Article in Press IJIMAI journal

Generative Artificial Intelligence in Product Design Education: Navigating Concerns of Originality and Ethics

Kristin A. Bartlett[1]*, Jorge D. Camba[2]

[1] University of Kentucky, Lexington, KY (USA)
[2] Purdue University, West Lafayette, IN (USA)

Received 21 August 2023 | Accepted 13 February 2024 | Early Access 20 February 2024

Abstract

Image-generative artificial intelligence (AI) is increasingly being used in the product design process. In this paper, we present examples of how it is being used and discuss the possibilities of how applications may evolve in the future. We discuss the legal and ethical implications of image-generative AI, including concerns about bias, hidden labor, theft from artists, lack of originality in the outputs, and lack of copyright protection. We discuss how these concerns apply to design education and provide recommendations to educators about how AI should be addressed in the design classroom. We recommend that educators introduce AI as one tool among many in the designer's toolkit and encourage it to be used as a process tool rather than for generating final design deliverables. We also provide guidance for how educators might engage students in discussions about AI to enhance their learning.

Keywords

Education, Generative Artificial Intelligence, Industrial Design, Product Design, Text-to-Image.

DOI: 10.9781/ijimai.2024.02.006

I. Introduction

PRODUCT design, or industrial design, is the design of objects for mass-manufacturing. Product designers are responsible for the design of products in a wide range of industries including housewares, sporting equipment, medical devices, consumer electronics, and more. Recent articles have discussed applications of machine learning, big data, and artificial intelligence (AI) to product design [1], [2]. However, little has been written in academic literature about the application of AI text-to-image or text-to-3D generators to the industrial design process, though the discussion is well underway in the faster-moving world of social media. Titles of YouTube videos published in the past year illustrate the growing relevance of AI to the product design discipline. For example: *AI Designed this Product: These Tools are the Future of Design* [3], *Using AI in Your Design Process (MidJourney, Stable Diffusion, Vizcom) – AI For Industrial Design* [4], *How to Design with AI #ai #midjourney #vizcom #chatgpt* [5], *Hyper-Real Prototyping for Speed and Control – AI for Industrial Design* [6], *A.I. Product Design – THIS Will Change Everything!* [7], *A.I. vs Pro Car Designer! Is There Still a Future for Us?* [8]. Videos like these discuss AI applications that generate digital images from textual descriptions, reference images, or reference sketches, as can be done in popular software programs including DALL-E, Stable Diffusion, Midjourney, Adobe Firefly, and more. The videos illustrate that AI is being presented to viewers, many of whom are design students, as a "must-have skill" for future designers. Thus, educators need to be aware of the capabilities of these AI tools and the accompanying pitfalls and advantages for design education.

As we will illustrate with examples in the Section III, most industrial designers are utilizing generative AI in the front-end of the design process for inspiration, to create mood boards, and for ideation, in other words, to come up with design concept ideas. Some are also using generative AI for refinement or to broaden their ideas. In a few cases, designers have begun to output images generated by AI as underlays for manual 3D modeling, or to create 3D displacement maps which are used to directly texture 3D models. While text-to-3D software applications are not yet widely available, some websites claim to provide these services and student designers may be misled to believe that they are paying for an automated software application to create a 3D model from their sketches, when there is really a human modeler working behind the scenes [9].

The possibility of AI-facilitated plagiarism is a common concern for educators. However, the onset of generative AI introduces issues besides plagiarism, as the training data for the models utilizes work from photographers and visual artists who did not give consent for its use and were not compensated. Furthermore, as with other AI models, generative image AI often exhibits harmful biases. There are also legal and intellectual property-related issues to contend with. The purpose of this paper is to discuss these issues and provide general recommendations for educators regarding generative AI in design education. The primary domains which are publishing about the application of generative AI are medicine and computer vision [10], and very little has been written on the application of generative AI

* Corresponding author.

E-mail address: kristibartlett@uky.edu

Please cite this article in press as:
K. A. Bartlett, J. D. Camba. Generative Artificial Intelligence in Product Design Education: Navigating Concerns of Originality and Ethics, International Journal of Interactive Multimedia and Artificial Intelligence, (2024), http://dx.doi.org/10.9781/ijimai.2024.02.006

in design education. Therefore, this paper addresses the audience of design educators, who must determine how best to address generative AI in the classroom as they prepare their students for the workforce.

Because the AI landscape is fast-moving, and because product design professionals often do not publish their work in academic journals, this paper draws material from multiple areas, including conversations with practicing designers and literature from the fields of computer science and design education. First, we describe related literature. After that, we provide examples of ways that generative AI is currently being used by professionals in the product design field. Then, we delve into the ethical and legal issues through a discussion of recent academic literature and news articles. We conclude with recommendations for design educators. While the examples we are focusing on in this paper are from the context of industrial or product design, our discussion should also be relevant to other areas of art and design education.

II. Literature Review

Many authors have argued that instead of replacing human designers, AI will become a powerful partner for human designers and enhance their capabilities. For example, Verganti and colleagues claimed that artificial intelligence has the capacity to reinforce the fundamental principles of design thinking, rather than displacing them [11]. Seidel et al. said that the emergence of autonomous design tools indicates that the role of human designers is changing [12], and Koch advocated the belief that systems leveraging AI can become collaborative partners in the design process [13].

Human-AI collaboration has been investigated in various stages of the design process, including early ideation and concept evaluation [14], later-stage ideation [15], management of the design team [16], aiding teams in design problem-solving [17], and aiding teams in the design of complex systems [18]. The addition of AI in the design process is not always found to be helpful. In one case, AI enabled broader and more efficient exploration of potential solutions [18]. In another case, however, AI was seen to hinder the performance of high-performing teams, though it did help low performing teams [17].

While the aforementioned studies all explored the application of AI to the design process, AI-human interaction in the engineering design process remains an understudied area [17]. This paper focuses specifically on image-generative AI applied to the design process. Generative AI is defined as the “production of previously unseen synthetic content, in any form and to support any task, through generative modeling,” where generative modeling means “modeling the joint distribution of inputs and outputs” [10]. Image-generative AI models are trained on large datasets of images paired with textual descriptions and work through a process called diffusion. Diffusion models add noise to data (image data, in this case) in a series of steps. Then, the process is run in reverse, and each step gradually denoises the image, leaving behind what the model predicts will be an image of the user’s prompted input [19].

While few authors discuss the application of image-generative AI to industrial design or product design, image-generative AI has been investigated in other related fields such as fashion design [20]. Researchers found that the majority of their generated fashion design images were thought to be created by human designers rather than being computer-generated [20]. Another team investigated image-generative AI which uses sketch-based input in the context of architectural design [21]. They commonly encountered a problem of the AI generating images that would be impossible to construct [21].

Rather than generating images, generative AI has been explored in the context of mechanical design to generate 3D geometry. A case study examined the use of generative design in a computer-aided design (CAD) software to perform structural optimization [22]. This process involves inputting a set of design requirements in the form of numerical constraints relating to materials and manufacturing, as well as defining some basic geometric constraints in the CAD software [22]. Generative AI is also being applied to larger-scale structural design problems, such as building structures [23].

