

# **THE NON-EXISTENT CHAIR SERIES: EVALUATING GENERATIVE DESIGN OUTCOMES**

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by

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# **THE NON-EXISTENT CHAIR SERIES: EVALUATING GENERATIVE DESIGN OUTCOMES**

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## **LIST OF SYMBOLS AND ABBREVIATIONS**

AI	Artificial Intelligence
GAN	Generative Adversarial Network
FID	Frechet Inception Distance
HYPE	Human eYe Perception Evaluation

## SUMMARY

Generative Design has been a hot topic in the design world for a while, earlier inventions like shape grammar and space syntax generate geometrical designs with sets of rules defined by the user. The latest invention of generative design is artificial neural networks like GAN (Generative Adversarial Network), which created a new logic of generative design. Earlier inventions focused on geometrical exploration with applied rules; therefore, the generated designs are calculated results. GANs, on the other hand, because of the nature of deep learning networks - are like a black box. Since there is no way of supervising what happens within, there are levels of randomness and uncertainty. GANs are also trained with images instead of geometrical shapes or forms. Making it capable of exploring colors, image depth, as well as overall composition. In a way, it changed the logical decision-making process in design into something more spontaneous.

This work aims to explore the usability and applicability of generative networks by coming up with non-statistical measurable features. How realistic does the generated designs need to be for it to be “viable”, for designers to be able to recognize the object for what it is? Is the pursuit of photorealism in image generation networks applicable to the field of design?

## **CHAPTER 1. INTRODUCTION**

Designing with artificial intelligence (AI) has been a trendy topic in the design industry, sparking an ongoing debate on whether it replaces or serve designers. There are several applications and areas of design using AI to assist with the design process in architecture, buildings, and urban planning, including many aspects of engineering design, and evaluate the outcome. However, the application of AI is much less done in industrial design. The objective of this study is to see how the algorithm can depict style, and more specifically if its understanding of sample images is similar to that of a human.

## CHAPTER 2. LITERATURE AND PRIOR ARTS REVIEW

### 2.1 The Chair

The chair is arguably one of the most symbolic design products. No matter which particular design area you specialize in, most designers start their design journey with a chair. As George Nelson (1953) pointed out, “every truly original idea, every innovation in design, every new application of materials, and every technical invention for furniture, seems to find its most important expression in a chair”. Therefore, the chair is one of the most quintessential objects in the modern era, as well as the most accessible and relevant to the public. The greatest designers of our time like Eero Saarinen, Zaha Hadid, Walter Gropius, and Frank Gehry have all designed chairs. It is a popular alternative for designers to distill their creativity, techniques and innovations into a new medium. (15 *Contemporary Architects Who Design Chairs*, 2022)

For every design movement, there is a chair that exemplifies its era. Moreover, “the chair offers us a glimpse into our collective ideas about status and honor, comfort and order, beauty and efficiency, discipline and relaxation” (Cranz et al., 1998). For example, the Bauhaus chairs were identified by a clear demonstration of the materials and construction process in the final product (Poon, 2019). One of the iconic representations is Mies van der Rohe’s Barcelona chair, which consists of stainless steel and foam rubber cushions, all of which are shown in the final product. It demonstrates the single-mindedness of Bauhaus’ idea of form and function. It is also difficult to pack and ship due to its weight (Poon, 2019). However, when looking at its mass-produced, consumer-driven predecessor like IKEA. Though many similarities descended from Bauhaus, it is quite

easy to distinguish the two style-wise due to the fact that IKEA's consumer learning approach incorporates ergonomic factors and its further simplification of the form. (Basak, 2021).

Chairs have become the symbolization of the technology and production revolution of the era as well. In the age of AI, "the chair" should also represent this new revolution and its impact on design.

## **2.2 AI in Design**

AI has influenced the way of manufacture, production, as well as presentation and interaction in many fields. (Murugaiah, 2021) For example, in the medical field, health data can be collected through smart watches and analyzed through AI to monitor and retrieve the history of day-to-day wellbeing of the user. It has also been widely utilized in manufacture and production. By using sensors and algorithms, companies are able to cut down cost and maximize efficiency. (Murugaiah, 2021) Although implementation of AI in design is relatively new compared to other fields, there has been many attempts in improving various aspects of design. For example, one of the successful implementations would be the generative design feature in Fusion 360 (*Generative Design for Manufacturing With Fusion 360 / Autodesk*, n.d.). Which not only deploys machine learning as a way to accelerate product development process, but proposing a new manufacture journey map.

The new journey map of end-to-end product development process reflected how AI can affect designers in numerous ways. It uses generative design algorithm to improve design freedom, then making a prototype out of CNC machines. Lastly, the prototype is casted



to use for injection molding to produce the final product. (*Generative Design for Manufacturing With Fusion 360* / Autodesk, n.d.)The production process leads us back to manufacture and production - how the machines' accuracy and efficiency has improved with the help of AI.

The reason why AI is capable of high efficiency is because it can process large amounts of data at a fast pace. And it is a mutually beneficial relationship, AI requires large amounts of data to be able to find patterns. At the same time, more data makes AI smarter as it progresses. ("Big Data and Artificial Intelligence," 2017) This led to the exploration of generative design, . However, creativity is considered the biggest difference between man and machine. Because creativity, by dictionary definition is the use imagination and original ideas to produce artistic work. (*Oxford Languages and Google - English* / *Oxford Languages*, n.d.)The creativity of the human mind is the biggest difference between machines and humans. Artificial intelligence helps designers improve their creativity by handling some daily tasks, thus saving designers time and energy on ideas.

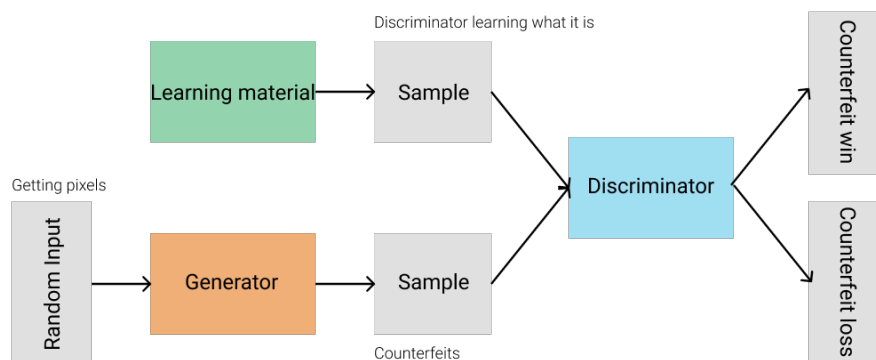
AI is good with large amounts of data, it can process data much faster than the human mind. More specifically, the AI can assist people to collect data or find relevant references faster, reducing the amount of time required for research (Smithers et al., 1990).

Besides, AI is a master at analyzing user behavior and preferences. The key is that AI can explore what your target audience likes now and what they will like in the future, down to the individual customers (Shi & Lewis, 2020). The algorithm identifies designs and

platforms that users like to spend time on. It provides a path for designers to follow so that they can produce consistent, user-friendly, and effective designs.

### 2.3 GANs – Generative Adversarial Network

With the advent of Generative Adversarial Networks (GANs), the scope of AI design has greatly increased (Sim & Duffy, 1998). GAN is a generative modeling method using deep learning methods (Aggarwal et al., 2021). Generative modeling is an unsupervised learning task in machine learning that involves automatically discovering and learning patterns in input data so that the model can be used to generate or output new examples that might be extracted from the original data set (Aggarwal et al., 2021). Think of it as a mouse chase where the generative model tries to create counterfeits, makes fake artworks and sells them without anyone noticing. While, the discriminative model is like cops, which try to catch fake artworks. Hence, the competition makes the generative model better at creating counterfeits, eventually to the point of being indistinguishable from the dataset (Goodfellow et al., 2014).



*Figure 1 Generative Adversarial Network Wireframe*

GAN frames the problem as a supervised learning problem with two sub-models (see Figure 1), training a generator model as well as a discriminator model. The former

generates new examples, the latter categorizing examples as real (from the domain) or unreal (generated). The two models are trained together in a zero-sum game against each other until the discriminator model is fooled about half the time, which means the generator model is generating reasonable examples (Brownlee, 2019; Taif et al., 2020). However, one of the biggest shortcomings of GAN is the lack of control over the style of generated images. Generators operate as black boxes, and an understanding of the generation process is still lacking (Karras, Laine, et al., 2018).

## **2.4 StyleGAN – StyleGAN2**

The inevitable downside to previous GANs was that 50,000 to 100,000 training images are required to train a high-quality GAN (*NVIDIA Research Achieves AI Training Breakthrough*, 2020). Using only thousands of images means:

*“...with limited training data to learn from, a discriminator won’t be able to help the generator reach its full potential — like a rookie coach who’s experienced far fewer games than a seasoned expert.”*

So StyleGAN2 was breaking through to generate high-quality images with smaller datasets. StyleGAN was presented by Nvidia in 2018 (Karras, Laine, et al., 2018), mainly to upgrade the original GAN generator to make it more style-based. This means it can generate a vector that does not have to follow the real image dataset’s distribution, giving it more creativity. It is also capable of synthesizing higher resolution and higher quality images, creating clearer images (Karras, Aila, et al., 2018). Most importantly, it is capable of combining multiple images in the generated outcome.

StyleGAN2 is an update from StyleGAN (Karras et al., 2020). Mainly to fix some of the problematic artifacts that commonly exist in StyleGAN images. Therefore, improving image quality even further while using less images and less high-resolution dataset. Making it easier for individual researchers with limited resources to high-quality, high-resolution image database to achieve their image generation.

## 2.5 GANs Applications in related fields

GAN is implemented by using a pre-trained generator that randomly arranges pixels and sends them to the discriminator. The discriminator is trained on a particular set of selected chair images. The generator continuously outputs images for the discriminator to examine. If it is similar enough, it will be determined as a true image and get outputted.

Aside from facial generations that are exemplary of GAN, one of the most well-known GAN projects is Artbreeder (*Artbreeder*, n.d.). While it makes it easier to experiment with incrementally generating images using AI, it is hard to quantify if the generated art lives up to expectations. They are more exploratory and experimental.

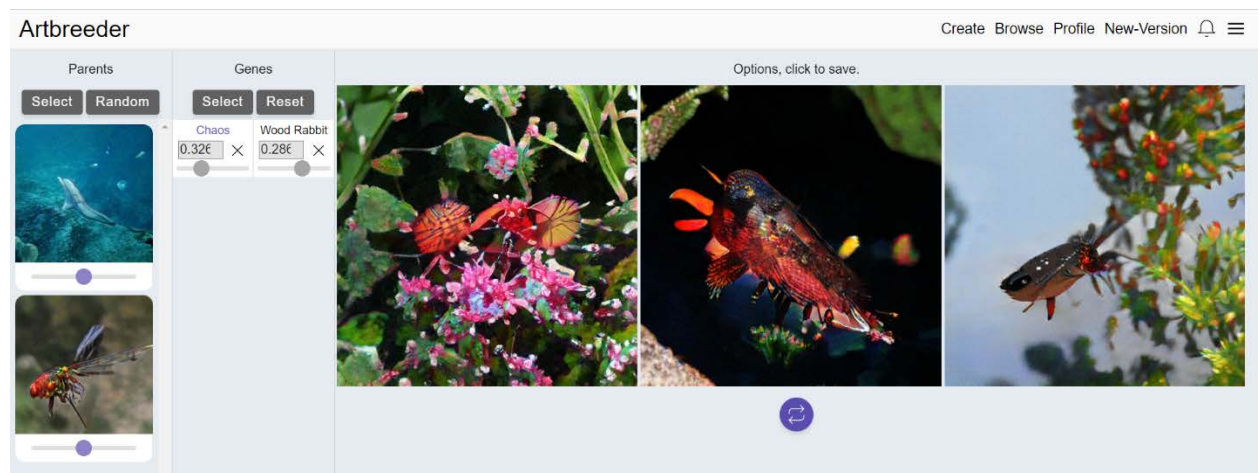


Figure 2 Artbreeder Interface (Source: Artbreeder, n.d.)

