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# BRIDGING THE GAP BETWEEN GENERATIVE ARTIFICIAL INTELLIGENCE AND INNOVATION IN FOOTWEAR DESIGN

MASTER THESIS

INTEGRATED PRODUCT DESIGN

FILLING PIECES

TU Delft



## **FRONT PAGE IMAGE**

*Render of 3D AI Generated Footwear Concepts for Filling Pieces*

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**FILLING PIECES**

# PREFACE



Figure 1: *Filling Pieces* Flagship store  
(*Filling Pieces, n.d.*)

During my youth, I spent countless hours trying to learn new tricks on my skateboard. I had to buy new shoes quite often due to the wear and tear from the griptape. I quickly learned the importance of having the right footwear, not only in terms of durability, but also in terms of style. I realized that besides appreciating aesthetics, the design made more impact on products, motivating my decision to start studying Industrial Design Engineering.

During my academic journey, I learned about design principles and techniques that made me even more enthusiastic about product design. I naturally realized that I could combine my passion for footwear with the design skill set that I had developed over the years. An earlier internship at Premium Inc. validated my dream to pursue a career in the footwear industry. Therefore I was eager to graduate as an industrial design engineer with a footwear focused graduation internship project.

I had developed an interest in innovative design tools and methods, such as Generative Artificial Intelligence, since I thought it could revolutionize the design process by enhancing creativity. The combination of all these realizations has provided me with the inspiration for this project; applying these innovative design tools on footwear design. During this thesis, I aimed to expand my knowledge about footwear design and development processes. This project provided a platform for me to more deeply explore the intricacies of the industry, broadening my understanding and contributing to my professional growth.

In essence, this graduation project was not just a conclusion of my academic journey; it was also an opportunity to merge my passion for footwear with my design ambition, and a stepping stone towards realizing my dream career in the dynamic world of footwear design. I am grateful to the people at Filling Pieces for providing the opportunity to do this internship.

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# ACKNOWLEDGEMENTS

First and foremost, I would like to express my gratitude to everyone who contributed to the success of this graduation project. It would not have been what it is today without the support and encouragement from many individuals.

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To the rest of the colleagues at Filling Pieces, thank you for creating a positive and supportive atmosphere. The knowledge sharing and friendliness within the team were essential in making this project enjoyable and achievable. The good atmosphere at the office, where I spent a lot of time during the internship, made the challenges easier to handle and the successes more rewarding. Their enthusiasm played a big part in the completion of this project.

Next, I would like to thank all my friends who helped support me throughout this process. Their willingness to spar with me on ideas and provide critical feedback when needed has made a significant impact. Without their input and encouragement, this project would not have been a much more bumpy ride. Thank you for being there when I needed a fresh perspective.

Last but not least, I am very grateful for my family for their continuous support and encouragement. Without them, I would never even have had the opportunity to pursue this path. They believed in my potential and have always been a driving force throughout my academic journey. I want to thank them for always standing by my side and pushing me to strive for the best.

In conclusion, I am deeply appreciative of all the individuals and organizations that supported me throughout this journey. Your contributions have been invaluable, and I am really grateful for each and every one of you. Thank you all for your support, guidance, and encouragement.

- *Joram Steen*



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# ABSTRACT

This thesis bridges the gap between generative artificial intelligence and innovation in footwear design, an industry that is quite conservative in its design methods despite the constant demand for innovation. Initial applied research showed that while 3D technologies have the potential to enhance efficiency in development, they are still time-consuming, as the 3D generative AI was not advanced enough yet and therefore left out of the scope. As a result, the research focused on applying AI on image generation, particularly using LoRA fine tuning to effectively capture brand identity and consistently produce high-quality results with reference images and ControlNet. To validate these findings, the tools and workflows were applied in a case demonstration to a design brief. Additionally, a user test was done with a designer of Filling Pieces, comparing the outcomes of the AI framework versus traditional processes in a survey. The findings showed that the AI framework significantly accelerates the generation of design concepts and enhances creativity by producing more novel designs. However, the study identified limitations in clarity, completeness, and production feasibility, emphasizing the need for AI-generated designs to be complemented with technical drawings for communication with the factory. The relationship between AI and human designers should thus be complementary to achieve the best results.

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# PROJECT INTRODUCTION

## BACKGROUND INFORMATION

The footwear industry is dynamic and fast-paced, reflected by the trend-sensitive nature of the fashion industry. Most of the innovation in design and technology happens within the top companies, which is explained by their resource allocation and the fact that it allows them to take more risks. For the most part, the footwear industry is quite conservative in their design methodology and approach, as it had been proven to work for decades. However, the Artificial Intelligence (AI) Revolution is transforming daily life and business operations at a rapid pace. While it replaces some routine tasks, it also creates opportunities and efficiencies. Understanding and adapting to the impact that AI models can have is crucial nowadays (Marr, 2023). Specifically generative AI is pushing innovation in the design industry, this could reshape the design process to a more collaborative approach (Dangi, 2023).

Market trends in footwear are evolving quickly due to technological advancements and changing consumer preferences. There is a notable movement towards innovative designs, incorporating cutting-edge technologies that enhance both functionality and aesthetics. This is also reflected in the fashion industry's blend of digital and physical realms, with digital tools increasingly shaping design and consumer interactions. To stay competitive, the industry must balance traditional design with innovative practices, meeting the demands of the market (WGSN, 2024).



Figure 2: *Filling Pieces store (Filling Pieces, n.d.)*

Currently, footwear design and development are time-consuming and costly due to the traditional methods they used in the industry. Filling Pieces (FP), a footwear company based in Amsterdam, also experienced these challenges. They are constantly looking for improvements in their business approach, making processes more efficient and innovating when beneficial. This graduation project, which came to fruition in collaboration with Filling Pieces, aims to introduce a fresh, innovative approach to their design process. Generative AI could facilitate this goal, by accelerating the design process and potentially bridging the gap between generative AI and innovation in the footwear industry.

## PROBLEM DEFINITION

The main issue is the cost and time intensity of conventional footwear development processes. The design process, which involves creating a lot of manual 2D sketches and technical vector drawings, is very time-consuming. There is a continuous strive for more efficiency within all departments of Filling Pieces, so also within the design process. There have been very few major changes in their approach, so this opens the opportunity to explore future innovations.

The lengthy processes of physical development, reliant on manual labor in Portugal, is also inefficient and expensive. Multiple sampling rounds cause delays, with few reaching final production. Canceling ideas before sampling can save costs and time, which is a situation to strive for. These processes contribute to a long time-to-market, which can be a problem in the trend-sensitive footwear industry. There is an ongoing need for an optimized development process with a minimal time-to-market.

New innovations like generative AI may seem complex when rooted in conventional processes, but as acceptance and proof grow, risk lowers, allowing brands like Filling Pieces to explore their use more confidently. Improving design efficiency, reducing sampling rounds, and ultimately cutting time-to-market benefits Filling Pieces and is therefore really desirable to achieve.

However, the problem with generative AI tools is that they are not very specific and lack knowledge of brands like Filling Pieces, which are not as big compared to Nike or Adidas for example. These larger brands are most likely better represented in the dataset the models are trained on. As a consequence, when prompting "Filling Pieces sneaker," the AI models generate very generic results (see figure 3 & 4). For example, Stable Diffusion does create the Filling Pieces Low-Top style, but it does not capture the brand identity good enough to design a new style. This is a problem to tackle if the goal is to use AI effectively.



Figure 3: *Midjourney output when prompted "Filling Pieces sneaker"*



Figure 4: *Stable Diffusion v1.4 output when prompted "Filling Pieces sneaker"*

## ASSIGNMENT AND SCOPE

AI technologies are evolving at a rapid pace, potentially offering solutions to these challenges. The goal of this project is to use these AI tools to innovate the design process at Filling Pieces, proposing a design framework that is AI oriented. The objective is to design and execute it to optimize and enhance the creative processes for the brand. Ultimately it aims to reduce the time-to-market and lower costs in the context of the trend sensitive footwear industry.

The project focuses on designing and implementing a framework to support creating new styles and updating existing silhouettes in line with seasonal design themes. An AI model will be fine tuned on footwear styles of Filling Pieces to generate concepts that match the aesthetic of the brand. This process includes experimenting with parameters and setting design boundaries. AI-generated images could quickly provide realistic representations of design ideas, enhancing creative exploration and improving visual communication within the design and development teams, to ultimately make the process more efficient in terms of speed, creativity, cost, and overall quality of the outcome.

This scope focuses only on the creative aspect of the footwear design process, excluding other stages of the product creation cycle. This project is for a graduation internship for Filling Pieces and was carried out in around 100 working days. It aligns with the objectives of the Integrated Product Design from the Industrial Design Engineering faculty, fitting within my personal expertise. The focus is thus on the design and method of application, not necessarily on intensive coding of the AI models.

## RESEARCH QUESTIONS (RQ)

1. *How can the integration of AI tools optimize the overall footwear design and development process for Filling Pieces?*

This question explores how AI tools can benefit Filling Pieces in terms of making the process more efficient, creative and innovative. By understanding this, the tools can be integrated into their workflows, to potentially reduce the time-to-market by speeding up the process.

2. *What are the key challenges when transitioning from a traditional workflow to an AI-oriented approach, and how can an AI framework effectively address these challenges?*

The challenges that can potentially be faced during the transition should first be identified and subsequently be addressed, in order to effectively integrate AI tools into the workflow. That is why this question is important, to make sure that the threshold of implementing the new tools is as low as possible.

3. *How is the footwear design and development cycle impacted by an AI framework?*

This question focuses on how the process changes when implementing the AI tools in the current workflows of the footwear design process. Understanding this can help to determine the impact the tools have on the process and how to measure it.

4. *What are the metrics to measure the performance of a creative process, when comparing the traditional versus the AI augmented processes?*

It is important to define the metrics of performance, when trying to measure what impact the integration of AI tools has on the design process. The aim is to find the metrics that assess the differences as objectively as possible.

5. *How does the quality of designs generated by the AI framework compare to those created through the traditional human design process?*

To measure the effectiveness of the AI framework, the quality of the designs should also be assessed. Comparing the output of a traditional process with the output of the AI framework will highlight the differences that will help to understand the impact that the AI tools have in terms of design quality.

## APPROACH

This project will not follow a traditional design process, since it emphasizes on the experimentation and practical application of the proposed tools. The main focus is on ideation and creation, while still researching to find new insights. By constantly evaluating throughout the process, the most valuable results will be achieved. A visual overview that emphasized this experimental and iterative approach of the process can be seen in figure 5, which also highlights which part of the report corresponds to each step in the process.

## PART 1 FAMILIARIZE & ANALYZE

This first phase involves conducting research on the context through desk research and interviews with stakeholders. In the report, this contextual research is divided into 3 categories: Filling Pieces, footwear and new technology solutions, with case studies to determine the potential opportunities for this project.

## PART 2 IDEATE, CREATE & ITERATE, VALIDATE & EVALUATE

This phase is the core of the project, focusing on the exploratory research and application of AI tools through iterative cycles to design an optimized framework. The findings from the experimentation are directly applied to iterate on the framework, train LoRA models, and improve each version. During this process, the tools are continuously evaluated on the performance and alignment with the project goals. The approach is process oriented, aiming to put the findings into practice by implementing AI tools and combining their functionalities.

## PART 3 DEVELOP & DEMONSTRATE

After completing the research, the final version of the framework is designed and developed to integrate all workflows into a comprehensive overview and explain the use. To demonstrate the capabilities and show the effectiveness and quality of the outcomes, the design process is executed through a case demonstration based on a design brief provided by Filling Pieces.

## PART 4 EVALUATE

To evaluate the effectiveness and usability of the designed AI framework, the workflows are tested with a designer from Filling Pieces. This user test assesses the success of the workflow by evaluating the requirements for both the process and the outcomes. The outcomes from this test are compared with those from the traditional process using a survey. The results from this two phase evaluation will be described and discussed.

## PART 5 CONCLUDE

Finally, the thesis project ends a general discussion and conclusion, synthesizing all findings to form cohesive answers to the research questions. This part forms the final concluding section of the project report.

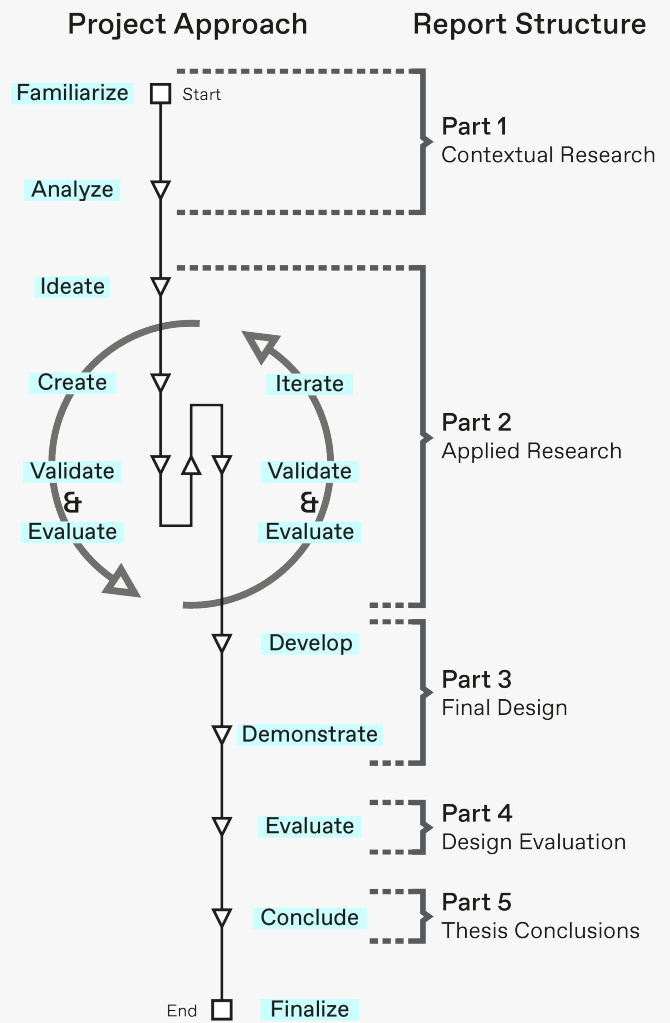


Figure 5: Visual overview of the project approach, with the corresponding part of the thesis report



# PART 1

## CONTEXTUAL RESEARCH

This chapter sets the theoretical foundation of the thesis, by combining insights that are gathered through a combination of desk research and interviews. Research on Filling Pieces and the footwear industry is done to understand the project scope. Moreover, innovative technologies that could shape future processes are researched, supported by case studies to identify opportunities for application.