Cai et al. introduced a generative AI tool which creates inspiration mood boards of generated images based on a text prompt [24]. They had a group of participants with experience in art or design compare the outputs to results of an image search on Pinterest. Participants found the generative AI tools to be more useful, inspirational, and enjoyable than the traditional image search. Having a larger diversity of images generated was only slightly favored by the participants, and in the search condition, the lower diversity of images was preferred [24]. This study did not demonstrate or investigate how effectively or ethically participants might then use those inspiration images, but these are important aspects to consider. While designers perceived the AI-generated images to be more useful, what does this really mean? Might AI-generated inspiration images limit someone’s thinking, or lead them to unintentionally plagiarize?

While clear-cut rules about plagiarism and citing sources exist in nearly every university regarding written work, the concept of plagiarism for visual design work is already quite murky. In the postmodern design context, there is no consensus of where to draw the lines between borrowing, referencing, and plagiarizing [25]. Writing in the context of the year 2011, Economou described a “remix” realm in which design students are operating [25]. How much truer is this today, when the “remix” realm has given rise to what is essentially an automated remix machine in image generative AI? Writing in 1994, Saffo asked, “will the act of creativity be reduced to assembling old ideas like so much digital clip art, as the once-sustaining web of tradition becomes a suffocating blanket of electronic recall?” [26]. These examples from earlier writings demonstrate that concerns about lack of originality in design work were around long before the introduction of generative AI, and generative AI is just the latest iteration of technology which may facilitate design plagiarism. Educators and employers alike have concerns about plagiarism, both for the integrity of learning and to protect businesses from a legal standpoint.

This review of the literature indicates that many researchers see the value in applying generative AI to design. While researchers are increasingly investigating applications of AI to the design process, there is a need for more work that focuses specifically on design education. Other reviews have focused on classifying and categorizing generative AI systems and outlining the technical requirements, without discussing ethics [27]. Writing on the related topic of text-generative AI argues that following “responsible practices to uphold academic integrity and ensure ethical use” is crucial [28]. Thus, this paper discusses the ethics of image-generative AI applied to product design, as well as concerns about plagiarism and originality.

III. Using AI to Generate Designs

A. Example 1: Using AI to Generate Inspiration Images

Most of the popular image-generative AI software products allow the users to input text or other images to “prompt” the AI and tell it what kinds of images to generate. For example, designer Caterina Rizzoni of Kaleidoscope input the following text prompt into Midjourney V3: “Light fixture lighting a brilliant, elegant light and airy crystalline patterns of light dancing photorealistic detailed plants greenery daytime bright modern beautiful balcony patio trees natural colors outdoors.” From this prompt, Midjourney generated multiple images, some of which are shown in Fig. 1.

Fig. 1. Design inspiration images generated by Midjourney V3.

In many cases, users may simply use these AI output images as they are, if their goal was to generate an image. However, in the case of product design, the end goal is to come up with a product idea. In many cases, the images generated by AI are not a perfect match with the design requirements and are instead used as inspiration material. Taking the generated images in Fig. 1 as inspiration material, designer Tom Gernetzke sketched various lamp concepts. These sketches are shown in Fig. 2. (The Kaleidoscope innovation team's process is described in further detail in [29]). The inspiration from the generated images is clear, but the human designer added other details such as structurally supportive bases and electrical cords which are critical to the feasibility of the final lighting design.

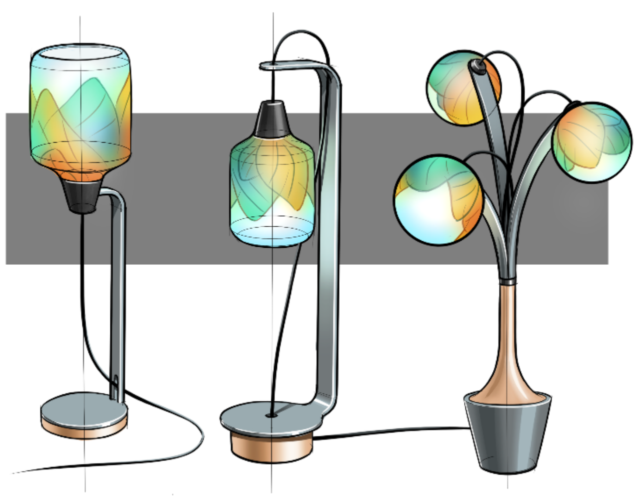


Fig. 2. Design concepts drawn by the design team, taking inspiration from the Midjourney images.

B. Example 2: Using AI to Generate 2D Images of 3D Topology

As Example 1 illustrates, using an output image generated by AI to get a production-ready design is currently a highly manual process, and most often the images are used as a jumping-off point for inspiration but differ largely from the final design. However, designers are increasingly pushing the use of AI to complete more steps in the design process. In Example 2, the designer moves directly from an AI-generated image to a 3D model. Designer Kedar Benjamin used the AI image generation software Dall-E to create an image of a shoe, shown in Fig. 3.

Fig. 3. Shoe image generated with Dall-E software by designer Kedar Benjamin.

A 3D model of the shoe was then built collaboratively by two designers, Benjamin and Svet Abjo, using the software packages Blender and Maya. The designers drew topology over the original image in the 3D modeling software to create the overall shape of the shoe (Fig. 4).

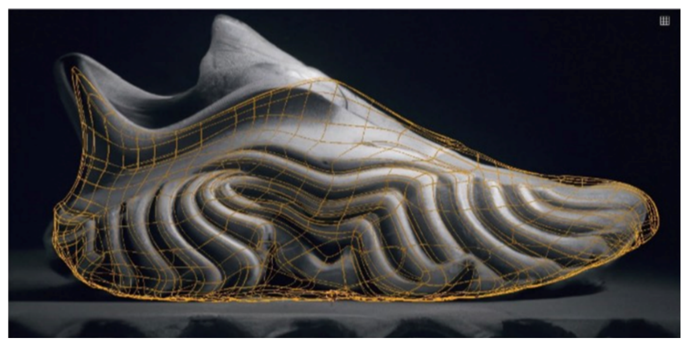


Fig. 4. Topology drawn over the original image to create 3D model of the shoe.

Fig. 5. Final 3D-printed shoes produced by Zellerfeld. The shoe is printed in fused 3D lattice.

The designers interpreted the shoe's topology from the AI-generated image but also made changes based on what they thought would be most appropriate for the final product, as well as adding their own designs for the parts of the shoe that are not visible in the generated 2D image. The final shoe, based on their manually built 3D model, is now in production from a made-to-order 3D printed shoe company, Zellerfeld (Fig. 5). While the shape of the final shoe is similar to the original image generated by AI, the creation of the final product required significant manual input from the designers in the creation of the detailed 3D model and the selection of a manufacturing method and material.