Other approaches include ArchiGAN (Chaillou, 2019a), which uses a modularized approach more inclined to create logical designs of floorplans. By creating functional layouts labeled with program repartition, such as living room and bedroom. A layer of floor plan drawings is then applied, which gives it the furniture layout. This very pragmatic approach was done under the simple imperative of organization.

Later on, as the researchers of ArchiGAN experimented with different styles:

*“We investigate architectural style learning, by training and tuning an array of models on specific styles: Baroque, Row House, Victorian Suburban House, & Manhattan Unit.”*



*Figure 3 ArchiGAN 2D to 3D Ideation Process (Source: Chaillou, 2019b)*

They had realized that the generated outcomes were stylistically biased due to their selected dataset (see Figure 3). That outside of the simple aesthetics of a style, it also carries the fundamental functional rules that defines and organizes a space (Chaillou, 2019b). Given that style is deeply rooted in the essence of design, each dataset is influenced by style. Thus, no generative design is truly objective. The research proved the impact of architectural style on generated floor plans.

## 2.6 Chair Generation using GAN

“The Chair Project” by Philipp Schmitt and Steffen Weiss was said to “generate an engaging ‘visual prompt’ for human designers (*The Chair Project (Four Classics)* —

*Philipp Schmitt, n.d.*.” The project was not aimed to create functional chairs but to explore possibilities of this design method. It used 562 selected images from Pinterest as the dataset, then interpreted the design, and finally built it into miniature chair prototypes. Later, they made the miniature prototypes into 1:1 scale prototype.



*Figure 4 "The Chair Project" Outcomes (Source: The Chair Project (Four Classics) — Philipp Schmitt, n.d.)*

Although the project was excellent at exploration, it was only trained with only 562 selected images, causing it to be significantly abstract. This was not a bad thing as it allowed for free interpretation in the design. Current output of 2D chair generation is only used for props. As seen in Figure. 4, a large portion of human involvement is required to

interpret the generated image into a readable, manufacturable sketch. And any designer could imagine the generated image differently. So, in this case, the true design generator is still the designer. Because a chair is a 3D object that even in isometric drawings should have certain number of facades to be able to qualify as a chair design.

Other attempts have also been made to produce more realistic or structurally sound chair designs. In Kleineberg's work (Kleineberg et al., 2020), she created a 3D GAN to generate objects. As a 3D object, it can be exported as actual 3D models, ready for 3D printing, so it is more legible than chairs and more manufacture friendly, pushing it one step further towards more autonomous design and production.

## **2.7 Summary**

Current researches that use GANs for design generation spans across a variety of areas of study. From 2D drawings to photographs to architecture and to industrial design. One constant problem is how datasets – that are selected by human researcher, are inevitably biased. Another problem is how do people determine if a generated design is good or bad and how to claim it as success. Instead of treating the inevitable bias as an obstacle, maybe there is a way to utilize those biases. In design generation especially, perhaps using the characteristics that are fundamentally possessed by design styles (layout, functionality, aesthetics, etc.) can help us decide whether if a generated design is a success.



## CHAPTER 3. METHODOLOGY

To acquire a sufficient number of datasets, an image scraper was used to collect images off of Google images by automatically input keywords such as “Designer name + Style” into Google search bar. The scraper then goes through every image on the search results page to download every image. The images were then manually filtered by comparing the scraped images against designer catalogs to filter out those that were not from the era. The rest would be used as learning material for the algorithm.

One of the hardest things was figuring out what to measure. Scholars (Z. Xu et al., 2019) (W. Xu et al., 2021) had conducted numerous studies on using GANs as stylizers and adopted different approaches to the algorithm. But the evaluation process had little to do with “style”. The incentive of these studies was to motivate refinement and improvement to the algorithm, not generated images. The evaluation process focused on quantitative data rather than qualitative, but quantitative evaluation remained an open problem. Most existing evaluation methods were done by measuring data and parameters like FID scores (Heusel et al., 2017; Yu et al., 2021) and IS (Salimans et al., 2016). Both were designed to measure the visual quality of generated images, by comparing the statistics of generated images to real images, not human evaluations or people with artistic style expertise.

Some qualitative methods that have been performed include HYPE (Zhou et al., 2019). HYPE is a method developed by Stanford researchers to evaluate results to differentiate realism in generated images. It is a developed benchmark for the human eye perception

of generated images. The longer it takes humans to determine whether they think an image is real or generated, the lower it ranks. This study took a similar approach. The fewer people who approve of the identifiable features of a certain style make it lower rank. While the purpose of this study is not to test “realness”, similar considerations have been taken. That is, to find an appropriate evaluation benchmark. This leads us to design styles. Design styles have scholarly defined areas and margins, which provide the images with a “goal” to achieve.

### **3.1 Process (trials and errors)**

To narrow the search and criteria for evaluation, the process included a consultation with an art historian and design style expert, Dr. Joyce Medina, who recommended a list of styles that she thought had distinctive characteristics. They were relatively apart chronologically so they were less likely to be confused with each other. After collecting a list of styles, several rounds of the test generation with different styles. We also applied the evaluated results to determine appropriate chair styles.

### 3.1.1 Tests

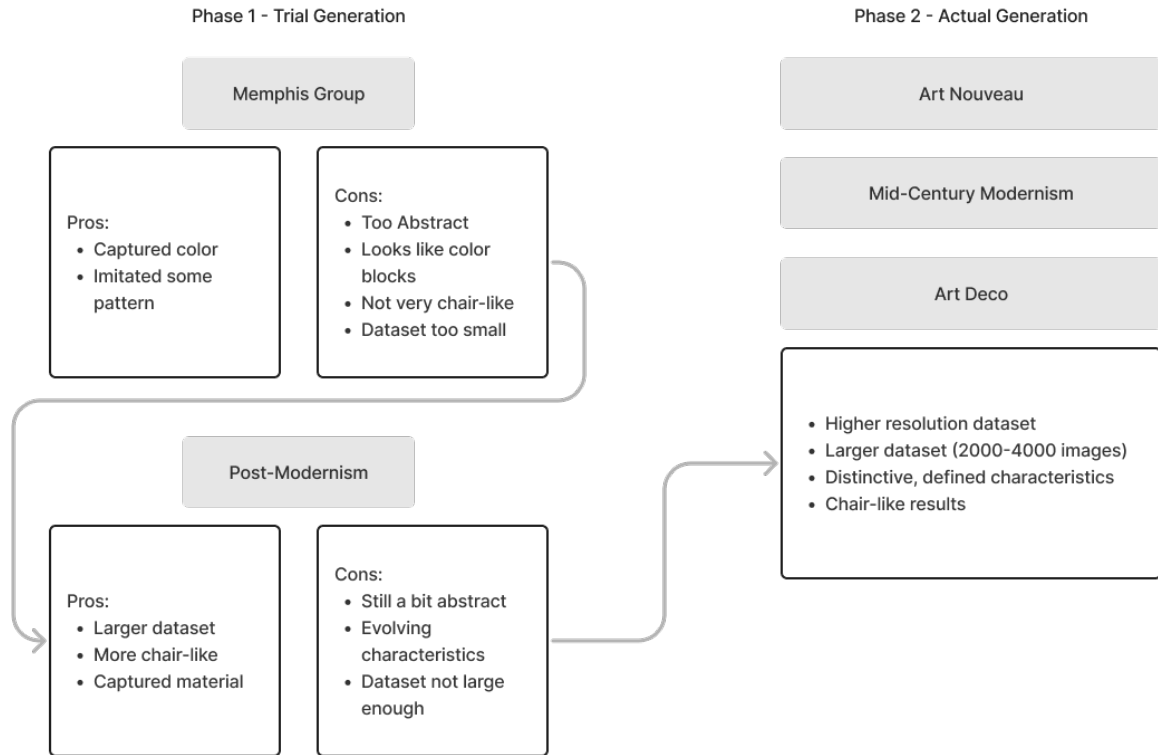


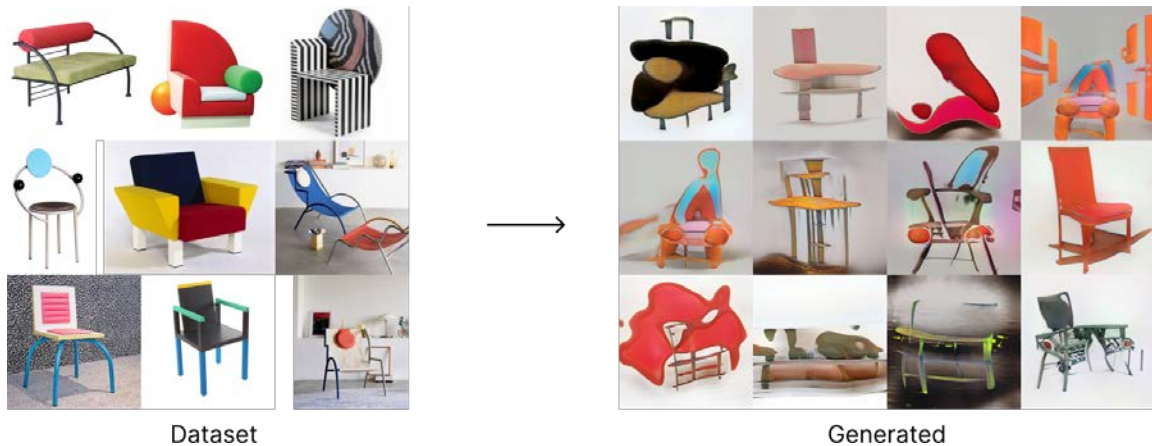
Figure 5 Process Diagram

#### *Memphis chair: Memphis design movement*

Memphis style emerged in the 1980s and was led by Ettore Sottsass (Ettore Sottsass, n.d.). The Memphis style is characterized by (Memphis, n.d.):

- Vibrant colors
- Decorative
- Bold patterns
- Stripes
- Clashing colors

- Abstract designs
- Plastic laminate



*Figure 6 Memphis Group Training Results*

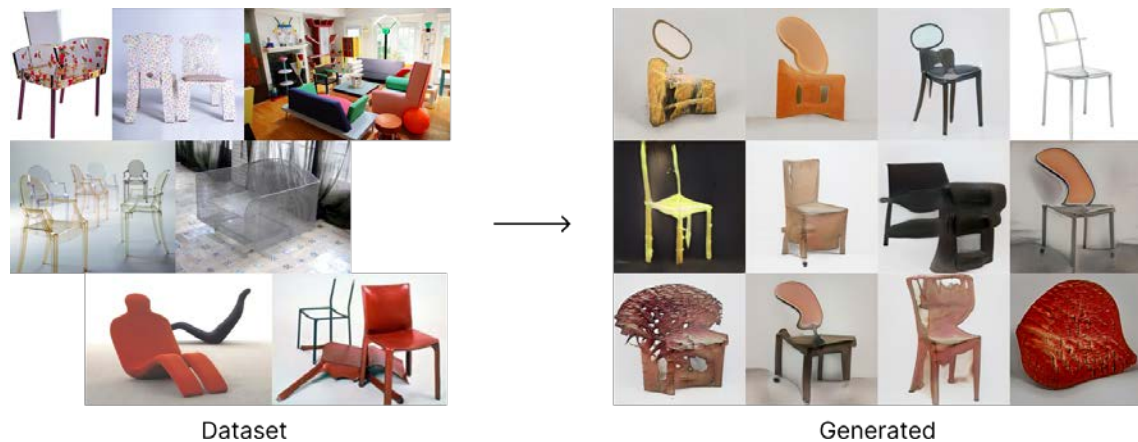
The Memphis style was chosen for the first aesthetic attempt because it was distinctly recognizable and stood out in the clash of colors and geometric shapes (Memphis Design Guide, n.d.) (Memphis, n.d.). It was designed to test the algorithm's ability to pick up colors and patterns as well as the reflectiveness of material, and how it reacts to irregular and abstract shapes. However, Memphis chairs did not work out well due to the number of images, and all of the work by the Memphis group had only 200 images, not enough to generate accurate or credible results. This seems to be a prevalent problem across GAN projects.