1 METHOD  
2 FILLING PIECES  
3 FOOTWEAR

4 INNOVATIVE TECHNOLOGY  
5 DISCUSSION  
6 CONCLUSION



Figure 6: Cruisers (Filling Pieces, n.d.)

# 1 METHOD

This chapter describes the methodology for the entire Part 1. It includes both desk and literature research, as well as interviews with stakeholders. The findings from these methods are combined into the following chapters to provide comprehensive insights.

## 1.1 DESK AND LITERATURE RESEARCH

The desk and literature research was conducted in an unstructured way, utilizing multiple search engines such as Google and Google Scholar. This method encompasses reviewing academic literature as well as collecting information from other sources beyond published works. When a valuable academic paper was found, the snowball method was applied to delve deeper into the topic, to discover additional relevant references.

## 1.2 INTERVIEWS METHOD

### 1.2.1 SEMI-STRUCTURED

Following the literature review, there were still gaps in the understanding of certain relevant topics. To address these gaps and provide a deeper, more specific addition to the literature review, interviews with stakeholders were conducted.

The aim of the interviews was to understand the thought processes behind the design and development processes of the Filling Pieces team. Next to that, the literature lacked a specific understanding of the perspective of Filling Pieces on the new technologies that are covered in this thesis. Their perspective would additionally help to set the needs and requirements for the framework.

The interviews were conducted in a semi-structured format to allow for rich data collection, the structure of which can be seen in figure 7. This method allowed for asking follow-up questions by deviating from the thematic interview framework for more detail and richness. Open-ended questions were used to stimulate a flexible dialogue. Through these questions, nuanced insights were gathered. The whole detailed interview guide can be found in appendix A.

### 1.2.2 INTERVIEWEES AND MEDIUM

The interviews were conducted with individuals (N=4) from the Filling Pieces team, who were directly involved with the design and development processes. The interviewees were both the end-users of the framework as well as experts in the footwear industry. The selection of these

interviewees was based on their expertise and knowledge, which complements my personal understanding and fills the gaps in knowledge, to shape the direction of the project effectively.

Since all interviewees were colleagues at Filling Pieces, in-person interviews were preferred, with online interviews as an alternative when necessary. Questions were asked in Dutch or English, based on the interviewee's preference. The audio of all interviews was recorded to allow for active listening and follow-up questions, without being distracted by taking notes. A thematic analysis method was used to categorize findings into key topics and identify patterns to form a conclusion. It also enabled identifying and discussing any missing information and biases.

The results of the interviews were thematically organized and summarized, with only the relevant findings presented in the report. Additional details and less significant findings can be found in appendix B.

### Exploratory Interview Structure

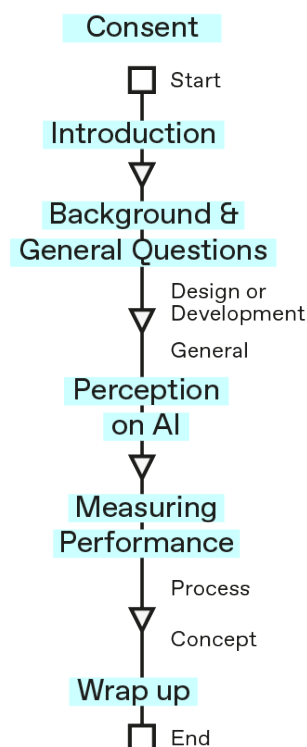


Figure 7: Interview structure

# 2 FILLING PIECES

Filling Pieces was founded in 2009 by Guillaume Philibert, who studied architecture at the time and had an obsession with footwear and fashion. However, he couldn't afford luxury brands as a student, so he mainly wore sportswear brands. This inspired him to bridge the gap between the two segments, streetwear and high fashion. The first design, the Low Top, launched with just 50 pairs and sold out quickly (Filling Pieces, 2021). Even today, the Low Top continues to be one of the best selling styles of Filling Pieces, alongside a diverse range of other footwear styles and a clothing collection.

In this project, various stakeholders play critical roles in ensuring the successful development and implementation of the proposed framework. Each stakeholder, categorized as main, direct, or indirect, has specific needs and expectations that must be addressed to achieve the project's goals (see figure 8).

## 2.1 BRAND IDENTITY AND VALUES

The "Bridge the Gap" vision is immersed deeply into the entire brand identity of Filling Pieces. They strive to be a meaningful brand, inspiring creativity and positive change by bridging gaps and pushing boundaries. They maintain high standards in both their team and products, which leads to a strong team dynamic and high-quality products (Filling Pieces, n.d.-a).

Filling Pieces has five core values that bring the company to life and serve as a guiding thread to all the activities they do. These values are:

- United by Diversity
- Driven by Culture
- Independent Creativity
- Pragmatic Ambition
- Transparency

These values are reflected in various ways, such as the use of responsible materials and transparent manufacturing processes, which they transparently show on their website. Additionally, Filling Pieces maintains a diverse and independent team and established a Culture Club to further creatively inspire and educate the employees. Moreover, the company actively supports charities, including donating products with small imperfections that would otherwise be destroyed to charities and fostering connections with immigrants and refugees (Filling Pieces, n.d.-b).

## 2.2 DESIGN PROCESS

- Collections are based on themes, inspired by uniting people, cultures, and creative disciplines that fit the brand's DNA. This is communicated through moodboards and design references.
- The current design process starts loosely with sketches and is gradually shifting from a manual towards a more digital approach, but still in 2D. The process is based on the designer's intuition and sales data from past seasons.
- Design adjustments are the reason for multiple prototyping and sampling rounds for development. They are communicated through techpack comments, but this results in a lengthy and costly process.
- The quality of a design process is subjective, but is dependent on a well-defined design brief, the quality of the design references and the experience and expertise of the designer.
- AI will be part of the future process, but human involvement will remain essential. A balanced and collaborative approach is important.
- AI has the potential to enhance the design and development processes, by serving as design inspiration, making communication more effective, facilitating data-driven decisions, minimizing reliance on prototypes and samples, and ultimately saving time and money.

## 2.3 FOOTWEAR DESIGN

Footwear design is a unique blend of product and fashion design. In product design, the focus is on solving real-world problems, considering and focusing on things like the usability, durability, and manufacturability of the product. Fashion design, on the other hand, emphasizes on aesthetic appeal and alignment with ongoing trends and brand identity. Footwear design merges these two approaches, creating shoes that are both functional and fashionable. A well-designed shoe must meet practical needs such as comfort and support while also appealing to aesthetic preferences, as well as thought out construction so the concept is feasible to produce.

The approach has not always been like this. Footwear used to be purely functional, but now they have become cultural symbols and must look good in order for people to want to wear them. Shoes remain functional, but are now also fashionable,

since they serve as a part of the identity of the person wearing them. As Peter Moore, the designer behind some of the most iconic Nike models like the Air Jordan 1, said: “In the past, the philosophy was just form follows function, but now it also has to look good” (Powis, 2021).

The traditional method of using 2D tech packs for communication with factories has proven effective, which is why many companies still rely on it. It makes sense to focus on AI for 2D design to enhance the current process, since it will only minimally change the current design process and will therefore be easier to implement. Most design work is done in flat technical drawings using Adobe Illustrator, despite shoes being 3D products. The 3D design of the tooling, such as the sole, is primarily done by the factory rather than the brand. They use tools like Rhino, and make the 3D model based on 2D drawings sent by the designer. In addition to

3D being used for development, some programs like Blender and Gravity Sketch are also used for design (Powis, 2021), although these are mainly adopted by larger brands with more resources for innovation.

Patterns are often made by hand in the factory, though there is a gradual shift towards digital 3D tools like Shoemaker Pro and Icad3D+ (Arsutoria, 2023). These tools have been available for some time but are primarily used by larger companies. The patterns are mainly still made by sketching the design on a taped last, to see how a 2D side view translates into a 3D shape on the last, to extract that shape again and make a flat pattern for cutting the materials.

## Stakeholder Map

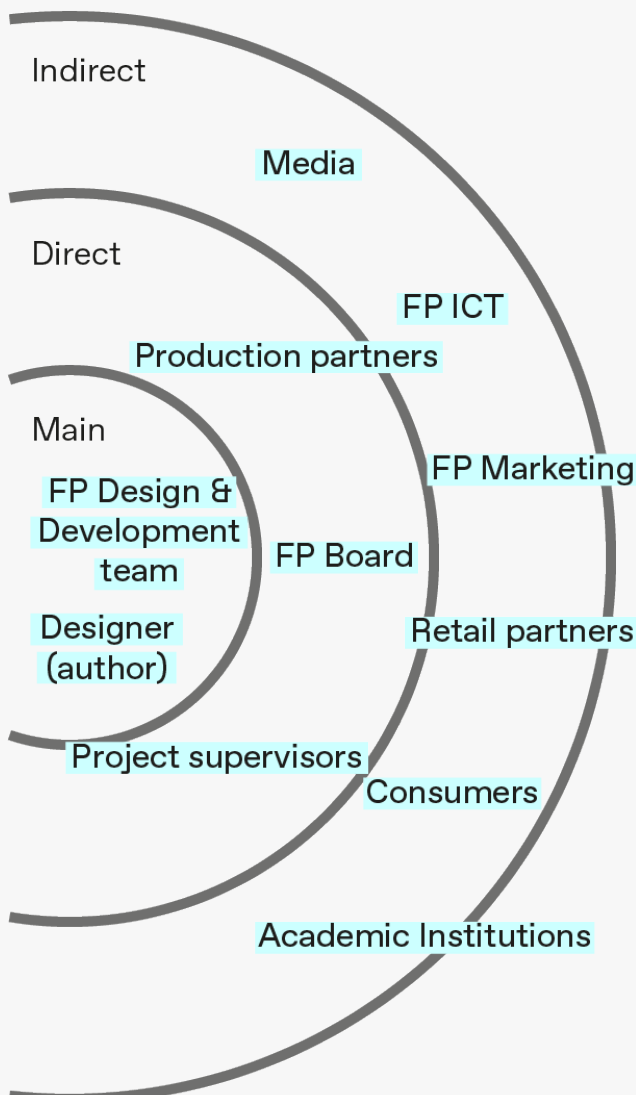


Figure 8: Stakeholder map

### STAKEHOLDER NEEDS

#### MAIN

**FP design and development team:** innovative solutions, optimizing the workflow, easy to use.

**Designer:** feasibility, innovation, alignment with objectives and academic requirements.

#### DIRECT

**Production partners:** efficient and clear product communication, continuous production without unnecessary sampling.

**FP board:** project alignment with strategic objectives, transparency, and progress updates.

**Project supervisors:** regular updates, adherence to project goals, quality outcomes.

#### INDIRECT

**Media:** access to information, transparency, potential for positive news stories.

**FP ICT team:** clear requirements, compatibility with existing systems, technical support.

**FP marketing team:** understanding of product features, alignment with brand strategy, consumer and market insights.

**Retail partners:** product information, alignment with market demand.

**Consumers:** desirable and aesthetic products, alignment with preferences and desires, quality assurance.

**Academic institutions:** Academic and innovative contributions, potential for further research.



# 3 FOOTWEAR



Figure 9: *First leather shoe found in Armenia (National Geographic, 2010)*

## 3.1 HISTORY

Modern footwear traces its origins back far in history, when technology was not as present as it is today. The earliest known shoes, dating from 9.000-10.000 years ago, were sagebrush bark sandals found in a cave in Oregon (Connolly, n.d.). The oldest leather shoes that were somewhat similar to modern sneakers (figure 9), date back to about 3500 BC and were made from a single piece of cowhide with a leather cord serving as laces (Pinhasi et al., 2010). Over time, shoemaking techniques evolved from medieval turnshoes that used the first lasting technique (Bartel, 2009), to industrial revolution innovations like sewing and sole-riveting machines for mass production ([shoead], 2010). Despite technological advances, manual labor remains essential in production. Modern technology has increased speed and efficiency, especially with the rise of glued soles. While shoes were once primarily designed for functionality, modern footwear design now equally emphasizes stylistic needs. This rich history is worth reflecting back on, as it sets the background to the exploration of the next big innovation in the footwear industry. Just like our ancestors, we must use the tools of our time to advance footwear design into the future.

## 3.2 COMPONENTS

To design a shoe, the designer must have a thorough understanding of the anatomy and its functions. Most shoes consist of many individually produced components, each adding to the complexity of the product (see figure 10). While most parts serve a functional purpose, some are just for the aesthetics (Nike, 2022). Understanding these components sets the fundamental boundaries for shoe design.

This knowledge is essential for both traditional and AI-oriented design processes. Traditional designers need it to meet specific functional and aesthetic goals, while AI frameworks require it to generate accurate and realistic designs. Both approaches rely on this understanding to ensure the final product aligns with the intended purpose.

The upper, often the most complex part of the shoe, includes various elements that secure it to the foot, using materials like leather, textiles, or sustainable alternatives (Design Museum Den Bosch, 2022). The inner lining is made from softer materials and provides comfort. The midsole, often made from EVA foam and (synthetic) rubber to offer comfort and cushioning. The outsole on the other hand is made from more durable materials, to withstand abrasion as it is the primary contact point with the ground.

## 3.3 DEVELOPMENT AND PRODUCTION

Once the design is complete, the development phase starts with the shape of the last, as the common saying in the footwear industry goes: “the last is first.” The shoe last, a foot-shaped form typically made from plastic, determines the final shape and fit of the shoe. Using this 3D shape, the pattern maker can translate the design into a 2D pattern that will fit the 3D last precisely.

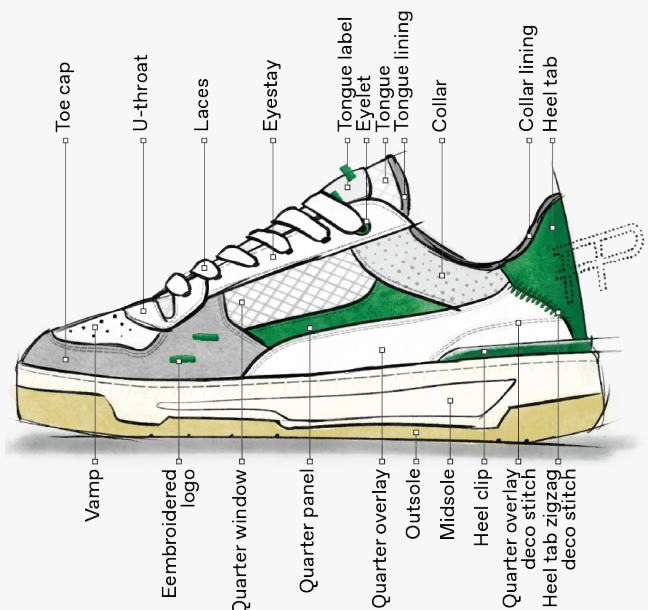


Figure 10: *Anatomy of a sneaker*

Production starts with cutting materials according to the 2D pattern. Each part is then sewn together in a step-by-step process, with each worker handling one step. As the upper is assembled, it transitions from a flat shape to a 3D form when the heel is connected. Hardware components like eyelets and logos are integrated in this process, balancing creativity with production practicality, which is key in the design phase to create viable and feasible designs.