C. Example 3: Using AI to Generate 3D Topology

In Example 3, designers added even more automation into the process of going from a generated image to a final product. Designer Marina Aperribay used Dalle-2 to create inspiration images for a shoe. Once she found the best prompt to create the desired outcome, she used this same prompt in Stable Diffusion 2.0, which has the capability to create a displacement map, or a texture, based on the image using the tool "depth2img." The final shoe image used to generate the texture is shown in Fig. 6.

Fig. 6. Shoe image generated in Stable Diffusion 2.0 used to create displacement map [30].

Designer Kedar Benjamin created an automated workflow using the software Houdini that allowed the displacement map to be wrapped around a basic shoe model. This final model was then 3D printed. The 3D model and 3D printed shoe are shown in Fig. 7.

Fig. 7. (L) 3D model created by wrapping displacement map around a basic shoe model. (R) 3D print of final shoe [30].

Unlike the previous example which required manual 3D modeling, this workflow was both fast and suitable for people with limited 3D modeling skills. However, the designers anticipated this workflow would soon be obsolete with the arrival of "text-to-3d mesh" AI applications [30]. At the present time, software that uses AI to generate 3D models does not appear to be available to product designers, yet many designers hope that such programs will soon be developed. The recent breakthroughs in text-to-image AI are dependent on datasets which include billions of image-text pairs. The same approach cannot be taken for generating 3D models because large scale datasets of labeled 3D data do not exist, and neither do efficient architectures for denoising 3D data [31]. However, researchers are working on other approaches that can generate 3D models from various combinations of 2D images, text prompts, and 3D priors [31], [32], [33], [34], [35], [36], [37].

IV. Ethical and Legal Concerns

While generative AI is a powerful tool that can create impressive images, the new field is fraught with ethical and legal concerns that designers cannot ignore. These issues are discussed in this section.

A. Biased Outputs

One problem with image-generative AI is that the images it creates often reproduce biases, particularly when depicting humans. For example, a research group studying DALL-E and Stable Diffusion found that the models "learn specific gender/skin tone biases from web image-text pairs" [38]. The creators of DALL-E 2 were aware of the biases in their output images, stating that the images produced overrepresent people who are "White-passing." Their model also overrepresents people who appear female for female-stereotyped jobs, such as a flight attendant, and overrepresents people who appear male for male-stereotyped jobs, such as a builder [39]. The DALL-E 2 team also found that their initial approach to filtering sexual content reduced the overall quantity of generated images of women, including images that did not contain sexual content [39]. Ultimately, these biases probably are not the largest concern for design students, since they are designing objects rather than people. Regardless, students should be careful to avoid representing people in biased ways in their imagery, and students need to be aware that AI tools often reproduce harmful societal biases.

Beyond images of people, the DALL-E 2 model also overrepresented "Western concepts" [39]. This certainly has implications for product design, as styles of design differ by culture and region. If AI models overrepresent Western styles of buildings, products, fashion, etc., then uncritical use of these AI tools could further perpetuate a Eurocentric bias in design. Students should be informed about cultural variations in design styles and be trained to recognize how AI may not present a very well-rounded sampling of styles from around the world. Design students are being trained to create the most appropriate design for the brief, and if AI generates a very narrow set of inspiration material, then the students need to recognize this fact and take their own steps to broaden their inspiration sources. (We note that although DALL-E was the primary example used in this section, the issue of bias is not limited to any single AI application.)

B. No Guarantee of Originality

Another serious issue with image-generative AI is the possibility that the output is not unique. The output that one user gets from a generative AI software may be the same as what other users get, or it may be very similar to the images used in the training data. Researchers ran an experiment on Stable Diffusion and found while most generated images did not contain copied content, "a non-trivial amount of copying does occur" [40]. They focused on object-level similarity because it could potentially be the subject of future intellectual property disputes. An example from their research is shown in Fig. 6. The left image was generated by Stable Diffusion, the right image is a nearly equivalent shoe image found in the LAION-Aesthetics v2 6+ dataset.

The DALL-E team also stated that lack of unique outputs is a concern for their software, though they focused on the possibility of the software generating the same output for multiple users, rather than generating something that is very similar to the training data. They said, "due to the nature of machine learning, output may not be

Fig. 6. (L) Image of athletic shoe generated by Stable Diffusion, (R) image of similar athletic shoe found in LAION-Aesthetics v2 6+ dataset.

unique across users and the Services may generate the same or similar output for OpenAI or a third party" [41]. Both the issues of copying the original input images or giving the same output to multiple users raise the concern that anyone using image-generating AI cannot be sure that they have generated something unique. The lack of assurance that a generated design is unique poses a problem for designers whose primary goal is to create a novel design.

Designer Benjamin from Example 2 shared that his team took special care when creating the 3D model to avoid a "swoosh" shape that would be reminiscent of the brand Nike. Through his experiments with text-to-image AI, Benjamin observed that, "text to image tends to generate swooshes [reminiscent of Nike] or three stripes [reminiscent of Adidas] on a lot of shoes, and even when it doesn't generate swooshes it sometimes makes design elements which resemble them. We have to be very careful about this."

Most of the terms of service for image generative software applications that we reviewed for this paper put the responsibility of ensuring that there are no intellectual property violations onto the users (for example, [41], [42]). This means that even though the AI companies trained their models on images containing other companies' intellectual property (IP), it would be the user's responsibility if the software generated an output that was too similar to the IP of those companies and the user decided to use this output as their own "original" design. Thus, designers who are using generative AI have to be knowledgeable about the brand language and IP of other brands and take care that they are not generating designs that infringe on that intellectual property.

C. Theft From Artists

Data is a fundamental building block of AI and machine learning models [43]. Many argue that the image generation programs like Midjourney are damaging to artists and photographers in that the training data contains millions of artworks and images without the creators' consent [44]. Stability AI, the company behind Stable Diffusion, is being sued by Getty Images, who argues than more than 12 million of Getty Images' stock photos were used to train Stable Diffusion's algorithm without permission or compensation [45].

Midjourney admittedly did not seek consent from living artists or work still under copyright because, according to their CEO, "there isn't really a way to get a hundred million images and know where they're coming from." [46] Midjourney's training dataset was built from "a big scrape of the internet" and they train across multiple published open data sets [46]. Artists cannot opt out of being named in prompts and none have had their work taken out of the training dataset [46]. This problem is not isolated to Midjourney, as the CEO further stated, "our training data is pretty much from the same place as everybody else's — which is pretty much the internet. Pretty much every big AI model just pulls off all the data it can, all the text it can, all the images it can. Scientifically speaking, we're at an early point in the space, where everyone grabs everything they can, they dump it in a huge file, and they kind of set it on fire to train some huge thing, and no one really knows yet what data in the pile actually matters" [47]. Stable Diffusion was trained on the 2b English language label subset of LAION 5b, "a general crawl of the internet created by the German charity LAION" [48]. There was also no opportunity for artists to opt-out of having their work included in the LAION 5b model data [48].