#### *Post-Modernism chairs*

Post-modernism was an attempt to broaden the number of designs so that more images could be collected for the dataset. It was also a style to which Memphis belonged, so a comparison would be made between the two. To enlarge the dataset, a list of designers was chosen so that there was a reference to compare the generated results. The list of

designers included Shiro Kuramata, Piero Gilardi, Philippe Starck, Gaetano Pesce, Frank Gehry, Ettore Sottsass, and the Castiglioni brothers. The consistent view of chairs ruled out other factors that might have interfered with the results. All chairs in this dataset were angled 45 degrees to the right. To maximize the amount of input, all images that were 45 degrees but facing in the opposite directions were mirrored. Images with simple backgrounds were also filtered. This would also give the most amount of information and made modeling/3D printing and prototyping easier.

Post-modernism is defined by the defiance toward modernism. It opposes clean logicity and proposes imbalance, disjunction, and spatial ambiguity (Clarke, 2010). It aims to be inventive and playful with bold colors, patterns, and the use of unconventional materials.



*Figure 7 Post-modernism Training Results*

Unfortunately, this designer list still did not have enough images (500). The limited dataset caused the generated images to be abstract and lacking details. Plus, post-modernism is still evolving and going on, so its styles have yet to be settled, and the results are inevitably abstract and unstable. Which made it harder to define than other

styles. The key insight from this round of test is that, only good input with high resolution and high quality can lead to the good output.

## **3.2 Actual Runs**

### *3.2.1 Art Nouveau*

Tested over generations and presented with images to design professionals, a consensus has been reached on a stable and consistent design style. More specifically, a style in the past where it is not constantly evolving, and it is scholarly defined and will never change (since it is in the past). Therefore, Art Nouveau is chosen for its distinct designs in abstract patterns vs. organic patterns, mixing of materials vs. no mixing at all, and symmetry vs. asymmetry in design. Art Nouveau is decorative, symbolizing flowing organic forms (Woodham, 2004). It is also closely tied to the Arts and Crafts movement, which emphasis on craftsmanship, a movement against the destructive effects of industrialization (V&A · *Arts and Crafts*, n.d.). This time, a wider list of designers was chosen as a reference and forewent the constraints of a certain chair perspective for the images. Following this filtering standard, we are left with 2000 images (2106) for the Art Nouveau dataset.



*Figure 8 Art Nouveau Training Results*

Art Nouveau furniture is defined by (Erlhoff et al., 2007; Gontar, n.d.).

- Abstract patterns or organic patterns as two different approaches, both in the pursuit of nature as a theme:
- The abstract comes from a scientific view and explored the organic forms. It resulted in a simpler visual language.
- Organic patterns come from reinterpreting the surfaces of an object. Using stylized, organic, and curvilinear forms that were inspired by flowers, botanicas, and sometimes seashells.
- Mixing of materials or No mixing at all
- An emphasis on the hardwood like oak and walnut is due to Japanese influences.
- Combining new materials from industrialization like metal, and glass with organic ornamentation.
- Symmetry or Asymmetry
- While some designers followed organic shapes and curvilinear forms.

- Others like Charles Rennie Mackintosh were known for geometric forms and planar areas with graceful horizontal and vertical lines.

### 3.2.2 Mid-Century Modernism

Despite Art Nouveau's great achievements, it still has limitations that cannot be ignored. Art Nouveau is heavily decorative, even excessive. In addition, it existed in an era where there was a heavy focus on décor and aesthetics, and has not yet been considered human comfort. Whereas Mid-century Modernism is simplistic, utilitarian, functional, and focuses heavily on ergonomics. Some also take the form of explorations like Eero Saarinen's womb chair or tulip chair (Roman et al., 2003). The Mid-Century Modernism dataset included around 4000 (4245) more recent images with more high-quality and high-resolution.



*Figure 9 Mid-Century Modernism Training Results*

Mid-Century Modernism is defined by (Nast, 2017).

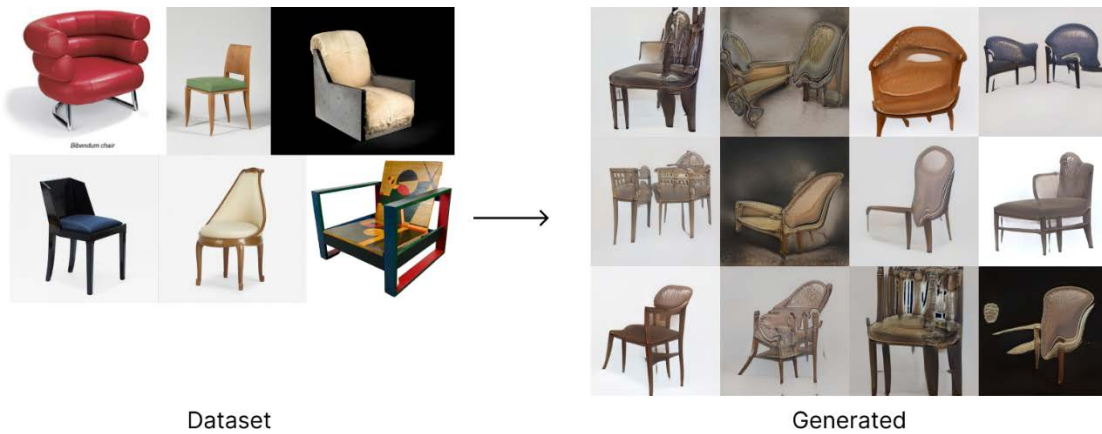
- Organic influences, furniture that work both indoor and outdoor



- Simple forms, no ornamentation or decoration, simplistic, minimalistic with form following function.
- Emphasis on function, conformation to the human body, a focus on ergonomics, and articulated form.
- Democratic, universal, designed for everyone.
- Material-wise, mid-century modernism was affected by the technology and manufacturing ability of its time. Materials include but are not limited to:
  - Laminates with synthetic resins.
  - Molded fiberglass, plastic.
  - Metal, aluminum legs.

### *3.2.3 Art Deco*

Another style of choice was Art Deco, which is a style between Art Nouveau and Mid-Century Modernism. It has decorative features like Art Nouveau, using lacquer and laminated hardwood. But it also has modernistic and geometric features like Mid-Century Modernism. Art Deco is special in that it encompasses a wide range of stylistic criteria. As a result, it comes in varied materials, such as stones, wood, and metal. The Art Deco dataset also includes around 2000 images, 1896 to be exact.



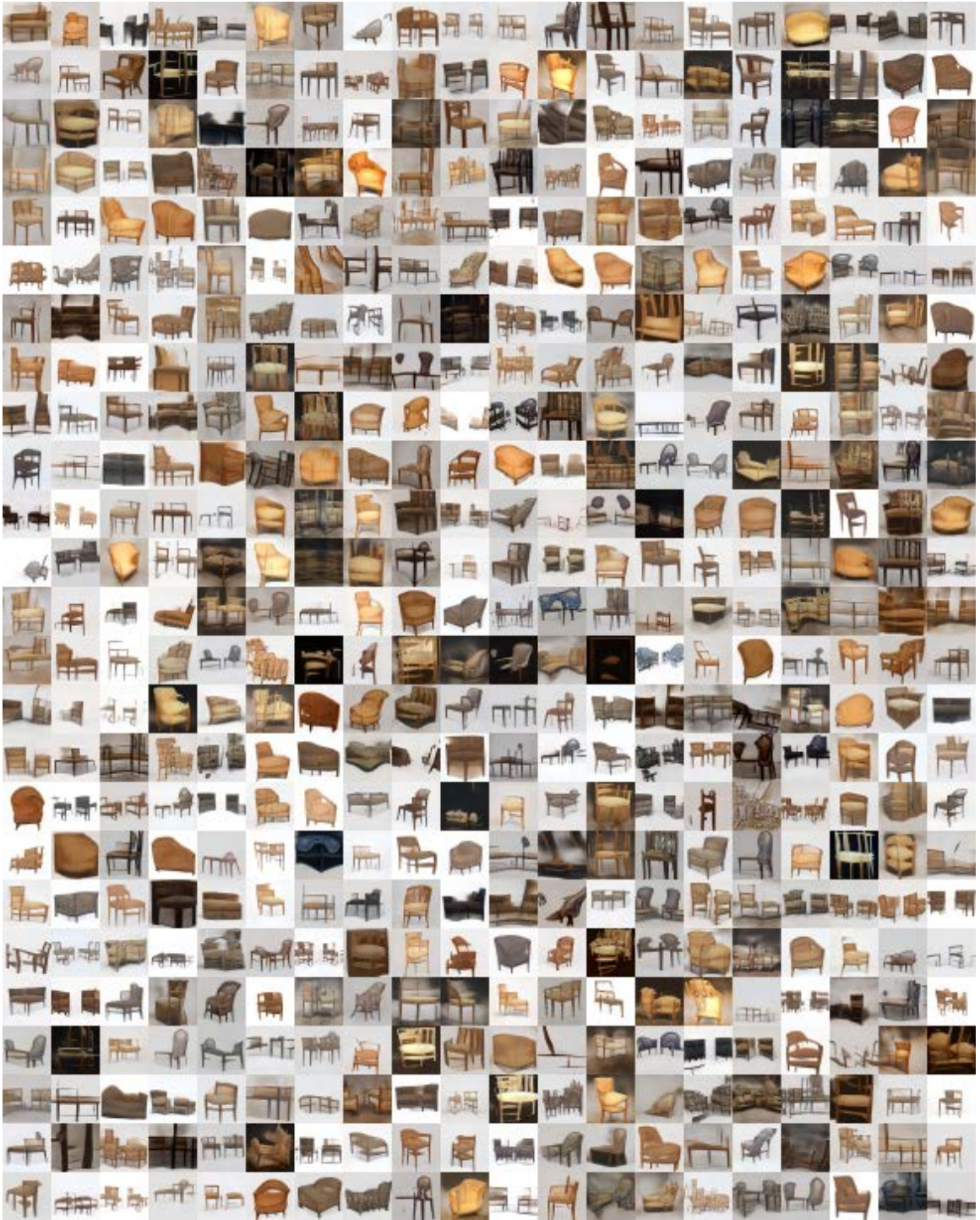
*Figure 10 Art Deco Training Results*

Art Deco is defined by (Erlhoff et al., 2007; Woodham, 1997):

- A focus on surface ornamentations, and stereometric and geometric forms (zig-zag and chevron).
- An emphasis on craftsmanship, and the use of rare, exotic, and expensive materials like stones, ivory, ebony, exotic woods, fine leather, bakelite, and aluminum.
- Showcasing the luxurious and flamboyant lifestyle and taste of a new class.