Molding the sole involves physical constraints and challenges, as complex shapes can affect material distribution and structural integrity. These challenges are tackled by specialized mold technicians. Each shoe size requires a separate mold, which is expensive, so standard “open” molds with customizable logo plates are often used.

The lasting process gives the shoe its final shape to complete the assembly. The last is inserted and heated to set the form, then the sole is glued to the upper and pressed together to ensure the bonding of the glue. Finally, the shoe is delasted and the insole added (Motawi, 2017).

Manual labor still plays a big role in this assembly line. Complexity in designs can increase the risk of errors, defects, and inconsistencies, leading to longer lead times and higher costs. Although digital design offers many possibilities, shoes are ultimately designed to be worn in the physical world. Therefore, it is important to keep in mind that the production process has its constraints and limitations that should be navigated.

### 3.4 FASHION LIFE CYCLE

All products have a basic Product Life Cycle (PLC), but for fashion products, like footwear, they can be categorized into three types. These are the Fashion Life Cycles (FLC), with unique curves depending on the product type (see figure 11) (Wasson, 1968).

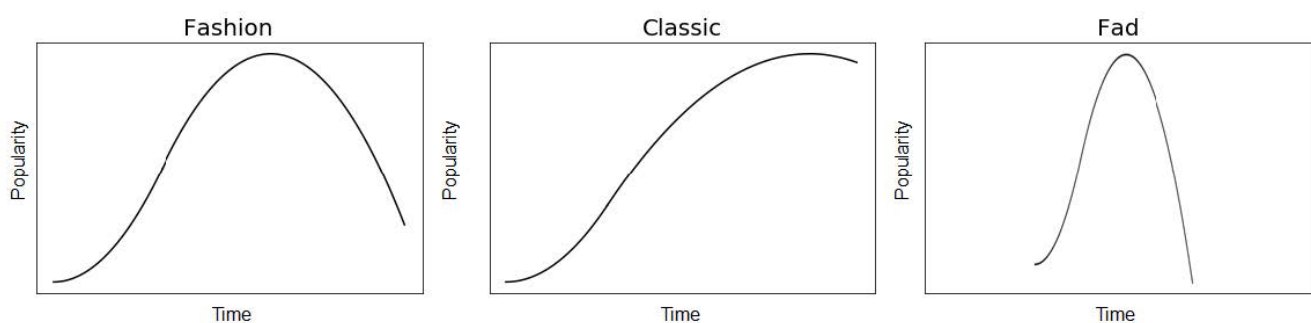


Figure 11: *Fashion life cycle (Wasson, 1968)*

Since fashion is a trend-sensitive market, the PLC curves of products in the industry are more sensitive to changing trends. Seizing these trends is therefore extra beneficial, in order to surf the trend and increase revenue (Ren et al., 2020). Trends come in and out of fashion faster than ever, with a high volume of trends circulating within the market. Fast fashion retailers prioritize speed over innovation, which leads to the recycling of trends and the phenomenon of trend re-emergence (Asif, 2018).

However, to stay commercially and culturally relevant, a brand should not only follow trends, but should also innovate. Merely focusing on trends can provide short-term growth, but innovation also ensures success in the long term. A balanced approach with a mix of innovative and more conventional styles helps the brands stand out and appeal to a wider audience, ensuring resilience in the market.

### 3.5 CONCLUSION

- Filling Pieces stands for bridging the gap between different worlds.
- Footwear history sets the background for using modern day tools for future innovation.
- Components are essential for construction of shoes and are mostly functional rather than just aesthetic. This sets the boundaries for the design.
- It is important to keep in mind that the production process has its constraints and limitations that should be navigated.
- Balance between following trends and innovation in design is important.

# 4 INNOVATIVE TECHNOLOGY

## 4.1 GENERATIVE ARTIFICIAL INTELLIGENCE

Recent technological advancements have enabled the generation of human-like content, whereas AI previously only focused on the perception and understanding of data (NVIDIA, n.d.). Generative AI are algorithms that create content from prompts, mimicking human intelligence to perform tasks (McKinsey & Company, 2023). Prompts are usually textual descriptions but can be supplemented by images, to describe the task the algorithm should fulfill.

This thesis uses various generative AI models, including ChatGPT, a Large Language Model (LLM) for text generation (OpenAI, 2022), and Retrieval-Augmented Generation (RAG) for tokenizing information to supplement the LLM (Lewis et al., 2020). The focus is on image generation using a Stable Diffusion (SD) model (CompVis, 2022a), with ControlNet for additional control (L. Zhang & Agrawala, 2023) and LoRA models for fine-tuning the SD model (Hu et al., 2021).

State-of-the-art diffusion models have a large distribution coverage, meaning that they are trained to produce high quality images of diverse subjects (Dhariwal & Nichol, 2021). Fine-tuning these models for specific needs requires coding, which can be challenging without expertise. Achieving a complete and cohesive workflow can be complex, since integrating multiple AI models and tailoring them to specific needs requires coding outside of my expertise and the scope of this project.

### 4.1.1 LARGE LANGUAGE MODEL

Large Language Models (LLMs) are transformer models, neural networks that track relationships in data, like words in sentences, and thus learns the context. Through training with machine learning, on a database with billions of parameters, patterns can be found that can be used to generate text (NVIDIA, n.d.). This application enhances productivity for humans and can enhance their problem solving abilities.

OpenAI developed ChatGPT, a free-to-use LLM that is trained on a very large internet dataset. Generally speaking a larger the dataset results in a higher accuracy and quality of the generated outcome (Ray, 2020). This AI model is used for this thesis, due to its quality and since it is free. Despite its effectiveness, it still has limitations and

the outcome can be flawed sometimes. The dataset can lack very specific data or knowledge, which can lead to hallucinations, a term for incorrect or nonsensical outputs (OpenAI, 2022). This issue can be mitigated if the data the LLM lacks can be accessed externally.

### 4.1.2 RETRIEVAL-AUGMENTED GENERATION

To compensate for the lack of specific data for LLMs, Retrieval-Augmented Generation (RAG) can be applied. It is a cost effective way to introduce new data to the LLM to broaden the usage capabilities (AWS, n.d.). This AI model can achieve this by tokenizing information from external databases, supplementing the LLM and therefore mitigating the lack of specific data. Leveraging external sources can mitigate issues such as hallucinations. By accessing an external database, RAG effectively fills these gaps in knowledge that cause these inaccuracies, by being suitable for specific and knowledge intensive tasks (Lewis et al., 2020). It enhances the completeness of available information, ensures more accurate and reliable outputs and consequently broadens the capabilities of LLMs (Merritt, 2023).

### 4.1.3 LATENT DIFFUSION MODELS

Text-to-image AI models are valuable tools to generate images from textual descriptions. These models have multiple advantages for the design and development process, especially when combined with the capabilities of other tools.

The first benefit is that AI image generation can enhance creativity. The ability to quickly create a large variety of designs promotes exploration, and thus divergent thinking (Eapen et al., 2023). Next to that, these models can also make the design process more iterative, since the dynamic nature of the algorithms allow for continuous evolution of the design through user feedback. This in turn can enhance design efficiency by refining the visual concept quickly over time (Rane et al., 2023).

Moreover, text-to-image AI plays a key role in enhancing the manufacturability and performance of a product (Tsang & Lee, 2022), by facilitating the visualization of the concept as well as facilitating visual communication in an early stage (Gu et al., 2023). These advantages can streamline the design process, which can result in a shorter time-to-market as well as increased competitiveness in the industry.



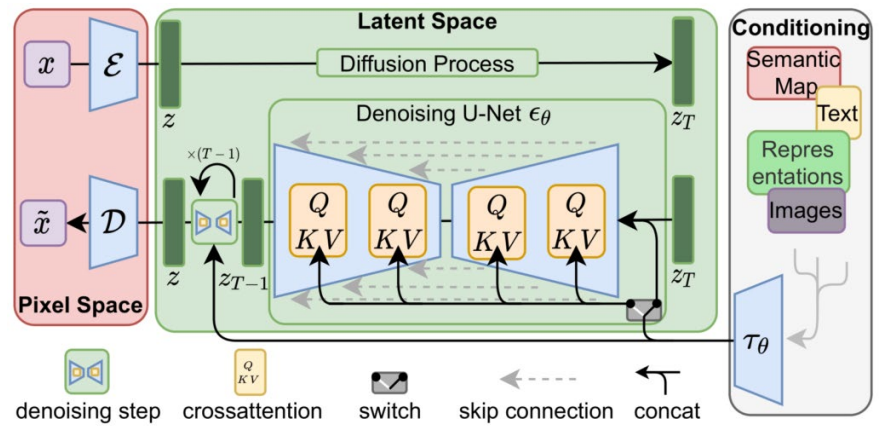


Figure 12: Visual representation of a LDM (Rombach et al., 2021)

#### 4.1.3.1 Stable Diffusion LDM

The first benefit is that using Stable Diffusion for image generation can enhance creativity. The ability to quickly create a large variety of designs promotes exploration, and thus divergent thinking (Eapen et al., 2023). Next to that, these models can also make the design process more iterative, since the dynamic nature of the algorithms allow for continuous evolution of the design through user feedback. This in turn can enhance design efficiency by refining the visual concept quickly over time (Rane et al., 2023).

The LDM comprises three key components:

1) ClipText (indicated by the  $\tau_\theta$ ): This component handles text encoding by employing a text encoder, which translates input text into tokens with a lot of mathematical dimensions. The output consists of 77 token embedding vectors, each containing 768 dimensions. This text conditioning has been learned from a dataset of images paired with captions, decoding both the image and text to compare their embedded representations using similarity metrics. This enables the model to predict the similarity between the image and text.

2) UNet (indicated by the  $\epsilon_\theta$ ): This part of the model is responsible for gradually processing or reverse diffusing information within the latent space (indicated by the green area). It takes as input the text embeddings and an initial multi-dimensional array that is noise, which serves as the starting point for creating and diffusing image information within the latent space. The UNet is trained using supervised learning, where input and output are known, and the model is trained to predict the noise present in the images. The output is a mathematical processed information array that represents the image.

3) Autoencoder encoder & decoder (indicated by the  $\epsilon$  &  $\mathcal{D}$ ): The computationally heavy reverse diffusion process is accelerated using an autoencoder, which compresses the latent image information array (with dimensions of (4,64,64)) and subsequently decompresses and reconstructs it into the final image. It “paints” the picture, by processing the generated information array, resulting in the final image. This image typically has dimensions of (3,512,512) representing the red, green, and blue channels and the dimensions of the image.



Figure 13: Reverse Diffusion steps

By combining noise prediction and text conditioning, the LDM generates the desired image from the initial noise, resulting in the creation of images based on specified criteria and textual descriptions (Alammar, 2022). The sampling steps gradually reduce noise following a mathematical pattern. This diffusion process transforms random noise into a detailed, realistic image, one small step at a time (see figure 13). The model predicts and removes the noise at each step.

### 4.1.3.2 Base models

The base model serves as the pre-trained foundation models for the output images. Each model is trained differently, both in terms of the training process and the dataset used. Ideally, a base model trained exclusively on footwear would be most useful for this project, but such a model does not yet exist. Creating a model like this is outside the scope of this project as it requires millions of images and heavy computational resources, which are not achievable within the constraints of this project.

The base models that are used are Stable Diffusion v1.4 (CompVis, 2022b; Rombach et al., 2021) and Stable Diffusion XL (SDXL) 1.0 base and refiner (Stability AI, 2023; Podell et al., 2023). The difference between these models is the size and amount of training data (512×512 px versus 1024×1024 px), which affects the ideal output image size. Consequently, the SDXL model is larger and requires more computational power, making the generation process slower. For comparison, SDXL1.0 has 2.6 billion UNet parameters, whereas SD v1.4 has 860 million (Podell et al., 2023).

The resulting output images are significantly different in quality, but also generation speed. For example, generating an image with SD v1.4 on my laptop (NVIDIA Quadro P1000 with 4GB VRAM) takes 38 seconds for 16 steps, using the SDXL model with the same generation parameters takes almost 6 minutes. Adding the refiner model on top adds another 5 minutes, as it processes the SDXL base output further (see figure 14).

The SDXL base and refiner models score highest in user preference, as shown in figure 15. They significantly outperform previous Stable Diffusion models, though compared here to v1.5 rather than v1.4, which is mostly used in

this report. The main difference between these models is the number of training parameters, with minimal impact on output quality that does not justify the longer generation time.

The SDXL refiner enhances image details and quality. While the base model focuses on composition, the refiner, which is trained on a separate database, uses the base model's latents for img2img refinement, a similar process as SDEdit, but slower due to higher computational demands (Stability AI, 2023; Meng et al., 2021).

### 4.1.3.3 Limitations of the models

Public Stable Diffusion base models are trained on large image datasets with generic text descriptions from the internet, covering various subjects. These descriptions are typically generic and lack specific jargon, so shoes are usually labeled by style, colorway, and material, not by specific components. No base model is specifically trained on shoes, so using a general model to just generate shoes therefore actually neglects the intended purpose, not fully leveraging large base models designed to generate a variety of subjects.

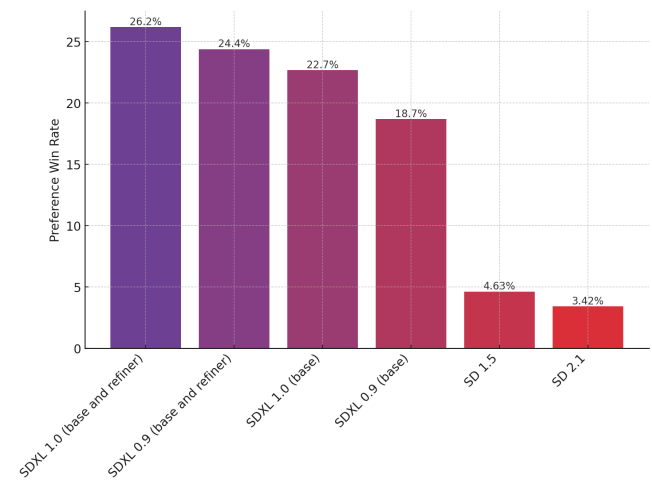


Figure 15: User preference of different stable diffusion models (Stability AI, 2023)



Figure 14: SD v1.4 and SDXL 1.0 base and SDXL 1.0 base + refiner with same seed, prompt: “minimal luxury sneaker, side view, white background”

#### 4.1.3.3 Graphical User Interface (GUI)

There are multiple ways to run a Stable Diffusion model. Essentially, Stable Diffusion is a deep-learning model, primarily written in Python with some C++ (Umar Jamil, 2023). To execute this code, you can either run it in a code editing software or use a graphical user interface (GUI).