One example of a different approach by an AI company is that of Adobe, who has trained their initial Firefly model on "Adobe Stock images, openly licensed content, and public domain content where copyright has expired" [49]. Many designers we have spoken with expressed excitement about using Adobe's Firefly software (currently in Beta), or other future software that takes a similar approach to not training on artists' work without permission, because many in the creative community have ethical concerns about creative work being used to train AI without permission. Adobe is also exploring ways for future creators to be able to train the model with their own assets so that they can generate content in their own unique design style or brand language without using other creators' content as source material [49]. This and other similar future solutions would also open future possibilities for AI as a design tool that could remediate some of the ethical concerns discussed in this section.

D. Other Hidden Labor: Annotators

While the artists and photographers whose work is fed into AI models represent one invisible labor group in the AI ecosystem, they are not the only such group. In discussions of AI taking away human jobs, we often overlook the fact that AI creates jobs as well, although as the case of the annotators illustrates, many of the jobs created are not high-paying, not highly skilled, and not necessarily desirable. Annotators, or people who label, caption, and characterize text, images, or other data to create training data for AI models, are another group whose human labor is often unacknowledged in discussions of AI.

Many AI companies outsource the job of annotation to overseas companies. One author interviewed Kenyan annotators who were making somewhere between $1 and $3 per hour. The work was not consistent and came in waves, and they could not always count on having tasks [50]. A study of annotators working in India found that the work practices served the interests of the companies and requesters rather than the workers. Many of the annotators had entered the workforce under the guise that this was an entry point to a career as an AI/ML engineer when this was not the reality for most workers. The work was tedious and repetitive, the workers sometimes had to work overtime hours which were not compensated, and the work was project dependent, if a project ended, so did the work [43].

In the world of product design, many designers are on the lookout for services which will save them time in their workflow, and building 3D models from images is a time-consuming task for many designers. Kaedim is a 2D image to 3D model service which many believe is misleading users by selling their technology as AI, but instead using human workers behind the scenes build the 3D models in real-time. Users thought that the way the 3D models were simplified from the images looked like something that would be difficult to train an AI model to do. Furthermore, Kaedim had previously posted a job advertisement looking for workers who could "produce low quality 3D assets from 2D images 15 minutes after they are requested" [51]. In response to the criticism of falsely advertising their services as AI, their CEO said, "We have a product that's starting to produce some exciting results — but it's far from perfect" [9]. She said that although images pass through their AI algorithm for reconstruction as 3D files, a quality control engineer takes a look at each output and improves it where necessary [9].

Humans manually working on processes that are advertised as AI brings in a serious concern when it comes to student work. While a professor might be fine with a student using software to automatically generate a file output, they would probably not be okay with a student paying another person to create the file for them, which is what is happening in cases of falsely advertised AI. Students need to be informed about the existence of such misleading services and advised by their instructors about what kinds of software and services are acceptable to use for class assignments.

E. Ownership of AI Outputs

The U.S. Copyright Office has determined that AI-generated images are not protectable under current copyright law because they are "not the product of human authorship." They said that Midjourney users have very little control over the final images in comparison to a human artist or photographer [52]. They also said, "the fact that Midjourney's specific output cannot be predicted by users makes Midjourney different for copyright purposes than other tools used by artists." [53]. At present, Midjourney only allows users to input text or images. It is not clear how copyright possibilities will evolve for cases such as Vizcom, an AI application which allows manual drawing in the input box, or a case where an artist could train a model on their own work. But at present, it is safest for design students and designers to assume that any images they create using image-generative AI software like Midjourney will not be able to receive copyright protection.

Furthermore, using free versions of AI programs often yields images that are explicitly open source. This is the case for Stable Diffusion Online [48] and for the free version of Midjourney [42]. Midjourney's terms of service state, "Midjourney is an open community which allows others to use and remix Your images and prompts whenever they are posted in a public setting. By default, your images are publically [sic] viewable and remixable. As described above, You grant Midjourney a license to allow this" [42]. Students must understand that AI-generated images are often not protectable as their own work, and depending on what software they are using, the outputs they generate may be considered open-source.

V. Recommendations for Educators

A. Engage Students in Discussions About the Ethical and Legal Implications of Using Generative AI

The use of AI is often marketed to design students as a "must-have skill" for them to stay up to date with the latest and greatest technologies. However, as the issues discussed in the previous section illustrate, AI is fraught with ethical and legal concerns that are not relevant to other design technologies like computer-aided design or rendering software. Design students must be aware of the ethical and legal issues. In-class discussions are one way that students could be engaged with these issues. Discussions could focus on the five issues we introduced in the previous section: bias, lack of originality/copying, theft from artists, hidden labor, and ownership of outputs. Portions of this paper could also be used as jumping off points for the class discussion.

Our recommendation would be to encourage students to choose AI applications that train on images that they own, rather than on scraps of the internet, and that allow artists to opt-out of having their work included in training data. We would also recommend that students not be permitted to use an AI-generated output as a final deliverable for an assignment, since what is generated may not be unique and may infringe on the IP of others. We recommend putting a clear policy in place that does not discourage the use of AI as a part of the design process. Our examples in section III illustrate that designers are using AI in creative ways to come up with unique design solutions. However, the final outputs of generative AI are not copyright protectable for the reason that the user does not have enough control over the output. For this same reason, an AI-generated output is likely not going to be a perfect design solution anyway, as human input is most likely needed to make sure that the output best meets the requirements of the design brief. Thus, students should be encouraged to keep going and keep refining their design solutions as much as possible, and not rely solely on what they can produce using AI tools. While these policies are our recommendation, students should be engaged in a discussion to help create a class policy regarding the use of AI, and that the policy can adapt and change as the AI landscape changes.

B. Concerns About Plagiarism

1. Should It Be Considered Plagiarism for a Student to Turn in an AI-Generated Design as Their Final Deliverable for an Assignment?

The general definition of plagiarism is presenting the work of someone else as if it were your own [54]. What constitutes plagiarism in creative design disciplines is far less clear-cut than in disciplines that ask for written solutions, where there are clear guidelines that can be taught to students for quoting, attributing, paraphrasing, and citing. In design, there are no such guidelines [25].

In courses where craft is the focus, for example, a sketching course or a CAD course, the students need to create their own sketches or CAD for the deliverables. Thus, using AI to create these deliverables and being dishonest about the origins of the work would certainly constitute plagiarism. However, in studio courses where the design outcome, rather than a specific design skill, is the main focus, the use of AI as part of the process should be acceptable, as in the examples shared in section III. Using AI to directly create final deliverables could still be problematic.

Based on the fact that generated designs are not necessarily original, as in they might have copied heavily from the training data and might be extremely similar to an output given to someone else, we do not think it is wise for students or designers to claim a generated design as their own original design at the present time. That being said, presenting an AI-generated solution alongside substantial background research that provides a robust justification for the novelty and suitability of the solution could be valuable. Perhaps future iterations of generative design software will offer features that can make a stronger guarantee of originality of the outputs.