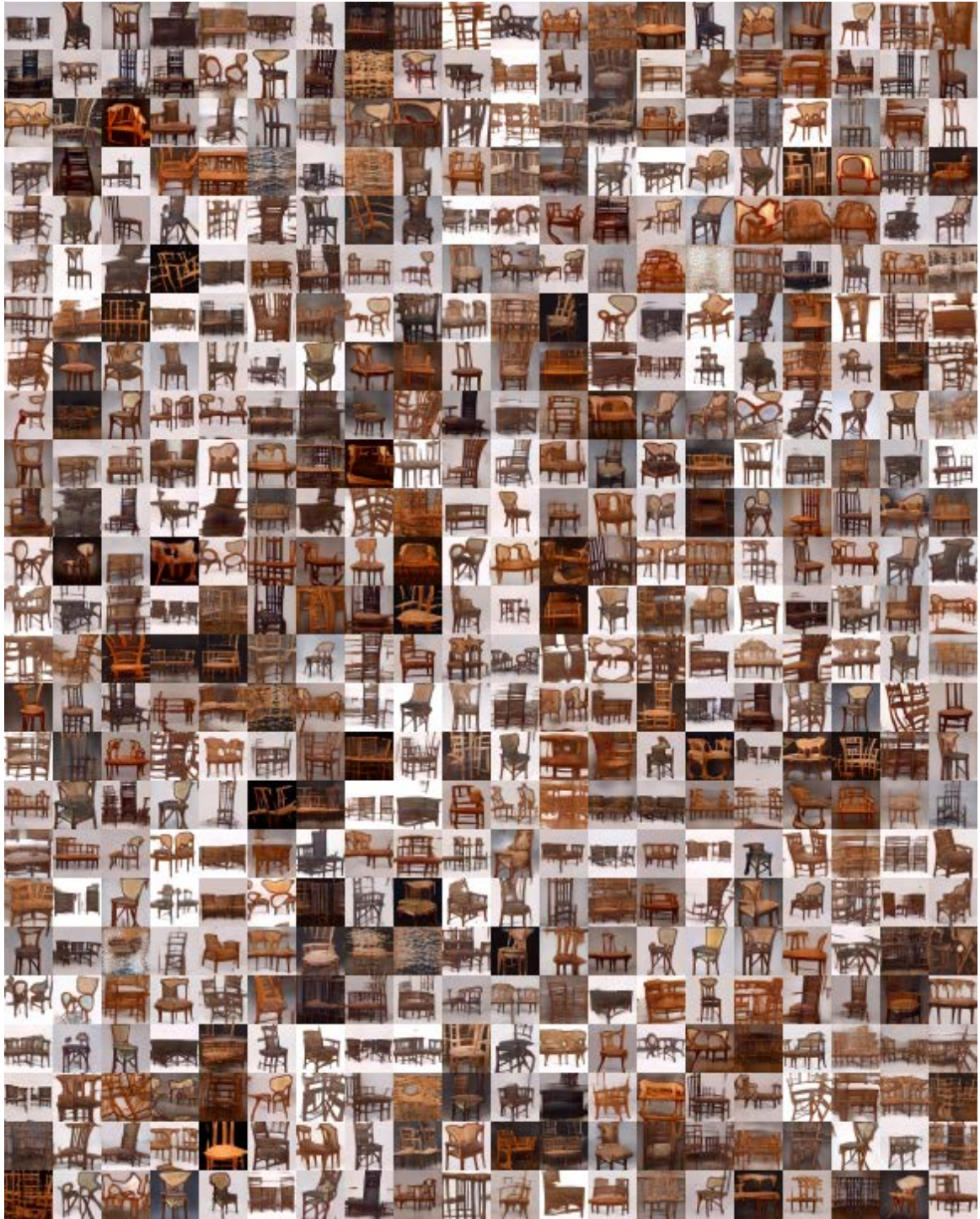
Using designers' work from a selected list of three different design styles, then implementing it into the algorithm. Each ran for 7000 steps and had an FID score of around 40. Generally speaking, a lower FID score is better, with 0.0 indicating perfectly identical to the real dataset. However, it is near impossible to reach 0.0, the researchers of styleGAN was only able to get their FID score down to single digits, with the lowest being 4.40 (Karras, Laine, et al., 2018). And in this case, 40 was the lowest number the algorithm could reach with the limited size and quality of dataset.

## CHAPTER 4. GENERATED RESULTS



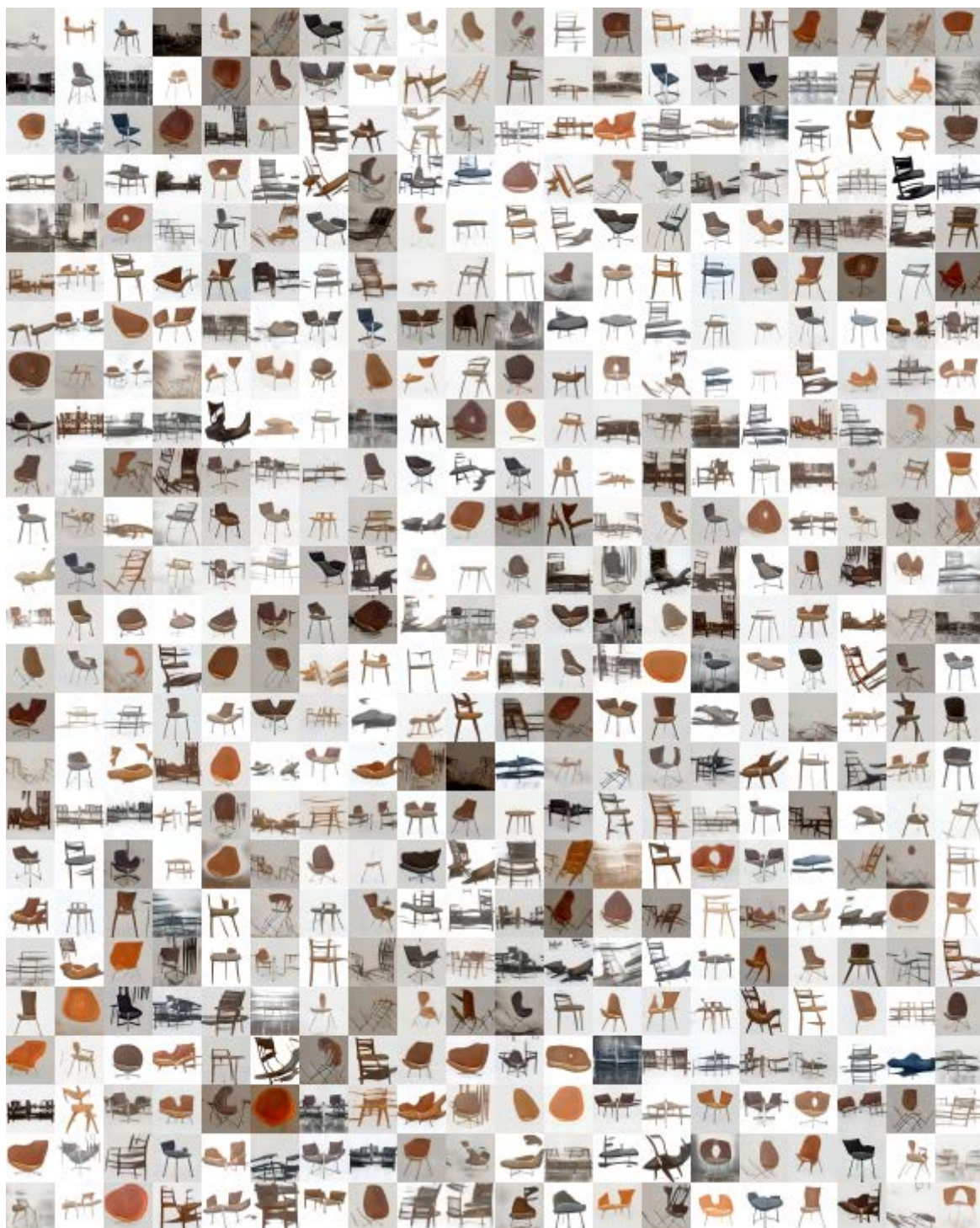
*Figure 11 500 Generated Images Using Art Deco Dataset*





*Figure 12 500 Generated Images Using Art Nouveau Dataset*





*Figure 13 500 Generated Images Using Mid-Century Modernism Dataset*



Figure 14 - 1a (Art Deco) Randomized 60 Images from 500 Generated Images



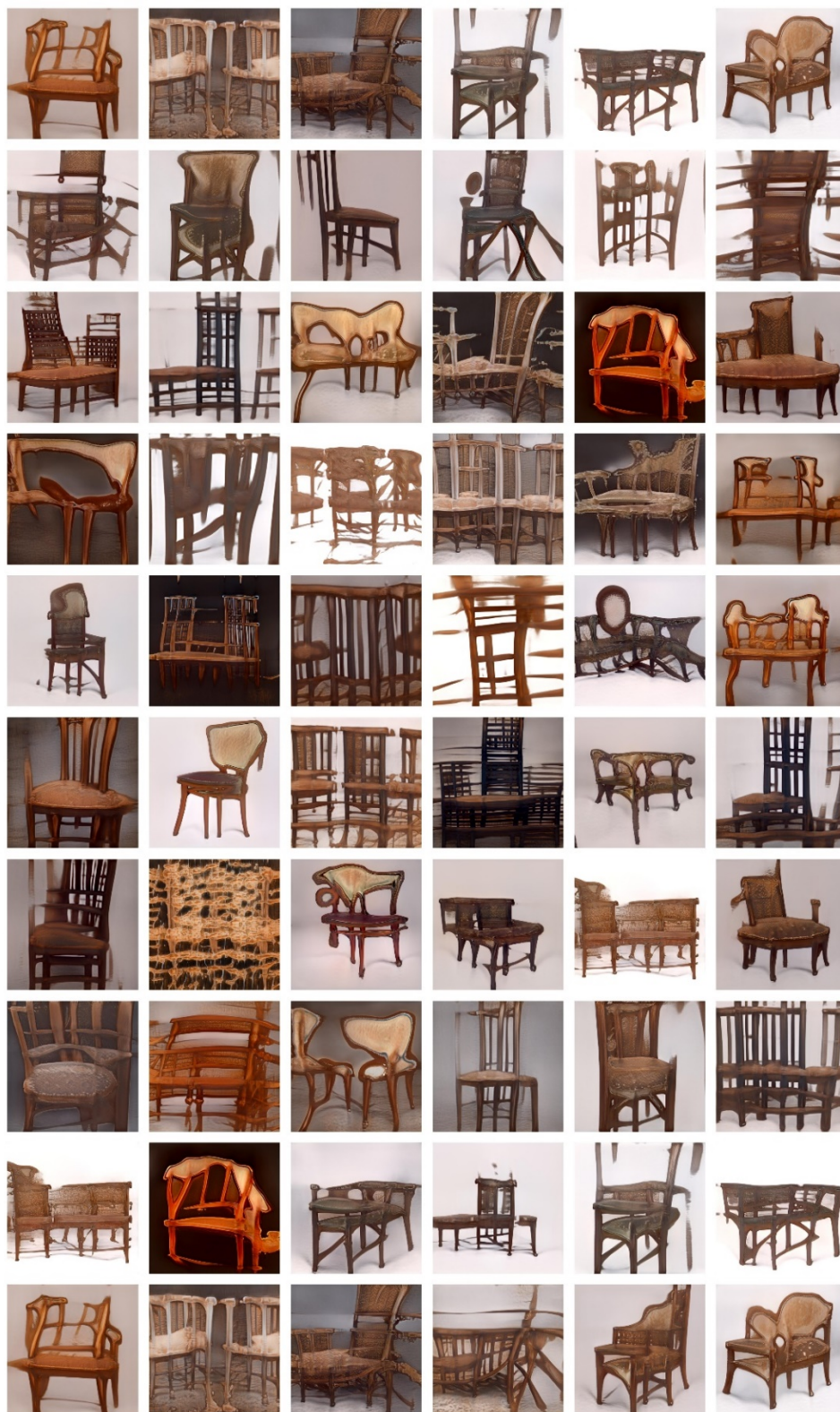


Figure 15 – 2a (Art Nouveau) Randomized 60 Images from 500 Generated Images



*Figure 16 - 3a (Mid-Century Modernism) Randomized 60 Images from 500 Generated Images*



## **CHAPTER 5. EVALUATION AND DISCUSSION**

The evaluation took the form of a semi-structured interview. Professionals and students who have a background in furniture design and knowledge of design history were recruited. Students familiar with design history and art movements were also recruited for the study. A total of ten students and three design professionals were involved. The questions were designed to narrow down their descriptions to see if they could eventually describe or name the styles of the generated chairs. They were 1) first asked whether they saw consistency or any repeating patterns in the generated images, then they were 2) asked to describe the style, or the nature of the consistency or patterns they saw in those images. Lastly, they were 3) given cheat sheets with ten different design styles from the twentieth century to match the most accurate ones that they saw fit.

### **5.1 Consistency**

The question started by asking for consistency, whether it was color, shape, form, symmetry/asymmetry, material, or whatever they first notice displaying images.