##### *AUTOMATIC1111 WebUI*

A commonly used GUI for running Stable Diffusion is the WebUI by AUTOMATIC1111 (2022). This interface graphically displays different parameters and settings for image generation (see figure 16), making the model more accessible and user-friendly. It allows users to quickly experiment with different settings and load different base models.

##### *ComfyUI WebUI*

ComfyUI is a web-based GUI for Stable Diffusion that offers greater power and modularity, enabling users to customize workflows with various nodes without coding. This provides complete control

over complex workflows, without the restrictions of other GUI's ([Comfyanonymous], n.d.). While initially challenging to set up and daunting at first sight, once configured, it runs with a single click and the workflow can be saved as a json-file. ComfyUI also supports SDXL better than other GUIs and allows for advanced technical workflows. It is compatible with Windows and Linux, with faster online alternatives available for rent starting at \$0.50 per hour (Ed, 2024).

ComfyUI displays all parameters and connections, making similar workflows look more complicated than in AUTOMATIC1111 (see figure 17), but offering greater versatility. Despite being harder for beginners, ComfyUI's flexibility and control allow for specific workflows that integrate multiple AI tools into a clear, comprehensible workflow. This eliminates the need to switch between different tools, creating tailored workflows for specific design steps, easily accessible for the Filling Pieces team.

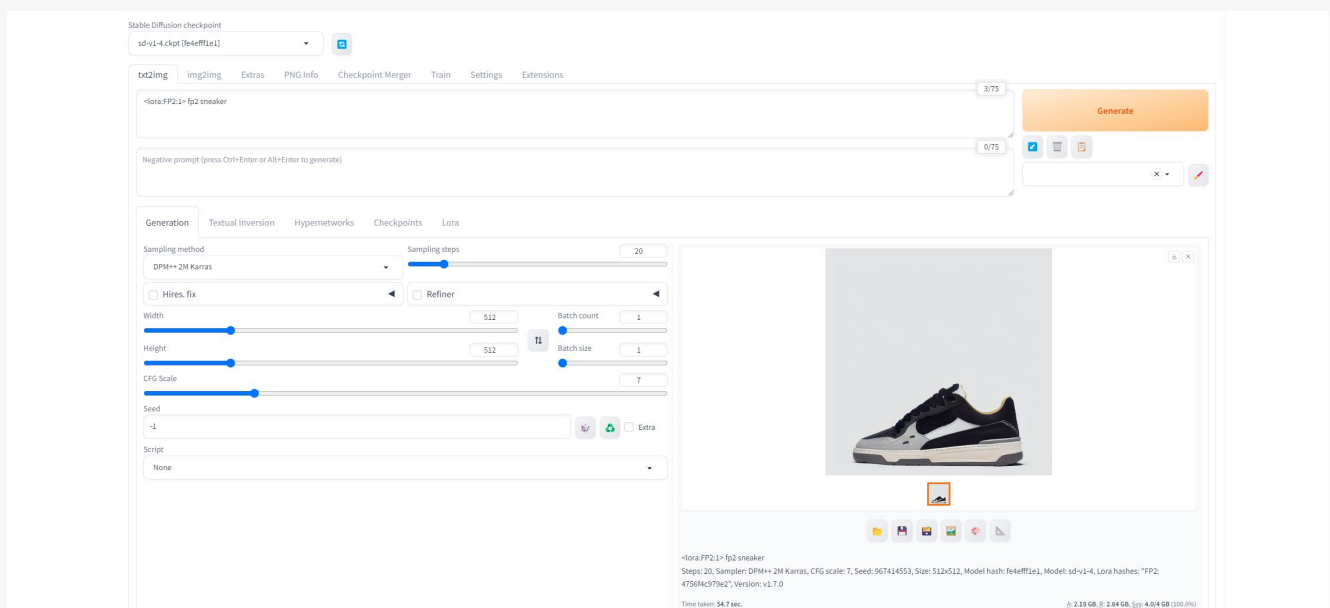


Figure 16: Interface of the AUTOMATIC1111 WebUI with a LoRA model

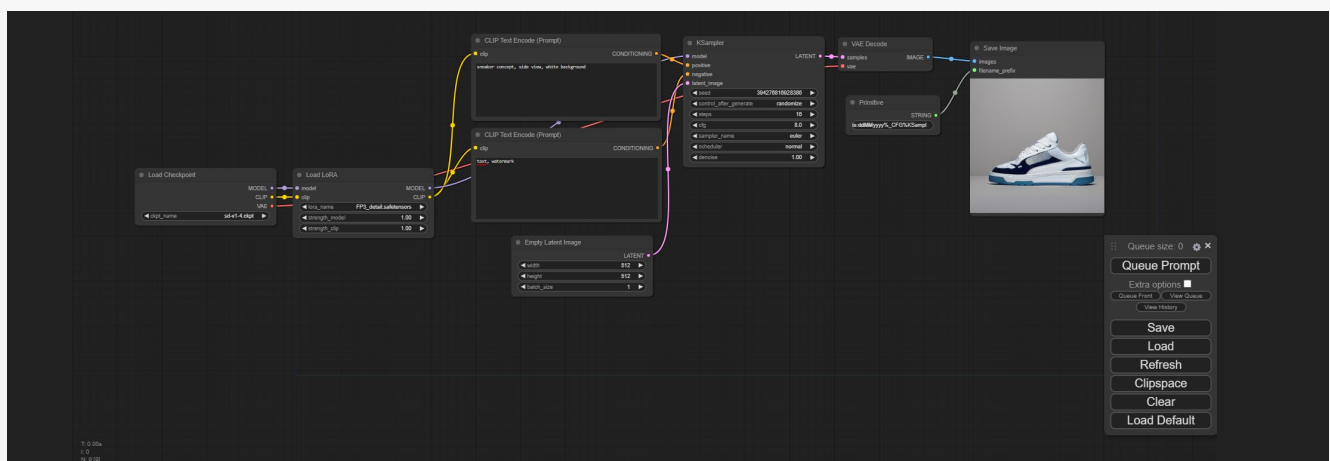


Figure 17: Basic ComfyUI workflow with a LoRA model (the same as figure 16)

#### 4.1.3.4 Important Parameters and settings

##### Seed

The seed is a numerical value that determines the initial noise, setting the starting point for image generation. It is the reason that you get a different image each time, even when all other parameters are fixed. By default, the seed is random and changes automatically with each generation. However, keeping the seed, prompt, and all other parameters constant will produce the same result (Diab et al., 2022). Using a consistent seed allows for controlled experimentation with other parameters, such as prompt variations, sampler, and scheduler settings (Novita.ai, n.d.).

##### Different samplers and schedulers

The noise sampler refers to the method used to gradually turn a noisy image into a clear one. This step by step process is sampling, because it produces a sample after each step. Ancestral samplers, indicated by an 'a' in their name, add noise at each step, making the output more random and thus less consistent. For more consistency, it's better to avoid these samplers. The noise scheduler controls the level of noise at each step, starting highest and reducing to zero by the last step (Andrew, 2024b). The Karras scheduler is slightly modified to give optimal results (see figure 18) and seems to give better results (Sharlinator, 2023).

Each sampler and scheduler combination has its unique benefits and use cases (McCormick, 2023b), and a few are shown in figure 19.

Findings from this experimentation and literature show that the Euler sampler consistently performs well, even with a low step range (see figure 20), making it ideal for quick and simple generations. This is particularly effective when combined with either a normal or Karras scheduler for straightforward use (Andrew, 2024b; Sharlinator, 2023).

Using 8-10 steps provides a good balance between generation speed and image quality. More steps does result in a better image quality, but not significantly enough to justify for the longer generation time. For high-quality images with many steps, the Automatic scheduler is preferable. However, during the creative phase, where speed is crucial, the Karras is more suitable for generating details even at lower step counts.

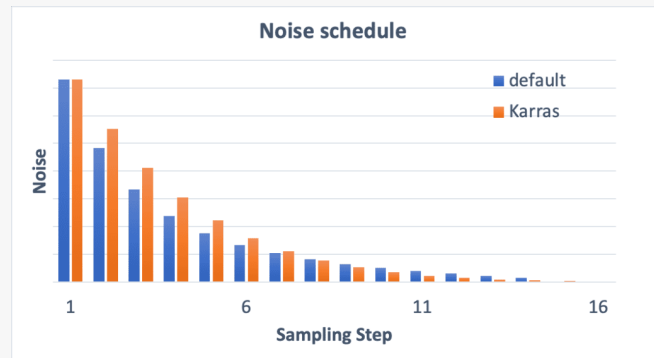


Figure 18: Noise schedule per steps for automatic/normal scheduler versus Karras (Andrew, 2024b)

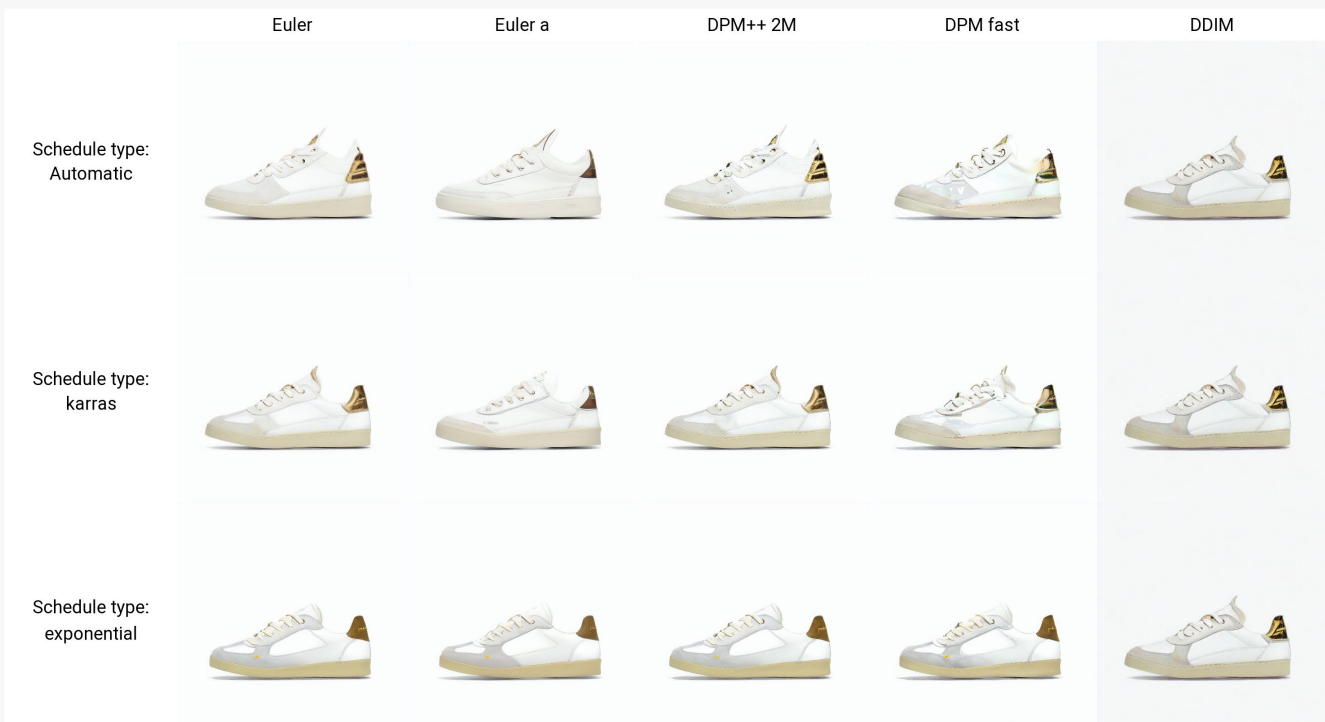


Figure 19: Different sampler and scheduler combinations at 8 steps. Image-to-image and combination of FP LoRA and prompt: "simple sneaker, white grey colorway, modern, minimal"





Figure 20: Automatic and Karras scheduler with different generation steps. FP and new styles LoRA, prompt: “neutral colorway sneaker, functional”

### Prompt text

A prompt is a text description you provide to the AI model, with the positive prompt describing what you want the generated image to look like. With Stable Diffusion, you can also use negative prompts to specify what should be excluded from the generated image, which is typically useful for avoiding low quality or blurry images.

### Reference images

In addition to a text description, you can also input an image to influence the final result. Instead of inputting random noise into the reverse diffusion algorithm, an alternative approach involves using a reference image to guide the direction of the output image, which is the image-to-image function of Stable Diffusion. The technique applied is called

SDEdit (Stochastic Differential Equations), which begins with an image that is buried under noise and gradually refines it similarly to the diffusion process. However, during this process, the image becomes less faithful to the original guide image, meaning that the final image is higher in quality and alignment with the prompt, but the pixel values differ significantly from the original input image (Meng et al., 2021). While the composition and color of the image remain to some extent recognizable for the algorithm, the addition of noise introduces variability. The interaction of the noise with the input image can be controlled by adjusting the denoising strength, which determines the amount of noise that is added. A higher value will add more noise and thus results in an output that less resembles the input (McCormick, 2022).