The fact that the original outputs of image generative AI are not protectable by copyright is another argument against allowing students to turn in AI outputs as part of their final design deliverables. AI outputs may be presented in process books and certainly should be documented if they played a part in the student's design process, but the final product should be crafted by the student. Take, for example, the sketches in Fig. 2 or the 3D prints in Fig. 5 and Fig. 7. These would be acceptable outputs of projects which used generative AI in the early stages of ideation, as the designers added their own creative hand in creating models and sketches of the final product.

2. How Would an Instructor Know if a student Was Trying to Pass Off an AI-generated Design as Their Own Original Work?

This question is not inherently different than asking how an instructor would know if the student was using a file they found on the internet and trying to pass it off as their own unique work. Thus, we will review the recommendations that are already in place for combatting plagiarism in classrooms of creative disciplines like industrial design.

Prior to the introduction of generative AI, it was already common practice for designers to reference inspiration images they find on the internet [25]. Eighty-five percent of design students reported that their first step in beginning an assignment is to conduct a Google image search or create an inspiration board using Pinterest, and they continue to reference these things throughout the design process [55]. In fact, many design instructors even encourage their students to collect a broad range of visual samples to draw inspiration from in their design process [56]. The problem comes when the inspiration sources are too similar to the final design submission, and design students face growing difficulty in navigating the lines between plagiarism, appropriation, homage, inspiration, and referencing others' work [25].

Educators have proposed various solutions to combat plagiarism in design education. Pedagogical approaches that discourage plagiarism are preferred over detection approaches [57]. For example, project-based learning has a lower risk of plagiarism because the instructors closely supervise students' work and students keep a logbook of their individual contributions to team projects [58]. Coorey argues that training students to engage in their own design process is the most important method of discouraging plagiarism [55]. Studio projects naturally lend themselves to this as there are many milestones along the way where students perform the different steps to develop their projects [59]. Process work should be emphasized in the assessment practice in order to place focus on the designer's role in developing the final solutions [25]. A process book , in which students show their process of ideation and revisions which led them to the final design outcome, can serve as an assessment tool for the instructors [55].

Design programs should provide lectures on visual plagiarism and appropriation theory, studio practice should include visual referencing systems to provide students a method to indicate their source material which they referenced to build to their final design [25]. One approach called "Beyond Style" guided students through a process of how to be inspired by creative precedents without plagiarizing, with the idea that this would also help students to respect the creative works of others [57]. An alternative option is to train students to write a statement of novelty, which may serve as a useful exercise in the context of design education where students may want to protect their IP in the future with patents [60]. Ultimately, art and design programs need plagiarism policy documents relevant to their disciplines [25]. Design instructors today need to ensure that their plagiarism policies address the use of AI and what is and is not acceptable in their classroom.

C. Ensuring That Students Build the Skills Needed to Be Successful in Industry

Can students expect to be allowed to use AI in their jobs upon graduation? We spoke with multiple design professionals about this question. Many designers who work in US-based consumer products companies were given restrictions by their legal departments about how they could use AI software at work. One company's training on AI said that using AI to make images can generate content that infringes on others' intellectual property rights, which could open the company up to lawsuits. They forbid inputting company data into AI software as prompts, as this could expose the company's own IP. Thus, they placed heavy restrictions on their design teams using AI.

A designer at another company was provided with a Pro license for the software Midjourney, however, the designers were only allowed to use Midjourney to generate images for storytelling or background material to explain the context or intentions behind a design and could not use Midjourney to generate actual design concepts. They were also forbidden to use any brand names in the text prompts. Another designer said that her team did not feel comfortable using generative AI for ethical reasons. They were specifically concerned about the ethical issue of AI using the work of artists without the artists' consent.

In contrast to the previous examples, a designer who works at a large tech company said that her company encourages the use of AI in their work since the company is in the business of creating AI applications themselves. Another designer pointed out that larger companies like hers were working with tech companies to develop proprietary AI applications that would not expose them to legal and IP concerns.

From these examples, it is clear that design students today cannot count on entering the workforce and being encouraged or allowed to freely use AI as part of their design process, especially if they enter in an industrial design role in a large consumer goods company (individuals who end up working for tech or small design consultancies without legal teams will likely face different policies regarding AI). While students should know the capabilities of generative AI, they should also be well-versed in the legal and ethical issues surrounding AI so that they will be able to make informed decisions that do not violate the guidance from their employers. They should also be fully capable of creating excellent designs without the aid of generative AI in the event that they work for an employer who does not permit its use. Students could end up in a situation where they use AI freely during their education, become reliant on it during their design process, and then graduate and are not allowed to use it in the workplace, which would not be ideal.

D. Design Competitions

While some companies are hesitant about adopting AI, design competitions appear to be taking a different stance. The iF Design Award considers that many winners already involve "AI" as they are smart products such as fridges or smart phones. So, they did not plan to differentiate entries that involved AI. The Red Dot Award focuses on the end results, and if AI plays a part in leading to an award-worthy physical product, then that product would still be eligible to win the award [61]. Thus, students who want to enter their work into competitions probably do not need to be concerned that using AI in their design process would disqualify them. That said, the students should still be transparent in their process books and portfolios about how and where AI was leveraged. Of course, students and educators should also check the policies of any design competition that they plan to enter to see if the policies place any restrictions on the use of AI.

E. Summary of Recommendations for Educators

Section V has consisted of an in-depth discussion of our recommendations for educators who are faced with the choice of introducing generative-AI in design classrooms. Table I provides a summary of these recommendations and the reasoning behind them.

VI. Conclusion

Image-generative AI is a promising new tool for product designers to use in their design process. In this paper, we presented three examples of projects which used AI-generated images as an inspiration source for design sketches, as an underlay for a 3D modeled design, and to automatically generate a texture. Image generative AI is still a new technology, and future iterations will be even more advanced. Product designers are increasingly looking for tools to help them generate 3D designs more quickly and efficiently and with increased control over the final outcome.

To help ensure that students are graduating with the most up-to-date software skills, educators would do well to introduce generative AI as one tool among the many tools in which they train their students. However, AI differs in many ways from traditional technologies, and should not be introduced without a clear discussion of the ethical and legal implications, and clear guidelines about the instructor's policies for how AI can be used in projects and final deliverables. Even if an instructor does not plan to introduce AI, these guidelines should be provided as part of the plagiarism policy given in a syllabus.

TABLE I. Summary of Recommendations for Educators

Recommendation	Reason
Introduce AI as a tool to be used in conjunction with other design tools.	Students should be familiar with the capabilities of AI but should not get the idea that AI replaces fundamental skills of designers at this time.
Do not allow students to turn in raw AI-generated content as a final product.	At this time, raw outputs of image-generative AI are not as refined as what is needed for professional design work. Students who use AI tools should build on the outputs of AI and refine them manually using their own critical thinking.
Encourage use of AI tools that give a high degree of control, such as tools trained on one's own work or tools that use sketch-based inputs rather than text-based.	Tools which give the designer a higher degree of control are more likely to result in original outputs.
Require students to document use of AI in projects, process books, and portfolios.	Students should make a clear distinction between their own work and AI-generated or AI-assisted work in order to avoid plagiarism concerns.
Ensure that students can still complete required tasks without AI.	Some companies do not permit design teams to use AI, so students cannot count on being able to use AI in all future jobs.
Engage students in discussions of ethical issues surrounding AI (eg. Bias in outputs, theft from artists, hidden labor, inadvertent copying, copyright and ownership).	Students should be aware of the many ethical and legal issues surrounding image generative AI to help them make informed decisions of how they might or might not want to use AI in their work.