*Table 1 Consistency Keyword Analysis Overview*

1a (Art Deco)		2a (Art Nouveau)		3a (Mid-Century Modernism)	
Keywords	Frequency	Keywords	Frequency	Keywords	Frequency
Wood/use of wood	4	Wood/use of wood	3	Modern	4
Between 2a & 3a		Decorative/Decor	3	Fluidity	3
Color	3	Classical/Neo-Classical	2	Minimal/Minimalist/Minimalistic/Minimalism	2
Decorative/Decor	2	Chinese/Asian	2	Molded form/Heat formed	2
Modern	2	Ancient	2	Metal	2
Soft	2	line/linear	2	Utilitarian	1
Scandinavian	1	Grid/Crossing lines	2	Abstract	1
Contemporary	1	Handmade/craftsman/crafts	2	Symmetry	1
Utilitarian	1	Ornate	1		1
Symmetry	1	Victorian	1	line/linear	1
Fluidity	1	Sculpted	1	Curved/curvature	1
Elaborate	1	Color	1	Ergonomics/User comfort	1
Ergonomics/User comfort	1	Stylistic	1	Color	1
Factory/Factory made	1			Factory/Factory made	1
Handmade/craftsman/crafts	1			Wood/use of wood	1
Mixing of materials	1			Leather	1

### 5.1.1 1a (Art Deco)

As shown in Figure 4, the keywords most commonly used by participants to describe 1a (Art Deco) were Modern, Soft, Consistency in Color, and the Use of Wood. Three participants also suggested that chronologically, 1a is between 2a and 3a. There were also mentions of Scandinavian, Contemporary, Utilitarian, Use of Fabric, and the mix of handmade and factory-made. Review the characteristics of the Art Deco style, including surface ornamentations, geometric shapes, and the use of exotic materials, including a wide variety of hardwood, and an emphasis on craftsmanship.

Table 2 Consistency Keyword Comparison between 1a and Art Deco Characteristics

1a (Art Deco)		
Keywords	Frequency	Art Deco Characteristics
Wood/use of wood	4	A focus on <b>surface ornamentation</b> <b>stereometric and geometric forms</b> (zig-zag, chevron, etc.)
Between 2a & 3a	3	
Color	3	
Modern	2	
Soft	2	An <b>emphasis on craftsmanship</b> , and the use of rare, exotic, and expensive materials like <b>stones, ivory, ebony, exotic woods, fine leather, bakelite, and aluminum</b>
Scandinavian	1	
Contemporary	1	
Utilitarian	1	
Symmetry	1	Showcasing the <b>luxurious</b> and <b>flamboyant</b> lifestyle and taste of a new class
Fluidity	1	
Elaborate	1	
Ergonomics/User comfort	1	
Factory/Factory made	1	
Handmade/craftsman/crafts	1	
Mixing of materials	1	
Fabric	1	

The participant's verbal descriptions of Art Deco characteristics overlapped fairly well with academic definitions. For example, when describing the lifestyle of the new class, participants used "between 2a and 3a" to indicate what they thought was a sketchy period of the design, as well as describing it as modern and elaborate (see Table 1). Geometrical forms like symmetry and softness were a bit off. However, this relationship was much weaker than the material description. In the case of Art Deco, materials and fabrication were perhaps the most similar defining characteristics. Participants depicted specific materials and manufacture, such as the use of wood, mixing of materials, and the use of fabric, some of which were handcrafted and some that had traces of industrial production. Art Deco utilized everything they talked about. Participants also described some features of specific events and details:

One of the participants mentioned that 1a looked like it was from a gift shop gallery.

*"I wonder if you remember when there was a kind of gift shop gallery  
in design history? 1a looks like it belongs to that era."*

This statement refers to as the salon of Jacques-Emil Ruhlmann (Woodham, 1997). The rooms are fully furnished and showcase a new lifestyle. It has lavish displays where customers can purchase anything they see in the room, from wallpaper to furniture.

Another participant also mentioned a scenario in which the participants believed these designs belonged:

*“1a ... looks like it belongs in a small apartment, townhouse environment. It looks more utilitarian and designed for everyday use.”*

This statement pointed out the oddities in the generated images. Because Art Deco promoted the decorated arts in all objects, practical or not (Goss, n.d.). Hence, participants may hint that the style was not purely Art Deco, but a modern, practical adaptation. This might be caused by the dataset.

#### *5.1.2 2a (Art Nouveau)*

In interviews, 2a was the set that people most recognize. As shown in figure 2, it is distinctively different from the other two both in color and structural complexity. A few participants have pointed this out at first glance:

*“There’s consistency in material and inconsistency in light/dark backgrounds. So even though I can comprehend that they are the same style within the (2a) set. It feels like the photos were taken at different times and presented differently.”*

*“Consistency of color and organic shapes. A lot of them look theoretically made of wood.”*

*“...most of them have the same type of like linear, like legs, sometimes even more of four legs, but they're all essentially chair-like structures.”*

*Table 3 Consistency Keyword Comparison between 2a and Art Nouveau Characteristics*

		2a (Art Nouveau)
Keywords	Frequency	Art Nouveau Characteristics
Wood/use of wood	3	Abstract patterns or organic patterns as two different approaches, both in the pursuit of nature as a theme:
Decorative/Decor	2	• Abstract comes from a scientific view and explored the organic forms, resulting in a simpler visual language
Classical/Neo-Classical	2	• Organic patterns come from reinterpreting the surfaces of an object. Using stylized, organic and curvilinear forms that were inspired by flowers, botanicas, and sometimes sea shells
Chinese/Asian	2	
Ancient	2	
Line/Linear	2	
Grid/Crossing lines	2	Mixing of materials or No mixing at all
Handmade/Craftsman/Crafts	2	• An emphasis on hard wood like oak, walnut, etc. Due to Japanese influences
Ornate	1	• Combining new materials from the industrialization like metal, glass with organic ornamentation
Victorian	1	Symmetry or Asymmetry
Sculpted	1	• Some designers followed the organic shapes and curvilinear forms
Color	1	• Others like Charles Rennie Mackintosh, was known for geometric forms and planer areas with graceful horizontal and vertical lines
Stylistic	1	

As shown in Table 3, when comparing the similarity of interview keywords, the use of wood was the highest mentioned term. One of the defining characteristics of Art Nouveau was the use of hardwood. A few participants also mentioned terms like “sculpted” or “decorative” pieces. Without a doubt, Art Nouveau was the most decorative style of the twentieth century. There were also mentions of grid-like or crossing lines and linear lines. These were characteristics of the work of Charles Mackintosh, whose designs included a lot of grided or lined chair back designs. This was also pointed out by two professionals involved in the evaluation. Interestingly, although Mackintosh’s designs only took up ten percent of the dataset, it has a significant difference from the generated results. Therefore, a question raised by one of the professionals was why did it make an impact over other

designs? This could be a point of investigation in finding out the algorithm's obsession with linear lines.

### 5.1.3 3a (Mid-Century Modernism)

As seen in Figure 4, four participants unanimously agreed that it was apparent that 3a is modernism. There were also noticeable overlaps in manufacture and materials, especially the combination of heat-formed fiberglass/plastic with aluminum/chrome-legged chairs, which was very symbolic in Charles Eames' designs. Leather/fabric in combination with aluminum/chrome-legged chairs was also very commonly seen in Charlotte Perriand's designs as well.

*Table 4 Consistency Keyword Comparison between 3a and Mid-Century Modernism Characteristics*

Keywords	3a (Mid-Century Modernism)	
	Frequency	Mid-Century Modernism Characteristics
Modern	4	Organic influences, furniture that work both indoor and outdoor
Fluidity	3	
Minimal/Minimalist/Minimalistic/	2	
Molded form/Heat formed	2	Simple forms, no ornamentation or decoration, simplistic, minimalistic with form following function
Metal	2	
Utilitarian	1	
Abstract	1	Democratic, universal, designed for everyone
Symmetry	1	
Soft	1	Material-wise, mid-century modernism was affected by the technology and manufacturing ability of
Line/Linear	1	its time.
Curved/curvature	1	
Ergonomics/User comfort	1	Materials include but are not limited to:
Color	1	• Laminates with synthetic resins
Factory/Factory made	1	• Molded fiberglass, plastic
Wood/use of wood	1	• Metal, aluminum legs
Leather	1	

Many also recognized the lack of ornamentation in 3a, with a few references to minimalistic or minimalism, as well as utilitarianism, as one participant quotes:

*“It is the embodiment of less is more.”*

## 5.2 Style

To investigate further, participants were asked to try to describe the style of the chair.

Descriptions can be roughly divided into three categories, namely chronological, material/manufacture, and stylistic/design.

*Table 5 Style Analysis – Chronological Descriptions*

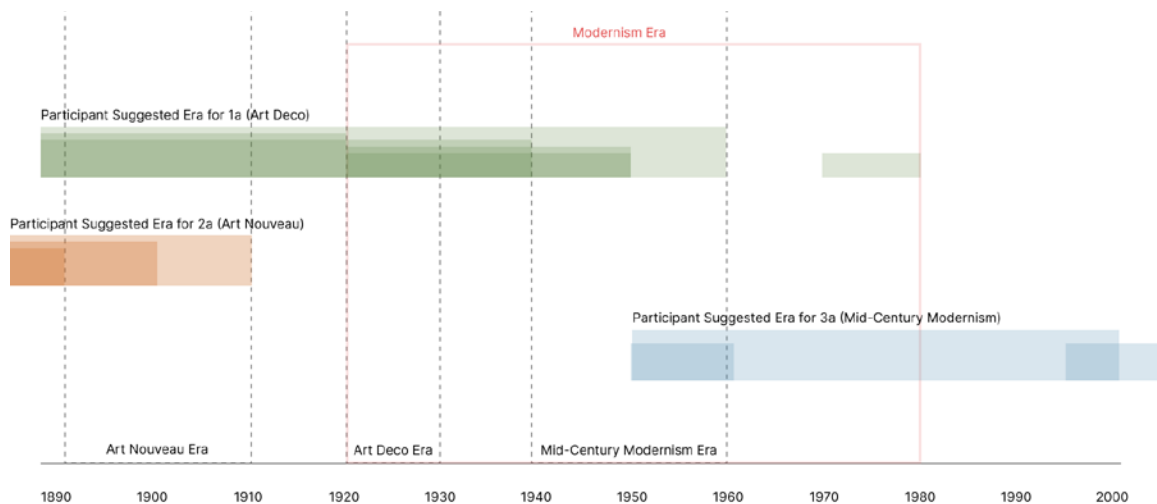
Chronological Descriptions							
1a	After Industrialization	Older than 3a	After the art and crafts, before modernism	Between 1920s and 1950s	After Art Deco	Somewhere between 2a and 3a	70s to 80s
2a	Before industrial revolution	Older than the other two	Progression between Victorian and Arts and Crafts	Ancient			
3a	Can see the progression from 2a to 3a	1950s onward	Most recent	Early 2000s			

*Table 6 Style Analysis - Material/Manufacture Descriptions*

Material/Manufacture Descriptions			
1a	Wood	Weaved Bamboo	
2a	Craftsmanship	Handmade	
3a	Metal & Leather	Aluminum legs	Recent technology

*Table 7 Style Analysis - Stylistic/Design Approach Descriptions*

Stylistic/Design Approach Descriptions									
1a	May get confused with 3a	Ant back chairs	Truth to Material	Ornamentation follow suit	Contemporary	Whimsical	Linear, geometric	Standard old school	Chairs at home
2a	Done by designer in Barcelona who did a lot of architecture, one with squiggly staircase in it.	Heavy on decoration but not so much on usability or comfort	Classical	Arts and Crafts	Art Nouveau	Decorative	Show-off	Uses a lot of useless decoration	Traditional
3a	May get confused with 1a	Ant back chairs	Modernism	Bauhaus, Mies and Eames influenced	Modernist period	Experimental	Streamline		



*Figure 17 Chronological Data Visualization*

As seen in Table 5, chronological descriptions of styles were very common among participants, and the descriptions within each style were fairly consistent. Art Deco in particular, as shown in Figure 16, although none of the participants found it to be Art Deco at this time, they were describing the era it belonged to. The style descriptions also



explained why some participants mistook 1a for Scandinavian rather than Art Deco. They described the materials in more detail as wood and woven bamboo. This is a shared feature of Art Deco and Scandinavian.

Two of the participants have stated the reason why they found it different from the other styles:

*“1a reminds me of the truth to material period.”*

*“All the ornamentation follow suit... that's like really what differentiates really like the same four-legged chairs.”*

In combination with their answers when asked about consistency, they were subconsciously framing Art Deco without naming it. And the same goes for the other two sets of generated images as well.