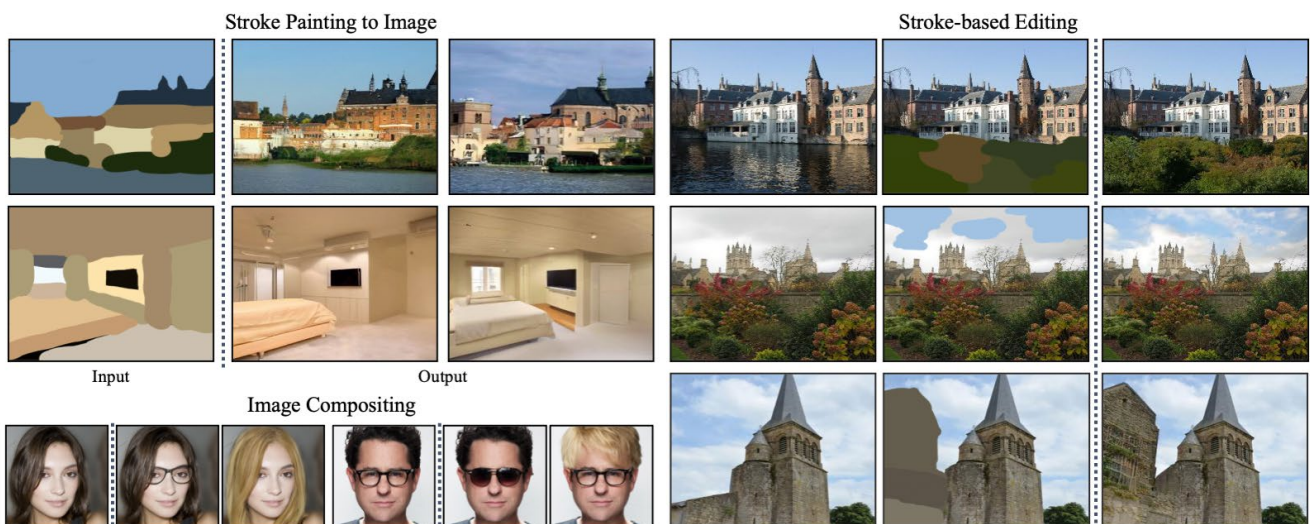


Figure 21: Example uses of image-to-image diffusion techniques (Meng et al., 2021)

### CFG value

The CFG value, which stands for Classifier-Free Guidance, determines how closely the image generation follows the prompt. A lower value allows for more creativity, while a higher value is more strict (McCormick, 2023a). Increasing the CFG value can enhance the consistency and quality of the image, since it aligns more closely with the prompt (Ho & Salimans, 2022). The LoRA activation text is also part of the prompt, so the CFG value will affect the influence of the LoRA model as well. To maintain the desired silhouette, use a CFG value in the mid to high range, 7-13 as recommended by McCormick (2023a), but personal experimentation with LoRA models has proven 7-10 to be more effective for consistently good results (see figure 22).

### 4.1.3.5 LDM Conclusion

LDMs can generate images from word descriptions and by adjusting some parameters, the user gets more control over the output. While Stable Diffusion v1.4 is more applicable to the specific context of this project, SDXL1.0 produces better results but with a higher computational demand. Images of shoes are just a tiny part of the dataset of Stable Diffusion v1.4, so without any training, fine tuning or the use of a reference image, the model cannot generate designs effectively.

### 4.1.4 LOW-RANK ADAPTATION (LoRA) FOR FINE TUNING

Diffusion models are powerful tools, but its training demands extensive data and time investment to achieve effective results. The latest models have training periods ranging from 150 to 1000

GPU days, meaning that a single GPU needs to run continuously for that duration. In addition, the amount of images in the datasets required need to be in the million to billion-scale (Wang et al., 2023). More and higher quality training data leads to better results, since the training data is the foundation of any AI model (Bieler, 2024). This training process also requires complex coding, since the UNet and Scheduler components need to be custom built (Hugging Face, n.d.). Given the time limitations and the shortfall of available images, such training is not feasible within the scope of this project. Moreover, the complexity of coding required exceeds my limited coding experience.

### 4.1.4.1 LoRA

Low-Rank Adaptation (LoRA) is a preferable method of tweaking a LDM, that requires low computational power but maintains the performance of the base model (Hu et al., 2021). It only requires a small dataset of images and can run directly on a local machine. The LoRA runs on top of the base model, and only changes the last few layers of the LDM, so this method is rather fine-tuning the model than actual training. It works by tweaking the Autoencoder component of Stable Diffusion that influences the processing of the image data, which means that the final 'painting' part of the image is influenced (Cuenca et al., 2023). Using a LoRA model can improve the quality and accuracy of the generated images, as well as giving more consistent results (Arnold, 2023). By training a LoRA model on a dataset of Filling Pieces shoes, the model learns the specific characteristics of the brand.



Figure 22: CFG scale values for LoRA without prompt (top row) and LoRA with prompt: "High top sneaker, white and blue leather" (bottom row)



Figure 23: Example outputs of LoRA model trained on Pokémon dataset (Cuenca et al., 2023)

By leveraging a pre-trained base model, which has undergone extensive computational processing on a large dataset, the heavy lifting is already completed. So faster and simpler results are achieved with minimal coding when using a LoRA model. The outcome quality depends on the input images, with more variance leading to a more diverse and creative output. Fine-tuning typically takes a few minutes to hours, depending on computational capacity (Romero, 2023).

One of the benefits is that with LoRA, you can generate images that the AI model is not trained on, by inputting images from your private collection ([knxo], 2024). However, if third parties use this same LoRA model, they can retrieve the images the LoRA is trained on with high fidelity. This process is called Membership Interference (MI), which means that if the images of the dataset of the LoRA are confidential, then the LoRA model itself must also remain private (Luo et al., 2024).

#### 4.1.4.2 Kohya-SS

Kohya-SS is a Python library for fine-tuning or training stable diffusion models, with a GUI that will be used. Regardless of the complex appearance and numerous settings, only a handful have the most significant impact ([bmaltais], 2023). These key settings and their functions are briefly discussed.

#### 4.1.4.3 LoRA Parameters and settings

##### *Training images dataset*

The training data is the foundation of the model. With a LoRA model, the base model still has the most significant impact on the final result. The LoRA only modifies the last few layers, acting as a biased lens through which the AI image generator interprets what to 'paint'. Despite this, the selection of training images still has the most impact on the performance of the LoRA model.

More images generally improve the output, but the quality of the dataset is important. It should be avoided to add low-quality images just to increase the size of the dataset (Ma, 2023). Too many images can decrease the training focus per image. Typically, 15-30 images are recommended, with additional images added only if they offer unique value and enhance the model's flexibility (Bieler, 2024).

The dataset needs a balance of variation and consistency. Consistency in design style and subject, focusing on Filling Pieces shoes, ensures the model generates shoes that reflect the brand's identity. Variation should be in colors, materials, and different shoe styles from Filling Pieces. For the

Cruiser LoRA model, the dataset should only include images of the Cruiser to maintain style consistency.

##### *Captioning*

Image captioning benefits model fine tuning by providing descriptive labels for dataset images, enhancing the accuracy and relevance of training data. This technique helps AI models understand and interpret image elements, ensuring that outputs closely align with specific images in the database (Bieler, 2024).

Captioning images can be done manually or with an AI model like Bootstrapping Language-Image Pre-training (BLIP), available in Kohya-ss GUI. It uses a Vision-Language Pre-training (VLP) framework for tasks like image-text retrieval and image captioning (J. Li et al., 2022). This process is quick and effective, but for precise captions, evaluating it manually and complementing it is best. BLIP serves as the foundation, saving time by allowing users to add details and correct errors.

Captioning was used for LoRA training in this project but did not significantly affect the results. This is likely due to the inability of the LDM to understand specific component names, a skill human footwear designers do have. The challenge increases when multiple components share the same color, making distinctions harder. While the model slightly improved in recognizing colors, it did not better understand the shoe components in the dataset.



Figure 24: *Captioning example: "a white gray and blue sneaker, white mesh window upper panel, green outsole, white midsole, side view, white background"*



### Learning Rate

The learning rate is a key parameter in AI training. A higher learning rate can speed up the training, but it can cause the model to miss details (Real, 2023). Learning involves adjusting the weights of the connections in the neural network to generate an image accurately. The weight of these connections determine the ability to generate specific aspects of an image. The balance between these weights is important, to avoid the model from only being too rigid and only able to generate one thing. Therefore, the weights are adjusted very slightly with each training step, gradually implementing the features of the images in the database, to stay flexible. The learning rate controls how much these weights are adjusted each time ([bmaltais], 2023).

An optimal training process is done with a variable learning rate, where the model learns the concept fast in the beginning and the details in the end (Real, 2023). The learning rate scheduler controls how the learning rate changes over time per steps, different types have different learning rate curves, as seen in figure 25.

### Training steps

Training steps refer to the total number of training steps performed during the training process, given by Eq. (1) ([bmaltais], 2023).

$$\text{Eq. (1)} \quad \text{Total Steps} = \frac{N \cdot R \cdot E \cdot RM}{B}$$

- N = Number of images: the amount of training images in the dataset.
- R = Repeats: how many times the training algorithm processes each image per epoch
- E = Epochs: the number of complete sets of training are done, one set being all the repeats for all images.
- RM = Regularization multiplier: the value is either 1 or 2, if regularization images are not used, it is 1, otherwise it is 2, doubling the training steps.
- B = Batch size: indicates how many images are trained simultaneously.

The key to LoRA training is balancing undertraining and overtraining, meaning the model creates unique images without missing details. Optimal training steps range from 1500-3500, but vary by subject and intended use (ControlAltAI, 2023). There's no difference in the resulting model whether using 1 repeat with 100 epochs or 100 repeats with 1 epoch, given equal parameters. Using epochs helps test performance throughout training, allowing for adjustments to avoid overtraining (Ma, 2023).

### Batch size

Batch size refers to the number of images processed at once. While it's common to lower the learning

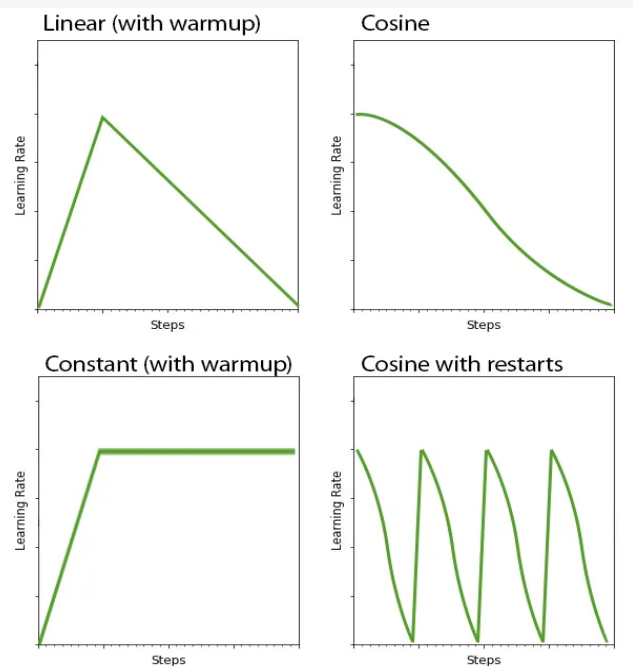


Figure 25: Different LR schedulers (Real, 2023)

rate for better results, increasing the batch size can also be effective, since Eq. 1 shows that batch size and learning rate are inversely proportional ( $B \propto \epsilon$ ). However, this requires more memory and thus a powerful graphics card, but the training time is shorter (Smith et al., 2018).

### Network Rank & Alpha

The Network Rank determines the dimensions or the amount of neurons of the neural network. A higher value will increase the expressive power of the model, but also increases the file size. This parameter has influence on the size and the performance of the model and is therefore one of the key parameters. For more complex subjects, a higher value is necessary to make sure that all the details are learned ([bmaltais], 2023).

The Network Alpha acts as a dampener to the learning, since it scales the weights of the connections in the neural network. A good rule of thumb is to set Network Alpha to half of the Network Rank ([The Other LoRA Rentry Guy], 2023). A high value results in less creativity and a stronger resemblance to the database subjects, whereas a lower value restricts alterations to the base model, allowing for more creativity but weakening the influence of the LoRA. This leads to more stable results but limits the model's ability to adapt (Junius, 2023).

### 4.1.4.4 Conclusion

Finetuning is another method of having control over the output, with LoRA being a particularly effective approach due to the relatively low computational requirements and a relatively small dataset. The choice of images in the dataset is important for the training, as it directly influences the capabilities of

the model and thus the quality of the designs (RQ5). More training steps is associated with a longer and more extensive training, but that is also dependent on the learning rate. It is however important to balance all settings to avoid overtraining. The combination of these settings determines the flexibility or rigidity of the model, influencing the ability to be creative in generating variations of designs, rather than making copies of images in the database.

#### 4.1.5 OTHER MODELS

Stable Diffusion alone does not always give the desired control you want to have over the output. When using additional models, you can add a layer of conditioning that sets restrictions for the generated images.

##### 4.1.5.1 ControlNet

Controlnet is a neural network that adds another layer to a LDM like Stable Diffusion (see figure 26). It allows different models to interfere with the diffusion process, by using a conditioning image to manipulate the generation process, providing control over the output to create more specific images (Steins, 2023). In this project, the ControlNet Canny Edge model is used (Zhang & Agrawala, 2023). This model uses a black and white linework as the conditioning image, generated from an input image that will lead to a replication of the linework for the output image.

##### 4.1.5.2 Vizcom

Vizcom is an AI-powered tool designed to enhance the creative process by transforming how creatives visualize their ideas. Their algorithms are based on image-to-image generation, allowing the user to simply input a simple sketch that gets rendered or refined to a realistic high definition image in seconds. Vizcom can boost efficiency and creativity, by rapidly providing realistic visual concepts from

simple ideas and enabling the user to iterate on their ideas without extensive manual effort. By streamlining the visualization process, Vizcom helps users focus more on innovation and less on technical execution (Vizcom, n.d.). The simple, no-coding interface is both an advantage and a disadvantage, since it makes the tool more accessible to the public by focusing on functional application. However, it also means users or brands cannot fine-tune it to meet very specific needs.

This tool offers a web-based alternative to ControlNet, by allowing the user to create photorealistic renders from sketch inputs (Vizcom, n.d.). However, it is important to note that in Render mode, the colors aren't considered. Vizcom sees the input as a monochrome "line map" and generates the rendering accordingly, which is a limitation of the technology (G. Mihály, personal communication, August 10, 2023). Even though it provides less control, its speed is a significant advantage, making it more practical for implementing the AI workflow and beneficial for the Filling Pieces team, as it lowers the threshold for implementation into their workflow (RQ2). Vizcom offers both a render and refiner model, both of which have its advantages and use cases.