We do not recommend students be allowed to turn in fully AI-generated files as their final project artifacts. It is unlikely that this will be permitted in their future jobs due to copyright and IP concerns. Furthermore, allowing students to use AI for final artifacts could hinder their skills development, as generative-AI does not currently allow for the same level of control over the final design outcome that other tools do. However, using AI alongside the traditional design tools could be an asset to helping students work more efficiently and could lead to new creative insights.

Educators should not naively cling to traditional techniques and methods but must remain open to the possibility that certain hand skills in design may decrease in importance in the future. No doubt educators in the past were afraid to introduce CAD, 3D rendering, and digital sketching for fear that students would lose hand sculpting and hand rendering skills. Both industry and education evolve as new technologies change designers' workflow and clients' expectations.

Saffo (1994) argued that originality was increasingly rare, and originality would eventually cease to be the true litmus test of creativity. Instead, value would be placed on passion, surprise, and insight [26]. As illustrated by the examples in section III, the designer's creativity is still critical to transforming the outputs of generative AI into a viable final design solution. At present, generative AI is not going to output a manufacturable final product. The designer must be the one to curate the best solution, taking into consideration the user needs, market appropriateness, and IP space. The designer can certainly leverage generative AI to help get to the final viable outcome, but designer's human skills are still of critical importance. Trend research, user research, understanding of branding and brand identity, and manufacturability knowledge may become increasingly valuable skills in the age of generative AI.

Although this paper focuses on product design education, and the examples that we presented are all from the product design field, we believe that our recommendations for educators apply to other design disciplines which have a visual emphasis, such as graphic design, architecture, engineering design, fashion design, interior design, and fine art. The fact that we only spoke with individuals from the discipline of product design is a limitation of this paper. However, our review of ethical and legal concerns was not discipline-specific, and we drew from a range of sources to write this section.

In conclusion, educators must take notice of image-generative AI, because their students are certainly aware of it and will be experimenting with the technology regardless of whether the educators address it or not. At present, the raw outputs of AI are likely not suitable for use as final deliverables in design education due to their lack of copyright protection and the possibility of copying and IP infringement. However, future AI tools are likely to offer more control over the final solution, and a stronger guarantee of originality. Future tools should also address the ethical issues surrounding bias and theft from artists. Generative AI offers exciting possibilities when used as part of a comprehensive design process, and engaging students in discussions about AI in design can help them think critically about their role as designers in the face of technological change.

Acknowledgment

The authors would like to thank Kedar Benjamin and Caterina Rizzoni for sharing insights into their design processes and images of their teams' work. The authors would also like to thank Linda Bui, Lindsay Malatesta, and Lea Stewart for sharing their insights on the use of AI in design workplaces.

References

[1] P. Fournier-Viger, M. S. Nawaz, W. Song, and W. Gan, "Machine Learning for Intelligent Industrial Design," in *Machine Learning and Principles and Practice of Knowledge Discovery in Databases*, vol. 1525, M. Kamp, I. Koprinska, A. Bibal, T. Bouadi, B. Frénay, L. Galárraga, J. Oramas, L. Adilova, G. Graça, et al., Eds., in Communications in Computer and Information Science, vol. 1525. , Cham: Springer International Publishing, 2021, pp. 158–172. doi: 10.1007/978-3-030-93733-1_11.

[2] T. Guo, R. Eckert, and M. Li, "Application of Big Data and Artificial Intelligence Technology in Industrial Design," vol. 5, no. 1, 2020.

[3] *AI Designed this Product: These Tools are the Future of Design*, (Aug. 12, 2021). Accessed: Jun. 22, 2023. [Online Video]. Available: https://www.youtube.com/watch?v=sy_llq2yq9U

[4] *Using AI in Your Design Process (MidJourney, Stable Diffusion, Vizcom) – AI For Industrial Design*, (Feb. 12, 2023). Accessed: Jun. 22, 2023. [Online Video]. Available: https://www.youtube.com/watch?v=2yI0zBnH2bk

[5] *How to Design with AI #ai #midjourney #vizcom #chatgpt*, (Feb. 08, 2023). Accessed: Jun. 22, 2023. [Online Video]. Available: https://www.youtube.com/watch?v=zzYdWkgGgUM

[6] *Hyper-Real Prototyping for Speed and Control – AI for Industrial Design*, (Apr. 10, 2023). Accessed: Jun. 22, 2023. [Online Video]. Available: https://www.youtube.com/watch?v=0Xo__LjsAc4

[7] *A.I. Product Design – THIS Will Change Everything!*, (Mar. 08, 2023). Accessed: Jun. 22, 2023. [Online Video]. Available: https://www.youtube.com/watch?v=bAQvlSbxl-U

[8] *A.I. vs Pro Car Designer! Is There Still a Future for Us?*, (Sep. 15, 2022). Accessed: Jun. 22, 2023. [Online Video]. Available: https://www.youtube.

com/watch?v=v-ZkVsjmXUk

[9] K. Psoma, "Response from Kaedim re our AI," Medium. Accessed: Jul. 17, 2023. [Online]. Available: https://medium.com/kaedim/response-from-kaedim-re-our-ai-931d3ef39c33

[10] F. García-Peñalvo and A. Vázquez-Ingelmo, "What Do We Mean by GenAI? A Systematic Mapping of The Evolution, Trends, and Techniques Involved in Generative AI," *International Journal of Interactive Multimedia and Artificial Intelligence*, vol. 8, no. 4, p. 7, 2023, doi: 10.9781/ijimai.2023.07.006.

[11] R. Verganti, L. Vendraminelli, and M. Iansiti, "Innovation and Design in the Age of Artificial Intelligence," *Journal of Product Innovation Management*, vol. 37, no. 3, pp. 212–227, May 2020, doi: 10.1111/jpim.12523.

[12] S. Seidel, N. Berente, A. Lindberg, K. Lyytinen, and J. V. Nickerson, "Autonomous tools and design: a triple-loop approach to human-machine learning," *Communications of the ACM*, vol. 62, no. 1, pp. 50–57, Dec. 2018, doi: 10.1145/3210753.

[13] J. Koch, "Design implications for Designing with a Collaborative AI," presented at the The AAAI 2017 Spring Symposium on Designing the User Experience of Machine Learning Systems, 2017, pp. 415–418.

[14] B. Camburn, Y. He, S. Raviselvam, J. Luo, and K. Wood, "Machine Learning-Based Design Concept Evaluation," *Journal of Mechanical Design*, vol. 142, no. 3, p. 031113, Mar. 2020, doi: 10.1115/1.4045126.