For 2a, two participants agreed that it belonged to the Arts and Crafts movement, and one participant was able to identify it as Art Nouveau. However, even participants who could not pinpoint the exact terms said:

*“Heavy on decoration but not much on usability or comfort.”*

*“Decorative”, “Show-off”, “Uses a lot of useless decoration”*

In particular, one participant stated:

*“It looks like it is done by a designer in Barcelona who did a lot of architecture with squiggly staircases.”*

This sounded like a reference to the work of Antoni Gaudi, a master architect other than furniture designs and known for “squiggly” architecture with lots of squiggly staircases. This design language has carried over to his other design fields as well. Gaudi was one of the biggest designers of Art Nouveau, his work was also included in the dataset. So, it made sense that the participant saw traces of his design in the Art Nouveau set.

In this round of style descriptions, seven out of the ten participants considered 3a to be Modernism or in the Modernist period. This was the most unanimous description of the three, and they did not provide much description because of the level of confidence and certainty. But for those who did provide explanations or descriptions:

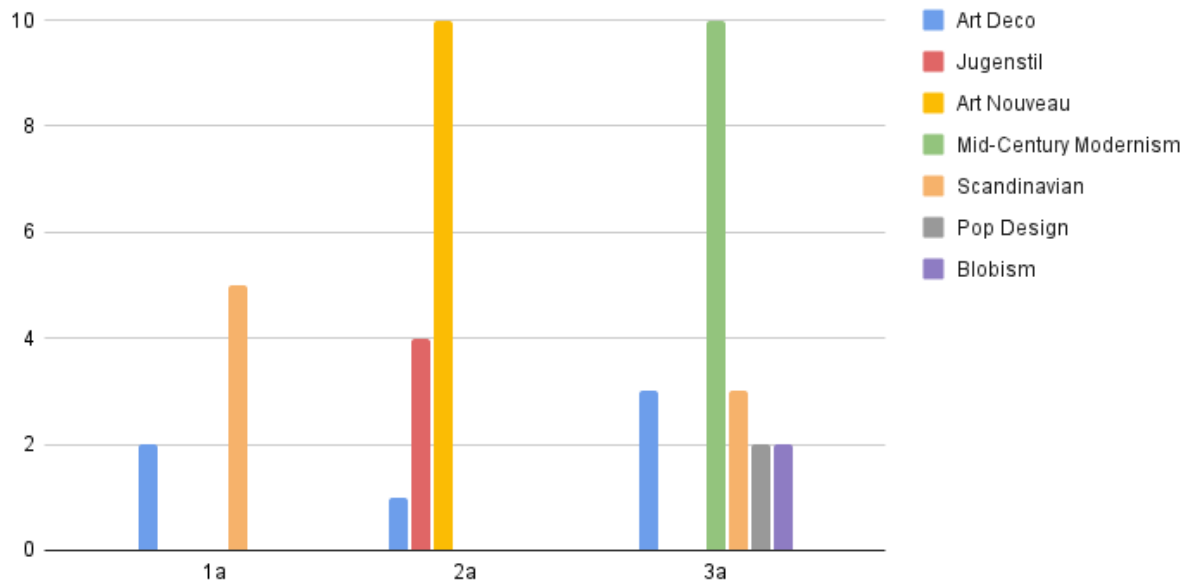
*“3a looks quite influenced by the Bauhaus and Eames, some of which look like Mies’ work.”*

*“3a is not Bauhaus, it is modernism. You know, there is too much curve for Bauhaus.”*

They have either identified it as a style very similar to Bauhaus or compared it to the style of the Bauhaus. Mid-Century modernism was an American depiction of the Bauhaus style, especially among teachers and students who arrived in the United States from Germany. Mid-Century Modernism was greatly influenced by the Bauhaus. Eames and Mies were also two of the most influential designers of Mid-Century Modernism. Their works were also included in the dataset. Therefore, it made sense for the participants to pick up traces of their work.

### 5.3 Cheatsheet

In the final round of questioning, participants were provided cheat sheets because a lot of users expressed that they have graphical memory. On the cheat sheets, there are descriptions and a few images for reference (see appendix D). Results using cheat sheets, confirmed what users reflected in the previous rounds trying to describe the patterns and styles that they saw in the generated images.



*Figure 18 Cheat Sheet Analysis*

As illustrated in Figure 10, Art Nouveau and Mid-Century modernism were the highest confirmed styles. However, Art Deco was recognized more as Scandinavian, and there were some Art Deco votes for the other two styles. This also aligns with our previous findings that participants suggested that 1a and 3a could be confused with each other. This just confirmed their decisions with sample images of these styles. For 2a and 3a,

there were a few instances where the participants also think that there is Art Deco in it, one participant described it quite well, which is that:

*“The problem is that for 1a, I see a lot of styles that are different from  
Art Deco.”*

Art Deco was an eclectic style that revolved around the new class’s obsession with traveling and the Machine Age. As such, the style incorporated eclectic historical and national imagery, inspired by ancient Egypt, Africa and Japan, and incorporated a wide variety of materials and manufacturing methods (*Art Deco*, n.d.). It is difficult to define in the traditional means of definition. It is also “in-between” between 1a and 3a. It is therefore not surprising that the progression from Art Nouveau to Modernism can be observed through Art Deco.

#### **5.4 Side by side comparison and ratings**

For the final reveal of generated images based on the dataset, all participants answered “yes”. Whether they saw the resemblance between the dataset and the generated images?

*Table 8 Performance Rating*

Participant	How well would you rate its performance in terms of style extraction? 1a	How well would you rate its performance in terms of style extraction? 2a	How well would you rate its performance in terms of style extraction? 3a
1	2	4.5	4
2	3	4.5	4
3	4	3	4
4	2	3	4
5	2	4	3
6	3	3	3
7	3	5	4
8	2	3	4
9	2	3	4.5
10	3	3	3
Average	2.6	3.6	3.75
Median	2.5	3	4

In terms of the rate of the performance of style extraction for each style, 3a (Mid-Century Modernism) scored the highest of the 3 styles.

2a got a fairly high score mainly because of its attention to detail. You can start to see the texture of the textile, including the details of the sculpted decors. This set it distinct and stood out from the rest of the generated images. 3a had the highest rating, and the similarity mostly focused on the shapes and contours of the designs, which made it highly rated by participants.

1a (Art Deco) underperformed with an average score of 2.6 and a median of 2.5.

Participants did not give specific reasons as to why they thought 1a underperformed.

However, they addressed that 1a produced images that looked mundane and bland with just brown on the side, making them less impressive compared to 2a and 3a.

## CHAPTER 6. CONCLUSIONS AND REFLECTIONS

Participants construct design styles in chronological order, style, and materials and manufacture. This is a great indicator that the algorithm has picked up each style. However, each style has a different focus. For 1a (Art Deco), the main characteristics picked up by participants were era and materiality, like wood, in part because Art Deco was harder to think of as a style. A few of the participants stated that they saw 1a as more than just a style. Diverse designs were also a feature of Art Deco, defined as eclectic. For 2a (Art Nouveau), the most recognized factors were the emphasis on details, the use of wood, and the handmade qualities. This almost seems odd, since one would assume that the styles with the most images in the dataset might be able to capture more detail, however, the images in Art Nouveau dataset were only half the size of Mid-Century Modernism. Mid-Century modernism would also have better quality and higher resolution images. Considering it is relatively recent, a lot of chairs are still sold on the market. Unlike Art Nouveau chairs where some images were taken decades ago. Therefore, the difference between the two styles in generated images is quite interesting.

### 6.1 Flaws

#### *6.1.1 Size of dataset*

It is understood that good input generally contributes to good output, therefore larger entities (i.e., companies or research labs with a resource-optimized database) are more likely to achieve photorealistic outcomes. This study showed that more resources equal better output. However, the question now is how far can we go and how well can we produce results based on existing tools?

Other projects like pokemonGAN (*PokemonGAN*, n.d.) or animal crossing GAN (*Runway*, n.d.) were representations of limited datasets. The number of pokemon and the number of animal crossing characters was fixed, around a few hundred different pokemon/characters. The outcome generated by these GANs was vague, so combined with the limited dataset like the Memphis group from this study, the apparent shortcoming was the lack of the number of images to learn.

Hence, it is necessary to expand the size of the input dataset, which brings us to design styles. In each design style, there are several designers, which brings our dataset to around 2000-4000 images per style. NVIDIA, however, suggested 15,000 images if users wish to achieve photo-realism. It is simply unachievable and time-consuming for a single researcher. Not to mention high-quality images with relatively consistent backgrounds (simple or blank) to maximize the potential of the dataset. The raw data scraped from google images consisted of around 10,000 images for each style. The majority of the raw data are not fit for training. Some are not actual work from the chose designer or the era, some have poor resolution, some have complex backgrounds that the chair itself is hard to recognize. Some designers' work is less photographed than others, so other sources like museum websites were used to expand the dataset.

#### *6.1.2 Dataset acquisition*

To acquire and clean up the dataset used in this study, it took a single researcher 10 days to clean one style of the dataset. Which adds up to 30 days for all three datasets. The images were scraped off of Google Images using a Python script. Each dataset went through 3 rounds of clean-up. First, remove images unrelated to the search result. For

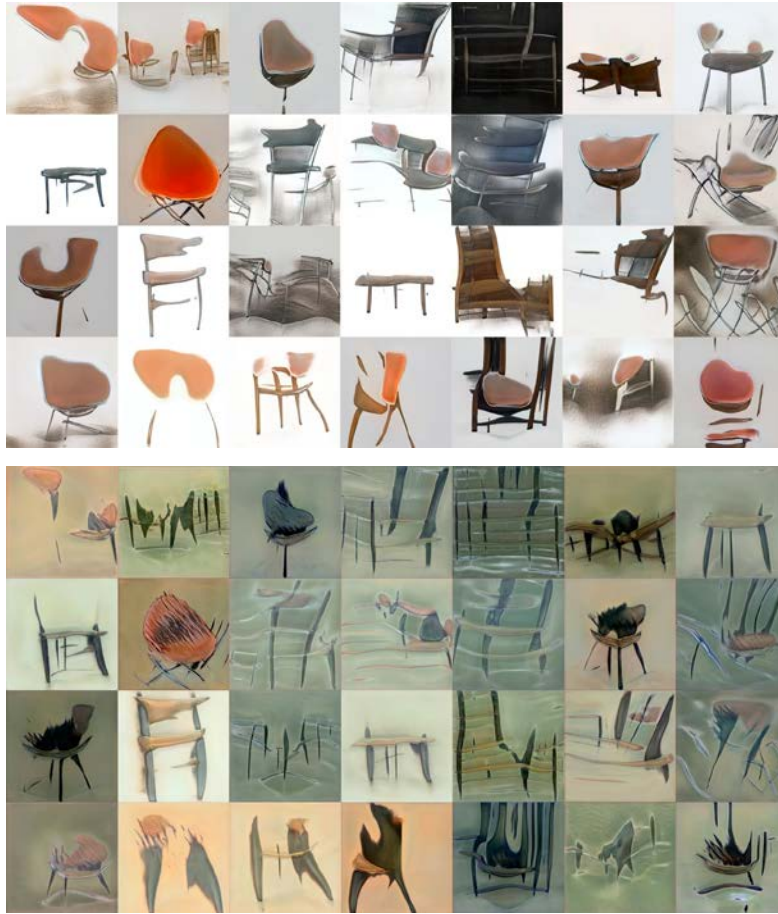


example, if the search uses “Rene Lalique + Chair”, then all images that are not chairs will be removed. The second round of clean-up removes low-resolution or blurred images because if there are too many low-resolution images in the dataset, it could affect the generated results, causing a reduction in resolution. The third round took the most amount of time, which is to cross-compare the scraped images with the designer’s catalogs and academic sources to ensure the images going into the dataset are in fact, authentic works from the designer. The process was very laborious and took up a great portion of time during the initial phase of the research. The amount of labor required for data mining and clean-up can also discourage user from incorporating generative machines into their design process. This was also shown in the evaluation since most of the participants voted for the one-click approach instead of gathering the dataset themselves if they were to use it.

Because of the difficulty acquiring a good dataset, also challenges the efficiency of generative AI. At the beginning of the research, literature reviews suggested that generative AI may improve efficiency in design by taking away laborious initial design ideation since it is capable of processing large quantities of data at once. However, if a user wishes to implement generative AI in their design pipeline, 10 days of work prior to generating images may be quite the contrary to efficiency.