Figure 27: Line map that Vizcom generates, which is very similar to the ControlNet Conditioning image of the Canny Edge model (G. Mihály, personal communication, August 10, 2023)

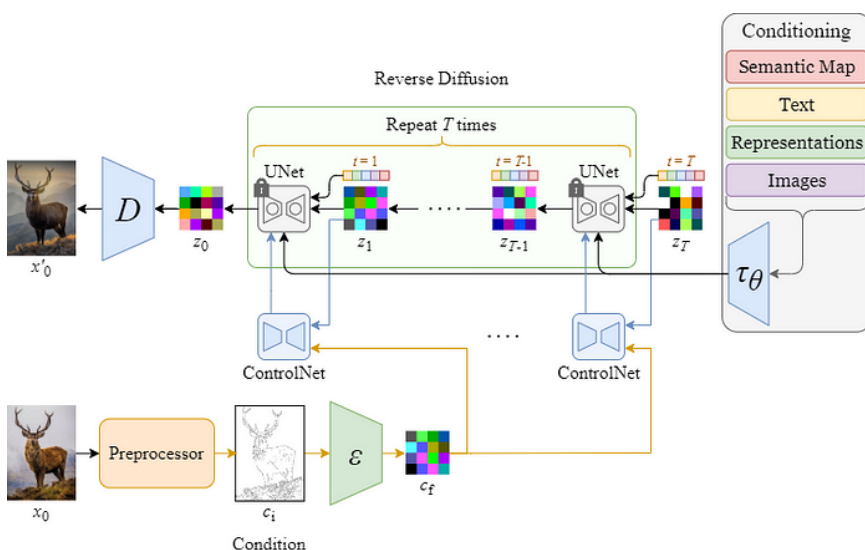


Figure 26: Visual overview of the reverse diffusion process in combination with a ControlNet conditioning model (Steins, 2023).

## 4.2 3D GENERATIVE AI

3D Generative AI revolutionizes 3D modeling by using advanced algorithms to create 3D models from 2D images or text prompts. This technology significantly reduces the time needed for 3D modeling, making the process more efficient and accessible. It automates and streamlines complex tasks that once required extensive manual effort (DRL Team, 2023).

A notable example is Shap-E from OpenAI, which uses a diffusion model trained on 3D meshes in combination with NeRF (Neural Radiance Field) for rendering. In simple terms, a NeRF is a technology that creates 3D scenes by understanding how

light and color interact at different points in space. It turns 3D coordinates and camera angles into densities and RGB colors, forming a 3D scene of an object (see figure 28). The diffusion model of Shap-E takes 3D assets as input and converts them into parameters for mathematical representations, which allows the model to deeply understand the relationship between the structure of the 3D assets and the corresponding subject. These parameters are then used to train a conditional diffusion model, which learns how to generate a variety of detailed 3D assets by sampling from this learned distribution. Additionally, Shap-E can generate 3D models from 2D images, further expanding its versatility and applications (Jun & Nichol, 2023).



Figure 28: A few OpenAI Shap-E examples (Jun & Nichol, 2023).

### 4.3 3D DEVELOPMENT

As manual labor costs rise, companies are adopting new technologies to streamline processes for quick design and changes. While computer-aided design and manufacturing for footwear initially focused on 2D shoe upper patterns when introduced in the 1970s, the shift to 3D has become more popular in recent years. This transition automates routine tasks, accelerates production, enhances consistency, and reduces human error, allowing designers more creative time. With these advancements, the footwear industry is gradually transitioning from predominantly 2D design and development methods to embracing the benefits of 3D technology (Luximon & Luximon, 2021).

Emersya, as a user-friendly 3D development platform, facilitates this transition by offering intuitive design customization, visualization, and real-time online collaboration. It can reduce the time-to-market, since the development of new footwear styles rely on the production of physical samples, bringing along logistical risks and delays as well. This dependence can be reduced with Emersya, since it allows for quick design validation through realistic 3D renders that can be created by uploading 3D models, materials and moodboard to the platform. This feedback round can be done collaboratively in real time, since the online platform enables this effective workflow. Emersya also automates the generation of production data and digital marketing content, streamlining workflows and potentially reducing costs (Emersya, 2022).

#### 4.3.1 CONCLUSION

The integration of 3D development into the footwear industry has some challenges, which is the reason why it is not yet widely adopted by companies. While the 3D tools can be effectively integrated and possibly enhance the current workflows, creating 3D models is time-consuming and requires expertise, making it expensive whether done in-house or outsourcing. For a 3D model to be useful in development software, it must consist of multiple parts for each component and realistically reflect the shoe in terms of appearance and proportions.

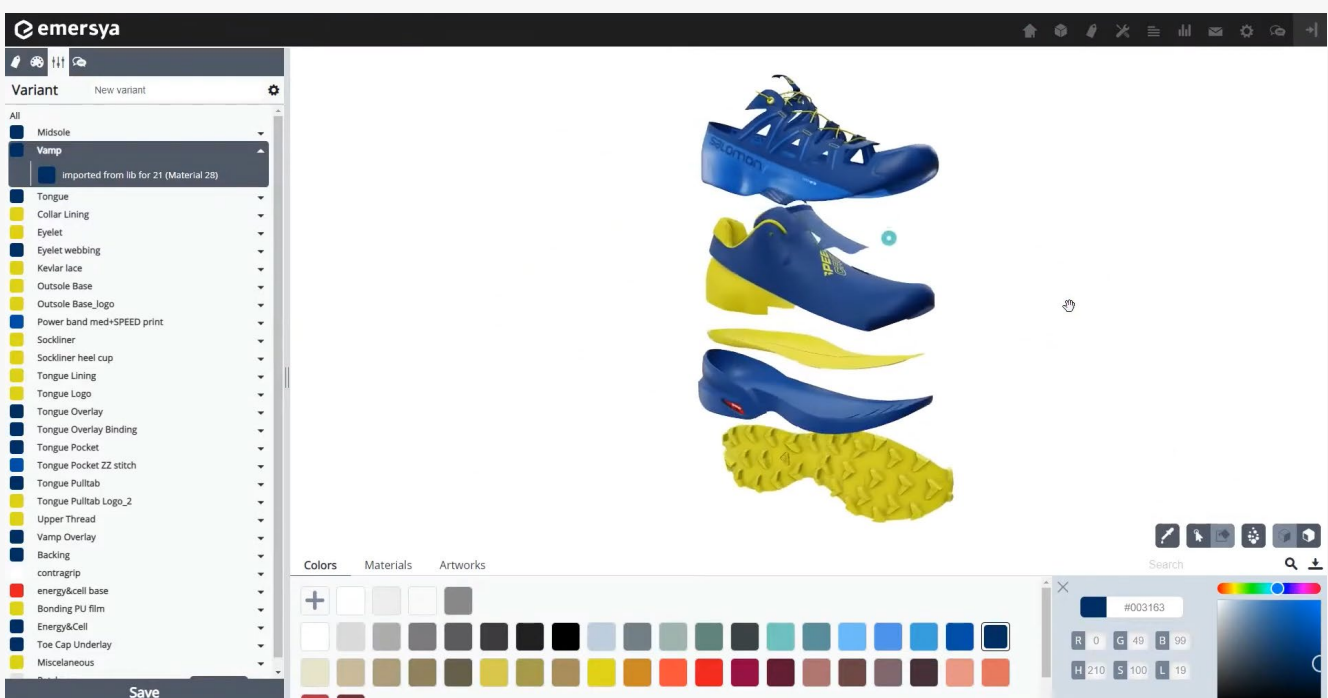


Figure 29: Emersya 3D development interface (Emersya, 2022)



#### 4.4 CASE STUDIES ON AI IMPLEMENTATION

To give concrete examples of how AI tools have already had an impact on the real world, case studies have been done to demonstrate the effect and limitations. The first use case of AI in the fashion industry was data-driven analysis, which has already been used for some years for marketing purposes. With the ability to process large amounts of data such as customer preferences, trends, and social media interactions, AI can adapt the product recommendations accordingly (Massobrio, 2023). However, the application of generative AI to create designs is a relatively new development.

##### 4.4.1 G-STAR RAW

A case where the application of generative AI was applied for a brand is the example of the G-Star AI Denim Cape (see figure 30). Midjourney was used to design a couture piece that would be brought to reality in their atelier. While the generated image served as a basis for the concept, human designers still had to make adjustments to translate the design into reality. With only one available image, the backside had to be designed by themselves. Furthermore, the illogical details and construction had to be made feasible in order for it to be possible to be made. The process did demonstrate the potential of AI, but also showed that it remains a complementary tool in the hands of skilled human designers (G-Star RAW, 2023).

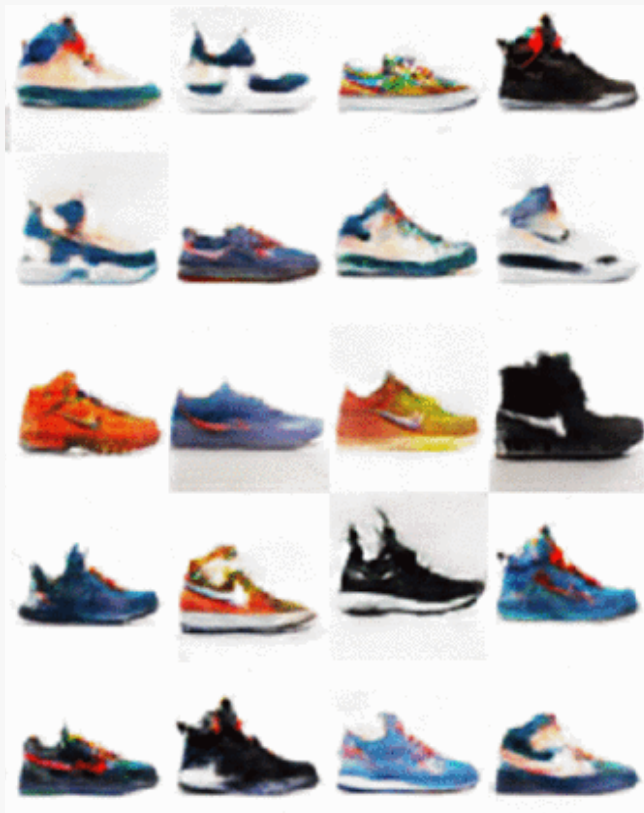


Figure 31: Sneakers created for inspirational purposes with a GAN-model (H. Li et al., 2020)

##### 4.4.2 NIKE A.I.R

The Nike A.I.R project demonstrates the potential of AI in generating innovative design ideas that expand the horizons of traditional aesthetics. However, the project also highlights the limitations of AI in practical applications, since the designs were impractical for producing wearable shoes. (Nike, 2024). This underscores the necessity of human intervention to bridge the gap between imaginative concepts and functional products. Ultimately, the project is more of an artistic exploration, showcasing possibilities of AI-driven design rather than creating real, wearable sneakers (see figure 33).



Figure 30: AI generated denim cape (left) and real cape crafted in atelier (right) (G-Star RAW, 2023).

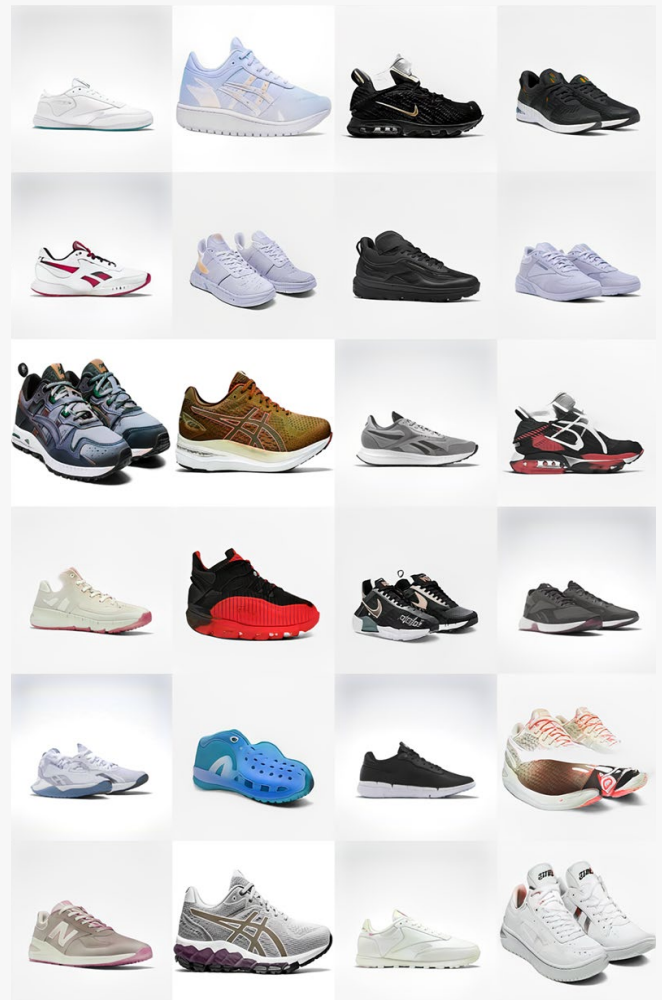


Figure 32: Inconsistent branding in sneakers created with a GAN-model (Yuan et al., 2023)



Figure 33: Nike A.I.R concept (Nike, 2024)

#### 4.4.3 GAN MODELS

Previous research has also explored the development of AI-based fashion design systems for clothing, but it encountered limitations. These systems lacked internal data analysis capabilities, hindering the incorporation of the brand's identity into the design output and resulting in designs that were not brand (Choi et al., 2023). Additionally, these systems were unable to handle the finalization aspects of design, such as creating tech packs and communicating with factories (Luce, 2019).

There have also been GAN-model (a type of generative AI) approaches to generative fashion, that successfully generated creative sneaker designs (see figure 31 & 32). However, the quality of the designs was inconsistent and the image quality was not very high. Some designs also lacked desirability, and could thus only serve as a means of inspiration for designers (H. Li et al., 2020). Although efforts were made to address desirability issues by integrating an image evaluation tool into the model to improve image quality, diversity between designs remained high, lacking the consistency necessary for a brand-specific model (Yuan et al., 2023).

The “This Sneaker Does Not Exist” project showcases another GAN architecture that is developed to generate new sneaker designs. By training a model on a dataset of approximately 50,000 sneaker images, the AI learns to generate realistic sneaker silhouettes that do not yet. This process allows the AI to understand what a sneaker looks like to create new and unique designs based on the training parameters (Van der Vossen, 2023). These designs however lack a clear brand identity, the personal touch of a designer, and overall consistency (see figure 34). While the AI can produce a wide variety of innovative silhouettes, it cannot replicate a distinctive style that human designers bring to established brands.

#### 4.4.3 CASE STUDY CONCLUSION

These case studies demonstrate that there is a gap in the application of AI technologies in the footwear industry, namely the implementation of brand specific design generation, as well as the influence from external sources in the generated output. These case studies thus highlight the opportunity to merge the creative potential of generative AI (RQ1), in combination with a clear and consistent brand identity, while still resulting in wearable shoes that are feasible to produce. This approach has not been explored yet in literature and is an innovative approach to AI-augmented design.

