transparency*. 1375–1386.
[137] Steven Zapata. 2023. AI/ML Media Advocacy Summit Keynote: Steven Zapata. https://www.youtube.com/clip/UgkxNwkkN9SnPpSJlnbkDK4q-NgxnaAyPHLL Presented through the Concept Art Association YouTube Channel.
[138] Steven Zapata. 2023. Who Makes the Art in Utopia? https://www.youtube.com/clip/UgkxNwkkN9SnPpSJlnbkDK4q-NgxnaAyPHLL Presented at TEDxBerkeley, Berkeley, CA.
[139] Viola Zhou. 2023. AI is already taking video game illustrators' jobs in China. *Rest of World* (April 11, 2023). https://restofworld.org/2023/ai-image-china-video-game-layoffs/