### 6.1.3 Training steps

Conversely, more steps are not always ideal during the training and image generation



*Figure 19 Training Results of 4000 steps vs. 5000 steps*

phases. Figure 18 shows the training results from 4000 steps and 5000 steps. The result of 5000 steps was more abstract and divergent. This is part of the nature of deep learning networks and can be addressed by gradient clipping. It is also normal for FID scores to fluctuate during training, and the user has to make a decision when they think this is the best solution. FID scores are also heavily affected by the dataset size and quality. For a limited dataset, it can only reach a certain level. Therefore, FID scores should not be used as the only measure of accuracy in this context.

#### 6.1.4 Image quality

The generated images inevitably have traces of image processing, normally looking like blurred or textured colored pixels. There are also issues with details. A few participants have reflected that:

*“As a whole, they all look similar to their dataset, but when it comes to individual images, it suddenly loses a little bit.”*

It seemed that a lot of the generated designs are still lacking in detail. And that even though from afar, they can fool the eye into thinking they are actual chairs. When observed up close, image qualities can sometimes betray the authenticity of the images.

#### 6.1.4 Structural Integrity

During one of the professional reviews of the generated images, a participant noted that although he can see stylistic characteristics, a lot of images can be identified as chairs but they are not structurally sound. This is one downfall of a purely 2D GAN. Some 3D GANs have been proposed (Hong et al., 2021; Liu et al., 2017). However, they either require images that inherently have all views of the object like MRI imaging, or are limited to pure shape and form explorations without material mapping. A recent study is GANverse by NVIDIA (*GANverse3D Extension — Omniverse Extensions Documentation*, n.d.), which still requires 20 views of an object to create a virtual asset. The effort to collect the dataset itself is unimaginable. GANverse is currently only trained on sedans and not usable on any object yet.

## 6.2 Bigger questions this might answer

Deep learning algorithms are often viewed as black boxes and that it is difficult for users to understand how they learn. However, during the professional review, one participant has said that:

*“All three datasets were obsessed with legs.”*

Another interesting thing is that there also seems to be an obsession with grid-like chair backs in the generated Art Nouveau images. Almost all participants in the evaluation and professionals have pointed this out. Apart from Mackintosh’s chair designs, there are not many grid-like lines in the Art Nouveau style. This leads us to believe that the generated results are likely to be influenced by the Mackintosh chairs in the dataset. However, the entire Art Nouveau dataset contains more than 2000 images, while Mackintosh accounts for less than 10%. Although there are other factors like randomized output and randomized selection to evaluate. This could be an opportunity to test how many grid-like designs are required to affect the threshold of the generated results.

This is also an attempt to fill empathy in improving GANs. GANs are often evaluated by statistical means. However, a lot of GANs, especially styleGAN, have been developed to generate style-focused images and designs. Therefore, traditional means of calculating similarity may not be enough to determine the quality of the generated images. In this study, for example, even though the FID score was nowhere near 0.0, it was sufficient for participants to recognize the characteristics and features of the style. They were also able

to draw inspiration from these images and expressed a willingness to interpret abstract images into their designs.

### **6.3 Future Applications**

Nine out of ten participants in the user study have expressed a willingness to apply AI as a helpful aid in the design process. Most of them suggested it as a novel, formative way to inspire designs in the early ideation processes. One participant in the professional review has also brought up ideas of utilizing the abstractness of the generated images. Although some participants have critiqued the abstractness of the images. The abstractness could be a good thing because it leaves room for the imagination and allows the viewer to interpret it in any way, they see fit. Both designers and non-designers benefit from this. For non-designers, if they do not have extensive knowledge of chairs, they may refer to something vague enough to inspire them. But clear enough so they see the defining characteristics. One possibility is for the algorithm to be able to generate a series of furniture in the same style so that users can envision them together in a space. It was also mentioned the reverse way of using it, which is to take an image of any chair, have an image recognition algorithm to identify what the style is, and then be able to generate chairs within the identified style. The majority of participants also wanted a one-click approach, which meant they opt out of the dataset collection process. This makes sense, as it would make the barrier to access and use the technology much lower, encouraging more potential users to experience it. Additionally, data collection and filtering take up a large chunk of time during research. The one-click approach would significantly reduce that time. Hopefully, this can be used as a designer aid for pre-training. Therefore, one source of revenue can come from paid databases. Datasets that

are easy to acquire are freely available to the public to attract users. For hard-to-get datasets, they can become paid services and produce better results.

Although generative AI is not enough to enter the market as a product, it is widely used in academia for research and exploration. As discussed earlier, difficulty in dataset acquisition can discourage the user from implementing generative AI in their design pipeline. But not just the dataset; often times users, especially designers without a technical background, are also discouraged by the unfamiliar technical portions of generative design. So, if the purpose is to include generative design in the design pipeline, two approaches can be attempted. One is to form a team of collaborators/researchers with different skillsets so it fulfills all that is required for generative design. Datasets will be collected by the data miner, and the algorithm will be tweaked and optimized by a computer science engineer. Lastly, the designs will be curated and developed by a designer. The other is to teach designers the skillset required for generative design. Current design pedagogy involves very little of the toolbox needed for generative design, and relies heavily on self-learning and personal exploration. While the trend in design teaching is increasingly focused on interdisciplinary and conceptual issues rather than on specific technical and skill requirements, generative design and its growing importance in the design field requires in-depth practice and study of techniques, processes and methods. There is no text book for teaching design-oriented the generative machine curricula. However, if there were a design-oriented text book for generative design, especially generative AI. The content should cover everything from data mining to generative programming, to understanding the aesthetics of generative design (Herr & Fischer, 2001).

To some extent, this limits generative design education to more traditional bottom-up approaches where skills are prioritized over applications, at least in the early stages of learning. This can be partially compensated by requiring students to develop non-computerized generative systems in the early stages of learning that do not require technical skills, but only a basic understanding of generative design.

## APPENDIX A. IRB DOCUMENTS

You are being asked to volunteer in a research study. The purpose of the study is to find out whether if generative deep learning model can be helpful to design processes and design ideation. The study will be conducted as a semi-structured interview to ask for your expert opinions on design styles and personal opinions on the implementation. The entire process should take about 20-40 minutes. You must be 18 and older to participate.

Please read through this consent form

### Voluntary participation:

Participation in this research is voluntary. You can withdraw your consent to participate at any time.

### Information collection and usage:

We will take notes and record videos of each interview session. Recordings are kept confidential and will not be shared outside of our research team. Your feedback and findings from the interview may be used to help evaluate the applicability of AI in design ideation. However, your name and other personal identification information will be coded to random strings to protect your identity. Should you have any questions about the details of this research, please contact the PI Kevin Shankwiler at [kshankwiler@gatech.edu](mailto:kshankwiler@gatech.edu) or Jiaying Wu at [jwu677@gatech.edu](mailto:jwu677@gatech.edu).

We will comply with any applicable laws and regulations regarding confidentiality. To make sure that this research is being carried out properly, the Georgia Institute of Technology IRB may review study records. The Office of Human Research Protections may also look at study records. If you have any questions about the study, you may contact Kevin Shankwiler at telephone (404)-229-5052. If you have any questions about your rights as a research subject, you may contact Ms. Melanie Clark, Georgia Institute of Technology at (404) 894-6942. Thank you for participating in this study.

### Inclusion / Exclusion criteria:

- All participants must be 18 years of age or older.

By continuing with the interview, you indicate your consent to be in the study.

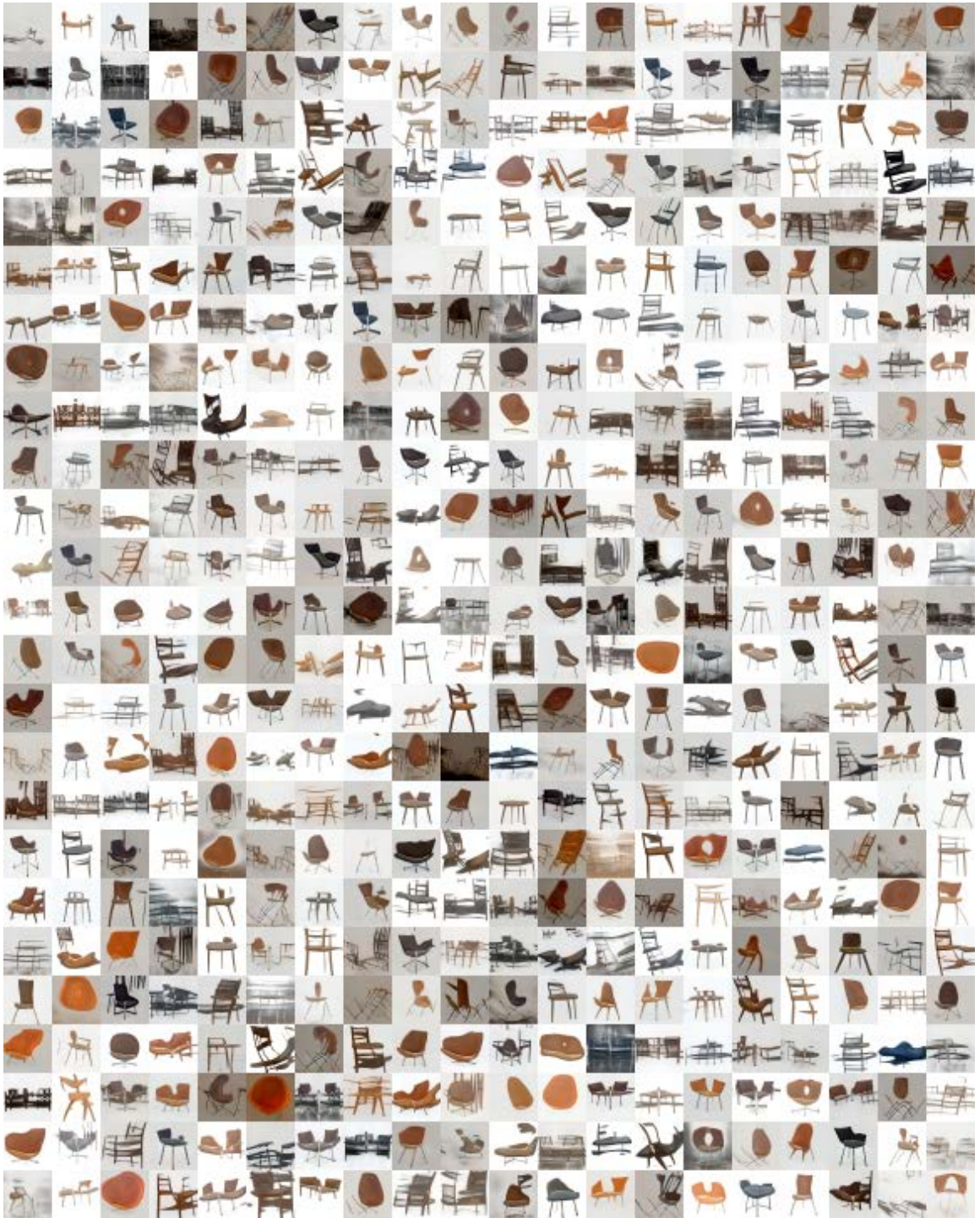
Thank you for your interest in participating in this research.