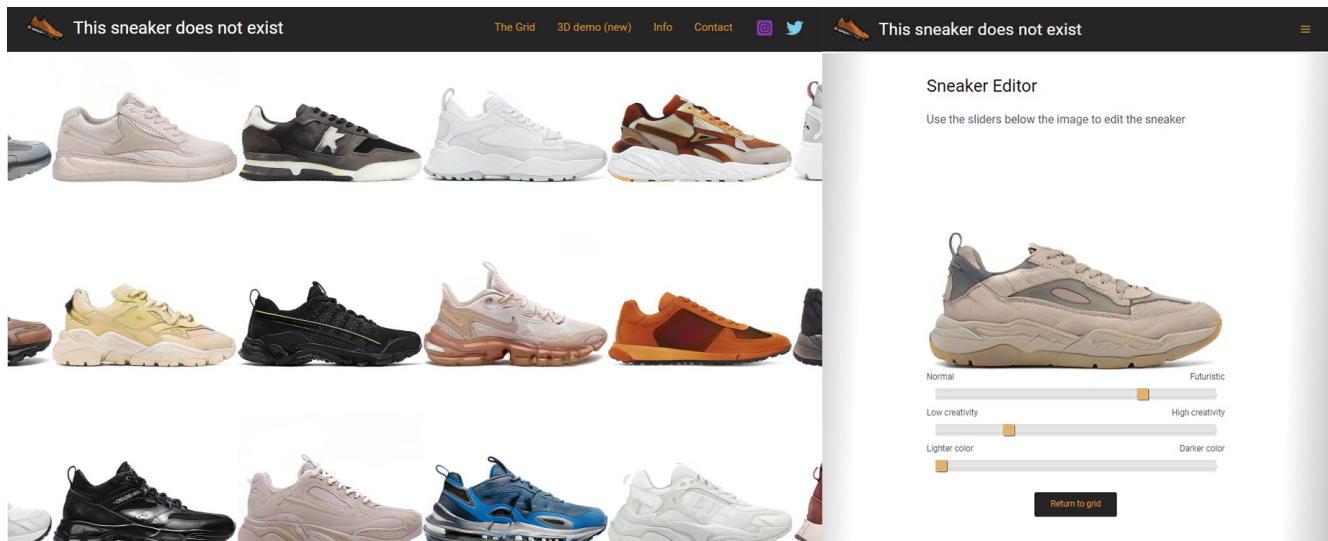


Figure 34: This Sneaker Does Not Exist project by Van der Vossen (2023)

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# 5 DISCUSSION

The findings from the interviews provided valuable insights into various aspects of the design and development processes, tools and methods used, as well as their perspective on the application of AI in the footwear industry. However, it is important to also discuss the limitations of these interviews and the findings to understand the conclusions in depth.

First of all, the interviews were conducted with only 4 interviewees. This limited sample size could impact the representativeness. A larger sample size would provide a more inclusive and comprehensive understanding and could potentially reveal other insights.

Since all participants are from the Filling Pieces team and the interviews were conducted at the office, their answers could be biased. They could have for example wanted the company and the footwear industry to look good, which could have positively influenced their answers.

The findings may also not apply to the entire design industry since they are obtained from individuals working in the footwear industry, particularly in the mid-luxury segment. Other segments of the footwear industry, such as performance-based sportswear brands, or even completely different design industries, may have different requirements, outcomes, and perspectives on the interview topic.

Finally, my personal interest in AI and the project's aim to influence the footwear industry positively with this technology, of which the interviewees were aware, might have influenced the approach of the interview and the interpretation of the results. It is possible that my subjective perspective and bias could have led to favorable outcomes for this thesis.

## 5.1 LIMITATIONS OF AI

The relationship between technology and humans has always been unidirectional (Giaccardi & Redström, 2020), meaning that humans have always been the producers of the technology and they made it with a clear function or intention in mind. It is also still dependent on humans to perform the function, without a command it will not execute an action.

While AI-generated images may provide visual representations, they lack the depth and understanding required to translate those images into actual designs, tech packs, or physical garments (Luce, 2019). Additionally, there are challenges related to industry-specific knowledge and communication. Designing footwear involves understanding jargon, specific nuances of manufacturing processes, and effectively communicating these details in the tech packs to ensure accurate production (Shashkina, 2023). AI models lack an intrinsic understanding of the complex and nuanced real world, thus human expertise will always be required to translate a concept into a final product.

Design problems often lack definitive solutions and require a deep understanding of the nuances and complexities involved in order to arrive at an effective solution (Song et al., 2020). Solving design challenges requires a multifaceted approach that incorporates thorough and critical decision-making as well as human creativity. Creativity is a uniquely human cognitive characteristic, something that is very difficult to fully replicate by AI. Creativity is about transcending traditional ideas, rules and patterns (Robinson, 2008).

AI lacks this true creativity because it operates merely based on programmed rules and patterns, rather than genuine imagination. While humans can generate novel and innovative solutions by drawing from their unique experiences and cultural backgrounds, AI systems rely solely on existing data. As a result, AI-generated outcomes are essentially combinations of pre-existing information, lacking the nuanced understanding and subjective judgment that humans possess. Additionally, AI systems struggle to apply subjective leniency to rules, making it challenging for them to produce designs considered as good or excellent. AI also lacks the capability to interpret the emotions and motivations underlying the needs and desires of target users, which is essential for creating designs that resonate with them. This human-centric understanding is a fundamental aspect of well-designed products. In the design industry, technology should be seen as a tool, since it is an algorithm that can assist you and will never replace the creative capabilities of a human teammate (Zhang et al., 2021).



# 6 CONCLUSION CONTEXTUAL RESEARCH

## 6.1 MOST IMPORTANT TAKEAWAYS

Stable Diffusion is an AI model that can generate images from text inputs. However, when using just the base model with a text input, the images of the resulting shoe designs are often not really good. To steer the output towards a more desirable result, a reference image can be used that influences the noise of the generation process. Next to that, fine tuning with a LoRA model can give even more control over the quality of the final output, making the images more specific and desirable.

Despite these advancements, AI models do have limitations, particularly in understanding and interpreting nuances. Creativity is a complex cognitive characteristic that is unique to humans. While AI can simulate certain aspects of creativity, it does not possess real creative thoughts. So given these limitations, AI tools should not be seen as a replacement for human creativity and capability, but rather as a powerful tool that facilitates collaboration between humans and technology, by enhancing the process.

To address RQ 2, the key challenges in transitioning from a traditional workflow to an AI-oriented approach are conveniently visualized in the SWOT analysis (see figure 35). Training AI models can be time and data-intensive, next to requiring significant computational resources. These challenges can be mitigated by using the LoRA model on an existing base model. This fine tuning approach is less dependent on heavy computational power, while maintaining the performance of the base model in combination with training on a custom database. Nevertheless, AI tools can still be complex. Once the training of the models is done, the process of using the tools should be simplified to make it easier to use. It is not a problem that training remains complex, since the designer only has to execute the AI design process with the trained models. Overcoming negative perceptions about AI can be achieved by demonstrating the possibilities and providing tutorials to enable users to effectively use the tools.

## SWOT ARTIFICIAL INTELLIGENCE

<b>Strengths</b> <ul style="list-style-type: none"><li>Advanced technological capabilities</li><li>Enhanced creativity</li><li>Efficiency and productivity in design and development processes</li><li>Improved visual communication</li><li>Models can be adapted to fit to needs</li></ul>	<b>Weaknesses</b> <ul style="list-style-type: none"><li>Training can be time and data intensive</li><li>Set-up and finetuning can be complex</li><li>Output can still be inaccurate</li><li>Not truly creative</li><li>Lacks nuanced understanding of industry specifics</li><li>Lacks subjective judgement</li></ul>
<b>Opportunities</b> <ul style="list-style-type: none"><li>Collaborative approach between humans and technology</li><li>Integration in workflow</li><li>Development of specialized models</li><li>Continuous improvement</li></ul>	<b>Threats</b> <ul style="list-style-type: none"><li>Dependency on computation resources</li><li>Limited access and scalability</li><li>People can have a negative perception on AI</li></ul>

Figure 35: SWOT Analysis on Generative AI

# LINEAR ABSTRACTION FOOTWEAR DESIGN PROCESS

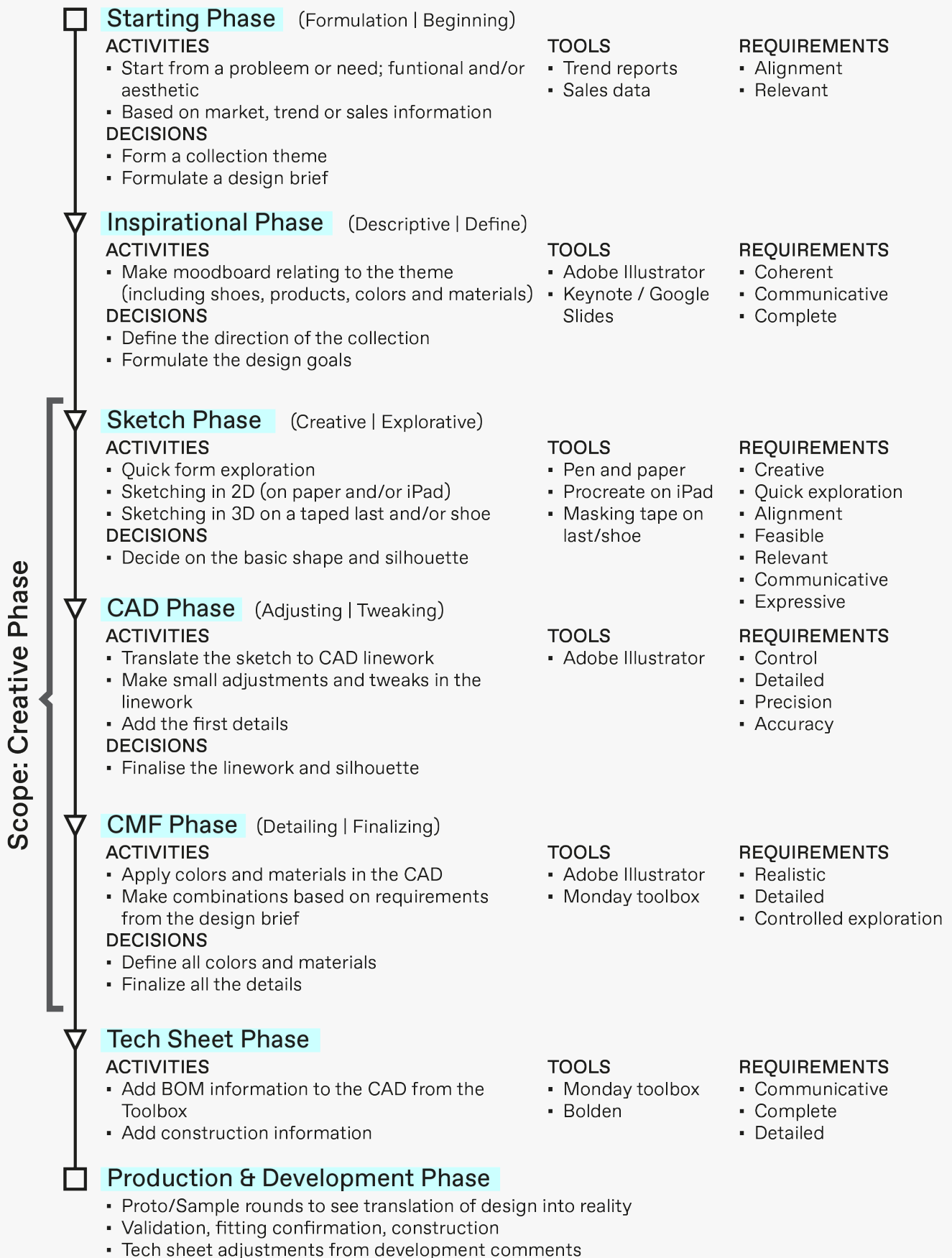


Figure 36: Linear abstraction of the traditional footwear design process for Filling Pieces

## 6.2 PROCESS OVERVIEW

The most important takeaway from the interviews was the overview of the current design process that could be abstracted from it, providing insight into how the team operates when designing a new collection. The linear abstraction of the footwear design process can be seen in figure 36, the requirements of each phase are elaborated on in chapter 6.3. This project aims to impact this process with AI tools that the team have mostly never used before. They shared their current methods and approaches, which needed to be abstracted and dissected to understand each step's requirements. By identifying these needs, we can determine the factors for a successful AI-oriented workflow. Addressing the same needs with a different approach makes the transition more accessible and increases the likelihood of success.

Note that the design process is always iterative and varies with each project. While the steps are mostly linear, they include iterative loops for design or development improvements. Design is subjective and based on the designer's gut feeling, making it challenging to create a one-size-fits-all solution. However, figure 36 is the fundamental structure of the footwear design process. The sketching, CAD, and CMF phases focus on visual aspects and the shoe concept itself, and this creative phase is the scope of the project.

From the interviews, the factors were identified that determine success and the functions the framework should include. These requirements, drawn from the interviews and literature, set the design boundaries and ensure the framework is useful and fits the project's scope. The needs of the Filling Pieces team, as the most important stakeholders, are crucial. Aligning the framework with their needs will greatly contribute to the success of the project.

## 6.3 REQUIREMENTS

In conclusion, the design goal was to optimize the footwear design process at Filling Pieces by addressing the issues of its time and cost-intensive nature of the traditional approach. The assignment involved creating an AI (and initially also 3D) oriented framework, to bridge the gap between generative AI and its application in the footwear industry, as identified through case studies. Additionally, the framework was executed in a case demonstration as well as a user test to evaluate the performance and quality of generated outputs. The requirements for a successful outcome were derived from the research conclusions, combining insights from literature and interviews.

### FRAMEWORK:

1. The framework should be easy to implement into the current workflow of the Filling Pieces team
2. The framework should optimize cost-effectiveness and speed up the design process, by reducing the reliance on prototyping and sampling rounds and ultimately shortening the time-to-market of new footwear styles
3. The framework should allow designers to have control over changing individual design elements to facilitate small design updates on existing styles
4. The framework should enhance creativity, by inspiring creative exploration
5. The framework should apply sales data and material toolbox information into the design input, to ensure data-driven design outputs

### OUTPUT GENERATIONS:

6. The output generations should consistently align with the design aesthetics and brand identity of Filling Pieces, as well as being relevant to the theme of the season
7. The generated image should be visually realistic, it should resemble the real-world outcome as closely as possible, to support visual communication
8. The output should be feasible to produce, it should not be an unrealistic design in terms of manufacturing
9. There should be a good balance between consistency and variation between the generated images, they should resemble each other to be reliable, yet vary enough to be interesting
10. The generated images should appropriately reflect the references that are used as input

These requirements should be incorporated into the framework, since they are a selection of the most important ones for a desirable minimal viable product (MVP). It is a selection out of all the needs, since these requirements have a higher priority than the others (the list of all requirements can be found in appendix C), since they have less impact on the success of the framework. The Pareto principle, also known as the 80/20 rule, will be applied for the management of requirements for the framework. This involves prioritizing the vital few requirements that have the most significant impact on the success of the framework, while disregarding the less influential ones to manage a higher likelihood of achieving success for the project (Ivančić, 2014).