[15] C. Yuan and M. Moghaddam, "Attribute-Aware Generative Design With Generative Adversarial Networks," *IEEE Access*, vol. 8, pp. 190710–190721, 2020, doi: 10.1109/ACCESS.2020.3032280.

[16] J. T. Gyory *et al.*, "Human Versus Artificial Intelligence: A Data-Driven Approach to Real-Time Process Management During Complex Engineering Design," *Journal of Mechanical Design*, vol. 144, no. 2, p. 021405, Feb. 2022, doi: 10.1115/1.4052488.

[17] G. Zhang, A. Raina, J. Cagan, and C. McComb, "A cautionary tale about the impact of AI on human design teams," *Design Studies*, vol. 72, p. 100990, Jan. 2021, doi: 10.1016/j.destud.2021.100990.

[18] B. Song, N. F. Soria Zurita, H. Nolte, H. Singh, J. Cagan, and C. McComb, "When Faced With Increasing Complexity: The Effectiveness of Artificial Intelligence Assistance for Drone Design," *Journal of Mechanical Design*, vol. 144, no. 2, p. 021701, Feb. 2022, doi: 10.1115/1.4051871.

[19] L. Yang *et al.*, "Diffusion Models: A Comprehensive Survey of Methods and Applications." arXiv, Mar. 23, 2023. Accessed: Jun. 24, 2023. [Online]. Available: http://arxiv.org/abs/2209.00796

[20] O. Sbai, M. Elhoseiny, A. Bordes, Y. LeCun, and C. Couprie, "DesIGN: Design Inspiration from Generative Networks," in *Computer Vision – ECCV 2018 Workshops*, vol. 11131, L. Leal-Taixé and S. Roth, Eds., in Lecture Notes in Computer Science, vol. 11131. , Cham: Springer International Publishing, 2019, pp. 37–44. doi: 10.1007/978-3-030-11015-4_5.

[21] C. Zhang, W. Wang, P. Pangaro, N. Martelaro, and D. Byrne, "Generative Image AI Using Design Sketches as input: Opportunities and Challenges," in *Creativity and Cognition*, Virtual Event USA: ACM, Jun. 2023, pp. 254–261. doi: 10.1145/3591196.3596820.

[22] F. Buonamici, M. Carfagni, R. Furferi, Y. Volpe, and L. Governi, "Generative Design: An Explorative Study," *Computer-Aided Design and Applications*, vol. 18, no. 1, pp. 144–155, May 2020, doi: 10.14733/cadaps.2021.144-155.

[23] W. Liao, X. Lu, Y. Fei, Y. Gu, and Y. Huang, "Generative AI design for building structures," *Automation in Construction*, vol. 157, p. 105187, Jan. 2024, doi: 10.1016/j.autcon.2023.105187.

[24] A. Cai *et al.*, "DesignAID: Using Generative AI and Semantic Diversity for Design Inspiration," in *Proceedings of The ACM Collective Intelligence Conference*, Delft Netherlands: ACM, Nov. 2023, pp. 1–11. doi: 10.1145/3582269.3615596.

[25] I. Economou, "The Problem with Plagiarism," in *Conference Proceedings of the Sixth International DFSA Conference*, Design Education Forum of South Africa, 2011, pp. 79–86.

[26] P. Saffo, "The Place of Originality in the Information Age," *Journal of Graphic Design*, vol. 12, no. 1, 1994.

[27] A. Bandi, P. V. S. R. Adapa, and Y. E. V. P. K. Kuchi, "The Power of Generative AI: A Review of Requirements, Models, Input–Output Formats, Evaluation Metrics, and Challenges," *Future Internet*, vol. 15, no. 8, p. 260, Jul. 2023, doi: 10.3390/fi15080260.

[28] A. M. Jarrah, Y. Wardat, and P. Fidalgo, "Using ChatGPT in academic writing is (not) a form of plagiarism: What does the literature say?," *Online Journal of Communication and Media Technologies*, vol. 13, no. 4, p. e202346, Oct. 2023, doi: 10.30935/ojcmt/13572.

[29] T. Siebel, "An Experiment in Collaboration," *Innovation: Quarterly of the Industrial Designers Society of America*, vol. 42, no. 1, pp. 34–37, 2023.

[30] footwearology_lab, "We are super proud to present the world's first AI-generated, 3D printed, wearable sneaker!," Instagram. Accessed: Jun. 22, 2023. [Online]. Available: https://www.instagram.com/p/Cl138IXo3mq/?igshid=MzRlODBiNWFlZA%3D%3D

[31] B. Poole, A. Jain, J. T. Barron, and B. Mildenhall, "DreamFusion: Text-to-3D using 2D Diffusion." arXiv, Sep. 29, 2022. Accessed: Jun. 12, 2023. [Online]. Available: http://arxiv.org/abs/2209.14988

[32] J. Xu *et al.*, "Dream3D: Zero-Shot Text-to-3D Synthesis Using 3D Shape Prior and Text-to-Image Diffusion Models." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2023, pp. 20908-20918.

[33] Q. Shen, X. Yang, and X. Wang, "Anything-3D: Towards Single-view Anything Reconstruction in the Wild." arXiv, Apr. 19, 2023. Accessed: Jun. 12, 2023. [Online]. Available: http://arxiv.org/abs/2304.10261

[34] R. Chen, Y. Chen, N. Jiao, and K. Jia, "Fantasia3D: Disentangling Geometry and Appearance for High-quality Text-to-3D Content Creation." arXiv, Mar. 28, 2023. Accessed: Jun. 12, 2023. [Online]. Available: http://arxiv.org/abs/2303.13873

[35] J. Gao, T. Shen, Z. Wang, W. Chen, K. Yin, and D. Li, "GET3D: A Generative Model of High Quality 3D Textured Shapes Learned from Images," presented at the 36th Conference on Neural Information Processing Systems (NeurIPS 2022), New Orleans, LA, USA, 2022.

[36] A. Jain, B. Mildenhall, J. T. Barron, P. Abbeel, and B. Poole, "Zero-Shot Text-Guided Object Generation with Dream Fields," in *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, New Orleans, LA, USA: IEEE, Jun. 2022, pp. 857–866. doi: 10.1109/CVPR52688.2022.00094.

[37] C.-H. Lin *et al.*, "Magic3D: High-Resolution Text-to-3D Content Creation," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2023, pp. 300–309.

[38] J. Cho, A. Zala, and M. Bansal, "DALL-Eval: Probing the Reasoning Skills and Social Biases of Text-to-Image Generative Models." arXiv, Nov. 14, 2022. Accessed: Jun. 03, 2023. [Online]. Available: http://arxiv.org/abs/2202.04053

[39] OpenAI, "DALL·E 2 Preview - Risks and Limitations," OpenAI Github. Accessed: Jun. 05, 2023. [Online]. Available: https://github.com/openai/dalle-2-preview/blob/main/system-card.md

[40] G. Somepalli, V. Singla, M. Goldblum, J. Geiping, and T. Goldstein, "Diffusion Art or Digital Forgery? Investigating Data Replication in Diffusion Models," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2023, pp. 6048–6058.