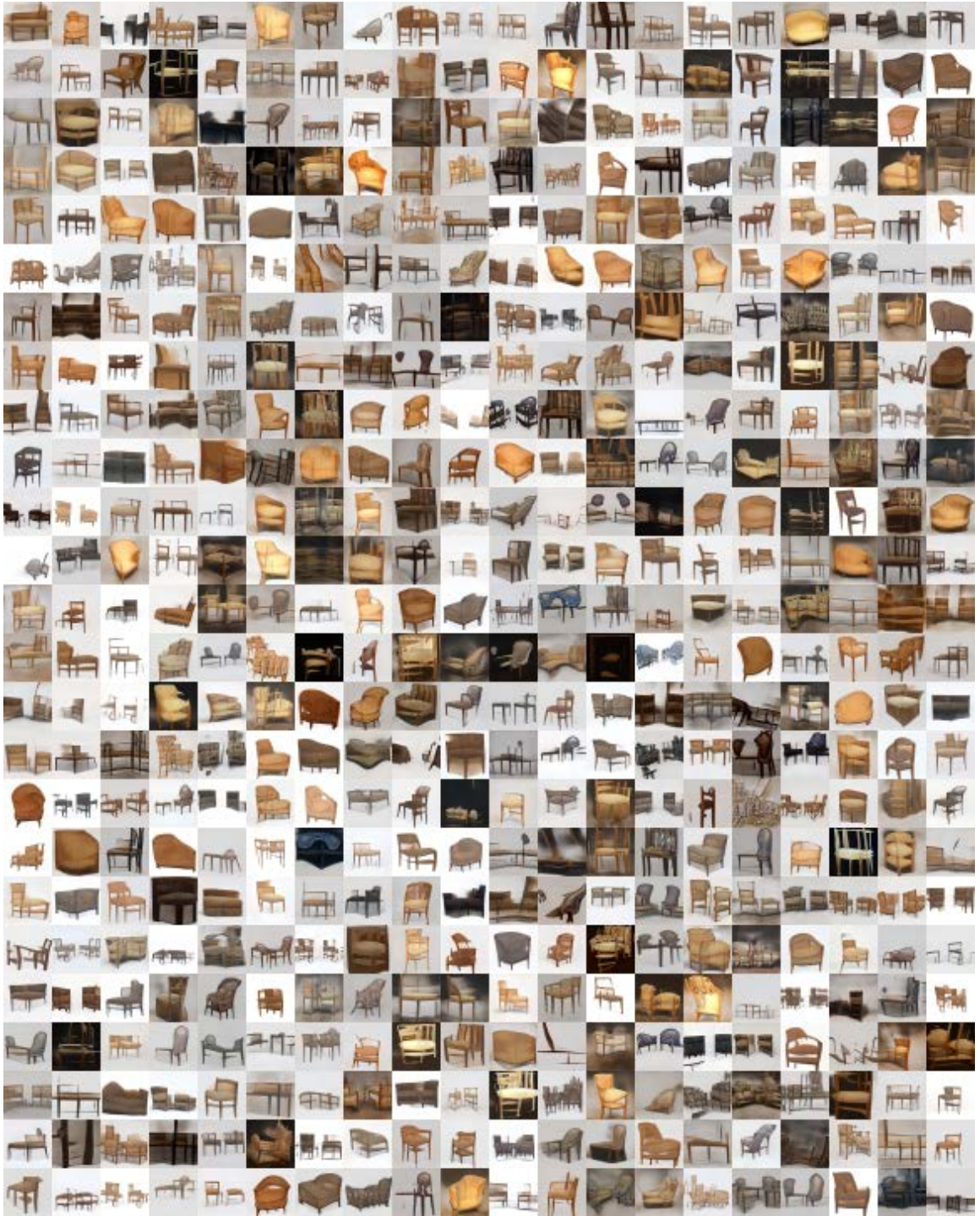
Consent Form Approved by Georgia Tech IRB: April 21, 2022 - Indefinite



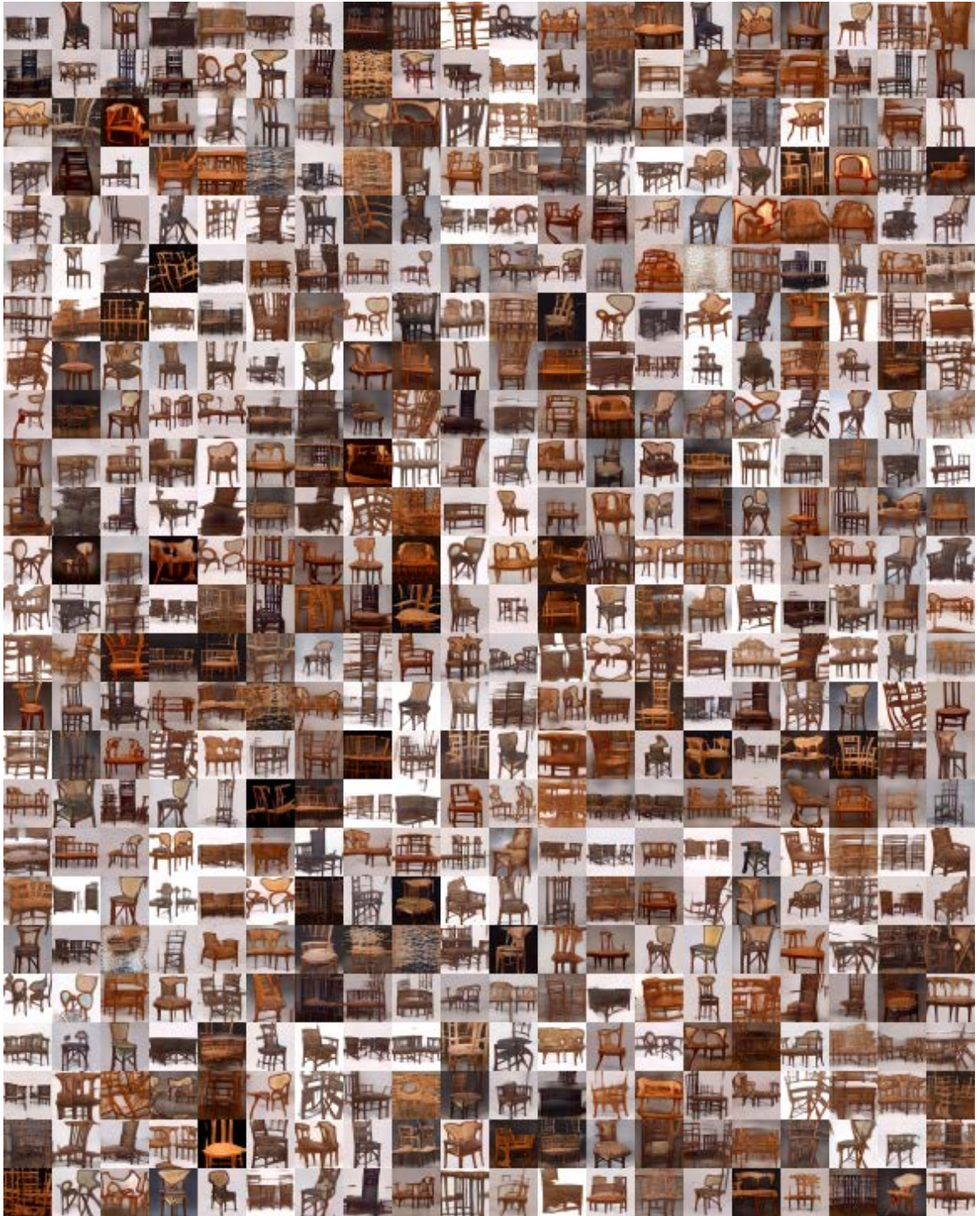
## APPENDIX B. GENERATED RESULTS











## APPENDIX C. USER FEEDBACK

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## APPENDIX D. INTERVIEW SCRIPT/CHEATSHEET

### Screening

What is your design background?

---

How long have you been in the design field?

---

What do you think best describes your current status? (multiple choice)

Student

Student with some experience

Professional with some experience

Expert

---

How familiar are you with design styles? Rate 1-5

---

### Survey/Interview

*Three different design style labeled as*

*generated: 1a, 2a, 3a*

*original dataset: 1b, 2b, 3b*

***Repeated 3 times for 3 different styles as comparison***

From first glance, what kind of object do you think they are?

Do you see any consistency/inconsistency in this set of images? (Are there any recurring patterns?)

Yes/Maybe/No

---

What are the patterns/recurring characteristics you see? (short answer)

materials/mixing of materials (wood, metal, acrylic, plastic), pattern, color, symmetry/asymmetry, shape, contour, manufacture

---

Do you think the following pictures are of the same design style?

---

What style do you think they are? Take a wild guess

---

[Cheatsheet] Here are 10 different design styles ranging from 1890s to 2000s with their characteristics. Out of the ten, which three do you think these three are?

---

In fact, this set of pictures are of XXX style (show dataset samples)

Can you match these 3 to the 3 different styles on the wall?

Comparing side by side, do you see any resemblance or shared characteristics of the two sets?

Can you use this sticky note to stick to which images has the highest resemblance?

---

What are the shared characteristics? (short answer)

materials/mixing of materials (wood,metal, acrylic, plastic), pattern, color, symmetry/asymmetry, shape, contour, manufacture

---

Cross compare 1,2 and 3?

**The truth is, the first set of images (1a, 2a, 3a) are generated by AI. It studied the characteristics of the dataset and generate images it thinks is the closest to the dataset. The AI was trained with the second dataset (1b, 2b, 3b) and is able to generate the hundreds of "fake" images in minutes. These fake images do not exist and is entirely original.**

How well would you rate its performance in terms of style extraction? Scale 1-5

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Do you think if the AI can be a helpful aid for designers? why

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Yes/Maybe/No/Need more work

Would you consider using the AI? What are the conditions/circumstances that you would consider doing so?

Yes/Maybe/No/Need more work

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If presented with the AI ready-to-use with your desired design style, and all you need to do is click a button to generate countless images, would you consider using it during your design process? Why/Why not?

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Do you think the AI is capable of replacing designers?

Yes/Maybe/No/Need more work

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# Destijl 1920s-1930s

## Characteristics

Focused on simplicity and an abstract language drawn from art. De Stijl designers made use of straight lines, in vertical and horizontal conjunction and the primary colors and black, white and grey.





# Art Nouveau 1890s to 1910s

## Characteristics

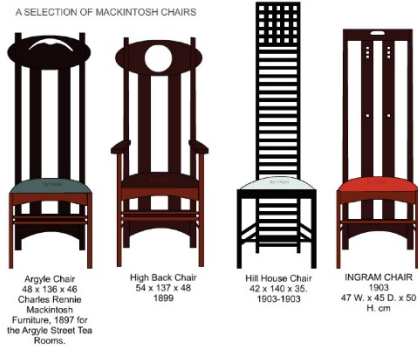
Geometrical idealization (symmetry vs. asymmetry, harmony, rational, "nature domesticated" "nature as dynamic")

Mixing of materials (wood & metal) vs. No mixing at all (wood)

Natural patterns (leaves, flowers, shells)



A SELECTION OF MACKINTOSH CHAIRS



# Art Deco 1920s-1930s

## Characteristics

Materials: veneering with exotic woods, ivory, ebony, shagreen, parchment, lacquer

Characterized by a use of expensive materials and high-quality decorative motifs

"decorative language": flat, geometricized concentric patterns and parallel patterns: zig-zags, chevrons, sunbursts, lightning bolts, paralleled lines  
Plentitude, the "too much"



*Bibendum chair*



# Mid-century Modernism 1940s-1960s

## Characteristics

Materials: Fiber glass, bent wood, laminates with synthetic resins

Descended from Bauhaus.

The utilization of modern technology and materials, and the rejection of ornament.

Admired for its classic, understated beauty and its fitness to purpose



# Jugendstil 1890s to 1910s

## Characteristics

geometrical structure; geometrical ornament, "applied ornament"

Gesamtkunstwerk

Jugendstil designers did use organic patterns but they favored "geometrical abstraction" that made use of solid outlining and static contours

rhythms: repetition; part-to-whole comparison

"stitching ornament"



# Pop Design 1950s-1960s

## Characteristics

Pop design's blatant graphics, high-voltage colors, oversized forms, synthetic materials, and simplified but instantly recognizable

curvi-linear patterns, sensuous organic metaphors, and anthropomorphic references





# Post-modern Appropriation 1980s

## Characteristics

Free of any necessary responsibilities to functionalism and social utility  
Often seen with vibrant colors, decorative, bold patterns & stripes, clashing colors, abstract designs  
Material spans widely from plastic laminate to metal



# Blobism 1990s-2000s

## Characteristics

Organic form and the technology that affords us to morph, undulate, twist, torque, blend

Softness, fluidity, blobular, tactile surfaces

No natural materials

Techno-organic design



# Scandinavian Design 1930s-1940s

## Characteristics

“Humanistic approach”: simple designs that celebrate the natural qualities of wood, a focus on the functionality of designs, and low-cost mass production

Neutral colors, simple lines, airy feeling





# Brutalism 1950s-1980s

## Characteristics

Metal Bashers, sheet metal, welding, seams  
Unpolished shapes, minimal, polished raw materials  
Heavy looking materials, straight lines



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