[41] OpenAI, "Terms of Use," OpenAI. Accessed: Jun. 05, 2023. [Online]. Available: https://openai.com/policies/terms-of-use

[42] Midjourney, "Terms of Service," Midjourney. Accessed: Jun. 05, 2023. [Online]. Available: https://docs.midjourney.com/docs/terms-of-service

[43] D. Wang, S. Prabhat, and N. Sambasivan, "Whose AI Dream? In search of the aspiration in data annotation.," in *CHI Conference on Human Factors in Computing Systems*, New Orleans LA USA: ACM, Apr. 2022, pp. 1–16. doi: 10.1145/3491102.3502121.

[44] B. Nicholls, "Midjourney founder basically admits to copyright breaching and artists are angry," Digital Camera World. Accessed: Jun. 05, 2023. [Online]. Available: https://www.digitalcameraworld.com/news/midjourney-founder-basically-admits-to-copyright-breaching-and-artists-are-angry

[45] B. Brittain, "Getty Images lawsuit says Stability AI misused photos to train AI," Reuters. Accessed: Jun. 05, 2023. [Online]. Available: https://www.reuters.com/legal/getty-images-lawsuit-says-stability-ai-misused-photos-train-ai-2023-02-06/

[46] R. Salkowitz, "Midjourney Founder David Holz On The Impact Of AI On Art, Imagination And The Creative Economy," Forbes. Accessed: Jun. 05, 2023. [Online]. Available: https://www.forbes.com/sites/robsalkowitz/2022/09/16/midjourney-founder-david-holz-on-the-impact-of-ai-on-art-imagination-and-the-creative-economy/?sh=2c41eb42d2b8

[47] J. Vincent, "'An engine for the imagination': the rise of AI image generators - An interview with Midjourney founder David Holz," The Verge. Accessed: Apr. 12, 2023. [Online]. Available: https://www.

theverge.com/2022/8/2/23287173/ai-image-generation-art-midjourney-multiverse-interview-david-holz

[48] Stable Diffusion, "Frequently asked questions," Stable Diffusion Online. Accessed: Jun. 05, 2023. [Online]. Available: https://stablediffusionweb.com/#faq

[49] Adobe, "Adobe Firefly," Adobe. Accessed: Jun. 22, 2023. [Online]. Available: https://www.adobe.com/sensei/generative-ai/firefly.html#faqs

[50] J. Dzieza, "AI Is a Lot of Work," The Verge. Accessed: Jun. 23, 2023. [Online]. Available: https://www.theverge.com/features/23764584/ai-artificial-intelligence-data-notation-labor-scale-surge-remotasks-openai-chatbots

[51] Partnerkin, "'AI Startups,' where Indians Freelancers Work Instead of AI, and a Selection of 15 AI Tools that You Can Use to Make Money Online," Partnerkin. Accessed: Jun. 22, 2023. [Online]. Available: https://partnerkin.com/en/blog/publications/ai-startups

[52] J. Lang, "U.S. Copyright Office Says AI-Generated Images Do Not Qualify For Copyright Protection," Cartoon Brew. Accessed: Jun. 05, 2023. [Online]. Available: https://www.cartoonbrew.com/law/midjourney-ai-images-us-copyright-office-226437.html

[53] B. Brittain, "AI-created images lose U.S. copyrights in test for new technology," Reuters. Accessed: Jun. 05, 2023. [Online]. Available: https://www.reuters.com/legal/ai-created-images-lose-us-copyrights-test-new-technology-2023-02-22/

[54] B. Rosamond, "Plagiarism, Academic Norms and the Governance of the Profession," *Politics*, vol. 22, no. 3, pp. 167–174, Sep. 2002, doi: 10.1111/1467-9256.00172.

[55] J. Coorey, "Removing Plagiarism from the Design Process: Stimulating Creativity and Originality in the Design Classroom," *The International Journal of Design Education*, vol. 12, no. 1, pp. 11–19, 2018.

[56] S. Izadpanah, "Evaluating the Role of Pinterest in Education and the Profession of Interior Architecture," *Idil*, vol. 10, no. 87, Nov. 2021, doi: 10.7816/idil-10-87-01.

[57] M. Mostafa, "Inspiration versus Plagiarism: Academic Integrity in Architectural Education," *The International Journal of the Constructed Environment*, vol. 1, no. 3, pp. 85–100, 2011, doi: 10.18848/2154-8587/CGP/v01i03/37482.

[58] A. Shekar, "Project-based Learning in Engineering Design Education: Sharing Best Practices," in *2014 ASEE Annual Conference & Exposition Proceedings*, Indianapolis, Indiana: ASEE Conferences, Jun. 2014, p. 24.1016.1-24.1016.18. doi: 10.18260/1-2--22949.

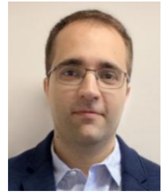
[59] J. Carroll, "Assessment, learning and judgement in higher education," G. Joughin, Ed., Dordrecht: Springer Netherlands, 2008, pp. 115–131.

[60] J. Everitt and A. M. Holmes, "Assessment of Novelty for Intellectual Property with Implications for Design Education: A Case Study," *The International Journal of Design Education*, vol. 10, no. 4, 2016.

[61] S. Sheth, "How are Design Competitions and Awards Planning on Dealing with Ai-Based Submissions?," Yanko Design. Accessed: Jul. 17, 2023. [Online]. Available: https://www.yankodesign.com/2023/06/29/how-are-design-competitions-and-awards-planning-on-dealing-with-ai-based-submissions/?fbclid=PAAabwNRK9KEg68snKy-db1LaUQ-9RORayGnDEmrXmTMB5scm7Yu7UagAd7OQ_aem_AQvHCdJF3_pbb6tnYc5jm879kQvSSAgfWyM5HWpDiaj47T2kIuPjCsEp29Kw2lbD0Q

Kristin A. Bartlett

Kristin A. Bartlett is an Assistant Professor in the Department of Product Design at the University of Kentucky in Lexington, KY. She holds a PhD in Technology from Purdue University in West Lafayette, IN, USA, a Master of Science in Industrial Design from the University of Houston in Houston, TX, USA, and a Bachelor's in Civil & Environmental Engineering from Rice University in Houston, TX, USA. Kristin's research interests include design education, gender equity in STEM, and applied research in the area of medical device development.



Jorge D. Camba

Jorge D. Camba is an Associate Professor in the School of Engineering Technology at Purdue University in West Lafayette, IN. Prior to joining Purdue, he taught at the University of Houston and at Texas A&M University. Dr. Camba is the author of 100+ peer-reviewed publications and nine books. His research focuses on 3D model complexity and optimization, design automation and reusability, human-computer interaction, and Model-Based Engineering.