These conclusions set the stage for the next chapter, where the practical application of the AI tools will be researched, synthesizing the insights gained to design and implement an AI-oriented design framework tailored to the needs of Filling Pieces.

# PART 2

## APPLIED RESEARCH

This chapter will be about the explorative application of the AI tools for the process. With this hands-on approach, we can get a better understanding and a feeling of how the settings of these tools can and will function in practice. The goal of this experimental approach is to determine the optimal value ranges of the parameters and their use cases, to identify effective combinations of tools and how they can complement each other.

1 METHODOLOGY OF RESEARCH  
2 IDEATION  
3 EXPLORATORY APPLIED RESEARCH

4 VALIDATION TESTING AND RESULT  
5 CONCLUSIONS



Figure 37: *Filling Pieces sneakers (Filling Pieces, n.d.)*

## 1 METHODOLOGY OF RESEARCH

An exploratory, trial-and-error approach is used to research the application of AI tools. By focusing on one tool and parameter at a time, the specific impact on results can be observed. These results of varying parameters are plotted to visualize the effects of the different values. These findings guide further exploration to determine optimal combinations of parameter ranges.

Initially, a quick ideation of potential framework designs was created and iterated on in the process, shown in figure 38. For each tool, its purpose, application, and the associated inputs and outputs, including parameter ranges, are explained. Finally, findings for each technique are summarized, how and if it can be effectively used.



# 2 IDEATION

Concluded from the interviews, there are two design directions for the framework important to be explored: creating completely new silhouettes and updating existing styles for new collections. Each direction has specific requirements, but for the most part they are overarching. As a result, these will be addressed as separate parts of the framework that will be tackled independently in the design process. However, a general overarching framework hypothesis was made to serve as the foundation for researching the application and correlation of AI tools, that can be seen in figure 38 that was synthesized from the findings in the contextual research.

For the first ideation and execution, the focus of the framework is only on the 2D aspect. A solid foundation needs to be set before moving into 3D for the next iteration. The design process of the framework will be backwards, by starting with training with the LoRA model, which has the most impact on the end result. Following this approach and moving backwards within the framework, the effect of each step can be assessed along the way based on the output generations. The next step

will be to incorporate the LLM and RAG models, to respectively create a standardized protocol for consistent generation and the implementation of data-driven generation. Finally, the image reference elements will be incorporated to reflect the moodboards. By using the best output generations made during the previous steps, they can be incorporated as input data for another LoRA training phase, which can enhance the quality of the model.

Initially, the focus was set on training the LoRA on images of the Cruiser style, so it could consistently generate that shoe to make updated versions for new collections. This was a practical decision, since by concentrating on a single style it becomes easier to assess the result of the LoRA finetuning. The quality of pictures can be more effectively compared with a similar subject, rather than comparing multiple different variations. It helps with understanding how to use the training parameters to get a good outcome, before applying this knowledge to the more complex case of designing new silhouettes.

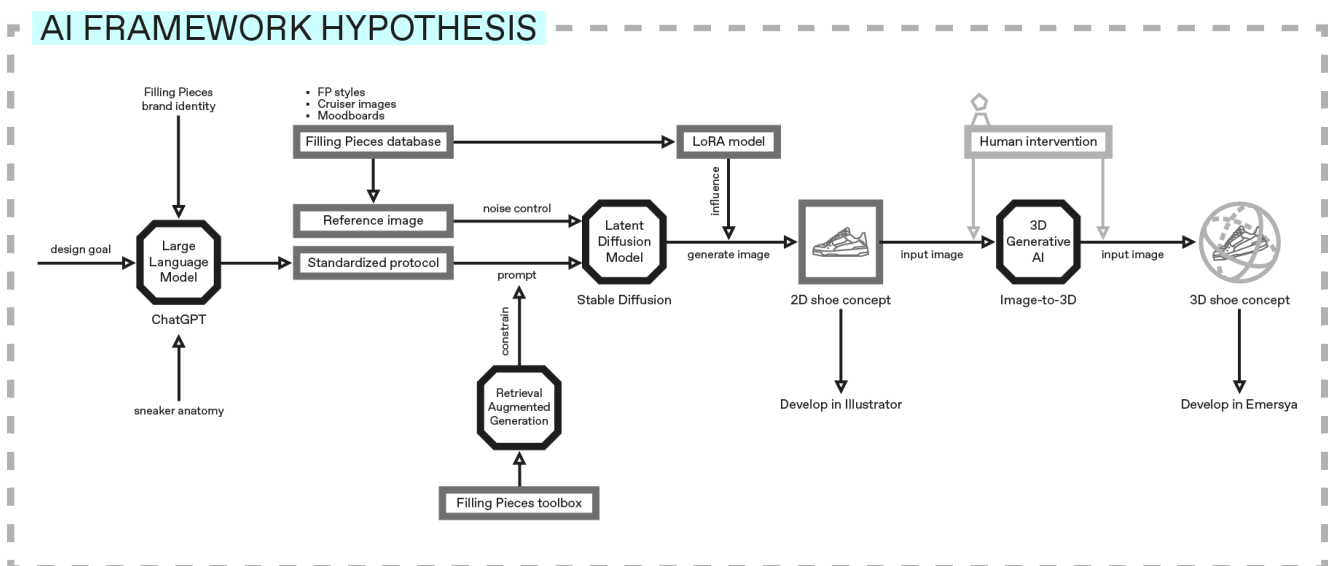



Figure 38: First hypothesized ideation of the framework

# 3 EXPLORATORY APPLIED RESEARCH

## 3.1 STANDARDIZED PROTOCOL

Making a standard format for writing prompts was attempted to simplify the process and improve consistency and quality of generated images. By using a large language model like ChatGPT, prompts can be formatted effectively into a standardized protocol, enhancing user inputs for the generative AI and taking away the effort of writing a detailed prompt.

The goal was to use ChatGPT to consistently describe a shoe, including all components, tackling requirements 3 & 7 by explaining changes to each part in the prompt. However, this approach faced challenges because image generation models are not trained on specific footwear anatomy and do not understand the industry jargon. While individual components could be described, the prompts created were too complex and lead to undesirable results (see figures 39 & 40).

 ChatGPT

"Create an imaginative visual representation of a futuristic sneaker concept inspired by its intricate components. Your design should highlight elements such as the dynamic outsole engineered for superior traction and durability, a midsole integrating cutting-edge cushioning technology for unmatched comfort and support, and an upper crafted from innovative materials for optimal breathability and style. Consider incorporating features like a sleek tongue design for enhanced fit, lacing systems that seamlessly blend functionality with aesthetics, and a reinforced heel counter for stability. Let your creativity shine as you envision a sneaker that pushes the boundaries of both form and function."

Figure 39: *Overly complex prompt provided by ChatGPT*




Figure 40: *Generated images with Stable Diffusion from prompt in figure 38*

This issue could be explained by the format of the prompt, which should be more descriptive, specific, and use keywords separated by commas (Andrew, 2024a). When ChatGPT was asked to change the format, it provided better results (see figure 41), but the generated images were still unsatisfactory (see figure 42). While the prompt improved, it was hard to describe the Filling Pieces brand identity and the output remained too inconsistent.

### 3.1.1 CONCLUSION

Using just a prompt generated using a standardized protocol made by a LLM resulted in undesirable outcomes when using it to generate an image with Stable Diffusion, while first experiments with a LoRA model without a prompt got better results. Therefore, the standardized protocol was excluded from further exploration and the focus shifted to finetuning the generation model itself.

 ChatGPT

"Photorealistic side view of sneaker concept, futuristic design, sleek silhouette, metallic accents, gradient color scheme, dynamic outsole, breathable mesh upper, innovative lacing system, urban environment backdrop."

Figure 41: *Formatted prompt provided by ChatGPT*



Figure 42: *Generated images with Stable Diffusion from prompt in figure 40*

### 3.2 RETRIEVAL-AUGMENTED GENERATION (RAG)

It was attempted to retrieve information from a database and use it to steer the generation process and make it data-driven to meet requirement 5. This could be particularly useful if the detailed material database of Filling Pieces (2024) could be linked to the prompts and output of the generative AI. Their database is managed in Monday.com, a project management software. The goal was to export this database to ChatGPT, enabling it to retrieve information and suggest material combinations based on prompted requirements, such as the cheapest material options. The materials, available at the office, could then be scanned and tagged with unique codes to create a LoRA model. These codes could then be used in prompts for specific components, leading to controlled image generation with realistic materials from the suppliers.

The database was exported to an Excel file (see figure 44) and then converted to a CSV file for ChatGPT to read. When asked to retrieve information and suggest material combinations, ChatGPT performed well, providing useful suggestions.

This proof of concept demonstrated that ChatGPT could use CSV data to generate material options (see figure 43). Due to the confidential nature of this information, unblurred versions of the figures can be found in the confidential appendix.

#### 3.2.1 RAG CONCLUSION

This approach was however not bulletproof. ChatGPT lacks the understanding of nuanced details, such as interpreting lead times listed as “3/4 weeks.” It neglected this data when generating the fastest lead time combination. To address this, either ChatGPT needs more specific training to understand nuances, or the database should be modified to be easier and more clear to read. Additionally, while ChatGPT is not specifically designed for RAG, other tools are better suited for this purpose, but they require more coding.

Scanning the material textures and implementing them in controlled generation was also not successful (see chapter 3.3.3.3). So regardless of the proof of concept, the RAG implementation was excluded from further research, since the outputs could not be used to steer the data-driven material combination into a shoe design.

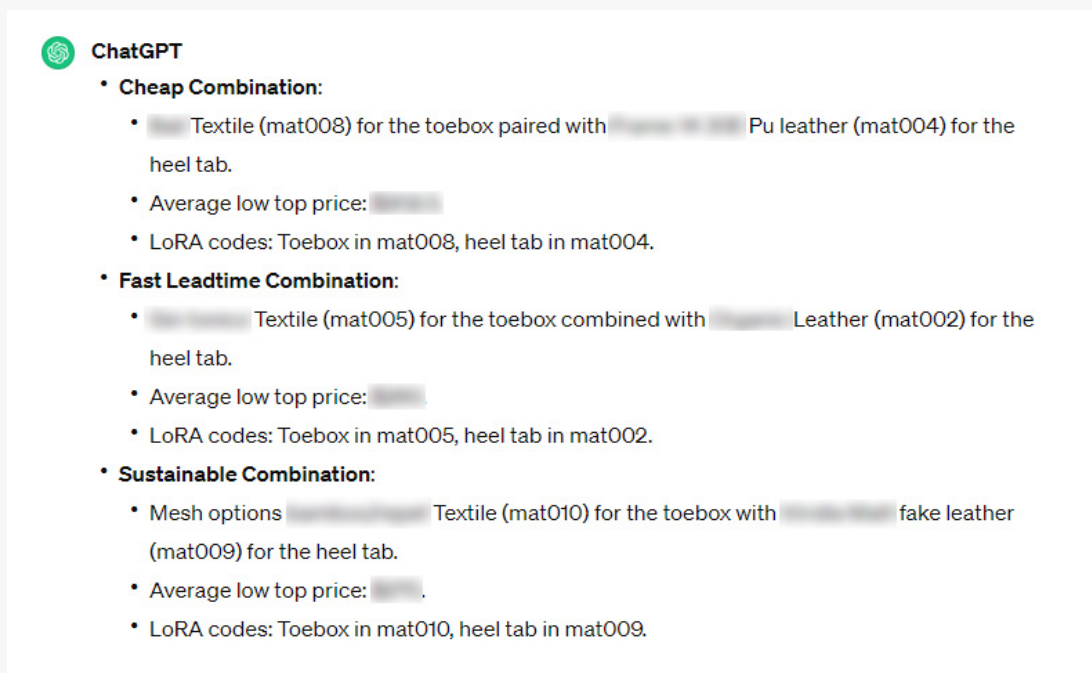


Figure 43: Material options generated from the material toolbox by ChatGPT

Name	Type of Material	Supplier	Min QTY	Production Price /feet	Per.	Selection	low top price	Leadtime	Status	LoRA code	Comment
[redacted]	Leather	[redacted]	no MOQ	[redacted]	feet	Entry Luxury	[redacted]	4 weeks	Available	mat001	
[redacted]	Leather	[redacted]	no MOQ	[redacted]	feet	Entry Luxury	[redacted]	3/4 weeks	Available	mat002	
[redacted]	Pu leather	[redacted]	no MOQ	[redacted]	feet	Entry Luxury	[redacted]	4/5 weeks	Available	mat003	
[redacted]	Pu leather	[redacted]	30 mts	[redacted]	feet	Conventional	[redacted]	4/5 weeks	Available	mat004	
[redacted]	Textile	[redacted]	no MOQ	[redacted]	feet	Trend Maven	[redacted]	4 weeks	Available	mat005	
[redacted]	Textile	[redacted]	25 meters	[redacted]	feet	Visionary	[redacted]	4/5 weeks	High MOQ	mat006	
[redacted]	Textile	[redacted]	150 mts	[redacted]	feet	Visionary	[redacted]	4/5 weeks	High MOQ	mat007	
[redacted]	Textile	[redacted]	no MOQ	[redacted]	feet	Conventional	[redacted]	3/4 weeks	Available	mat008	
[redacted]	fake leather	[redacted]	no MOQ	[redacted]	feet		[redacted]		waiting for email address	mat009	sustainable
[redacted]	Textile	[redacted]							waiting for email address	mat010	sustainable

Figure 44: Excel file export of the Monday.com material toolbox (Filling Pieces, 2024)



### 3.3 GENERATIVE AI IMAGE

#### 3.3.1 PROMPT

Certain words in the prompt have more influence on the output than others. Some examples of word combinations are shown in figure 45, where they were applied on the same seed to show their influence on the output. The main subject, in this case the type of shoe, has the most notable effect on the image. Descriptive words, such as the style or color, have less impact but do influence the style of the generated shoe.

#### 3.3.1.1 Conclusion

It is important that the prompt accurately describes the subject that you want to generate, so it must be written in accordance with the design language to reflect the input of the theme (requirement 10) and generate the desired outcome. When running the model locally, each image took 12-16 seconds to generate, meeting requirement 2. Additionally, the structure of the prompt should be descriptive keywords, separated by commas. This structure is not part of the design, but rather the way Stable Diffusion best handles input (Ramos, 2024).

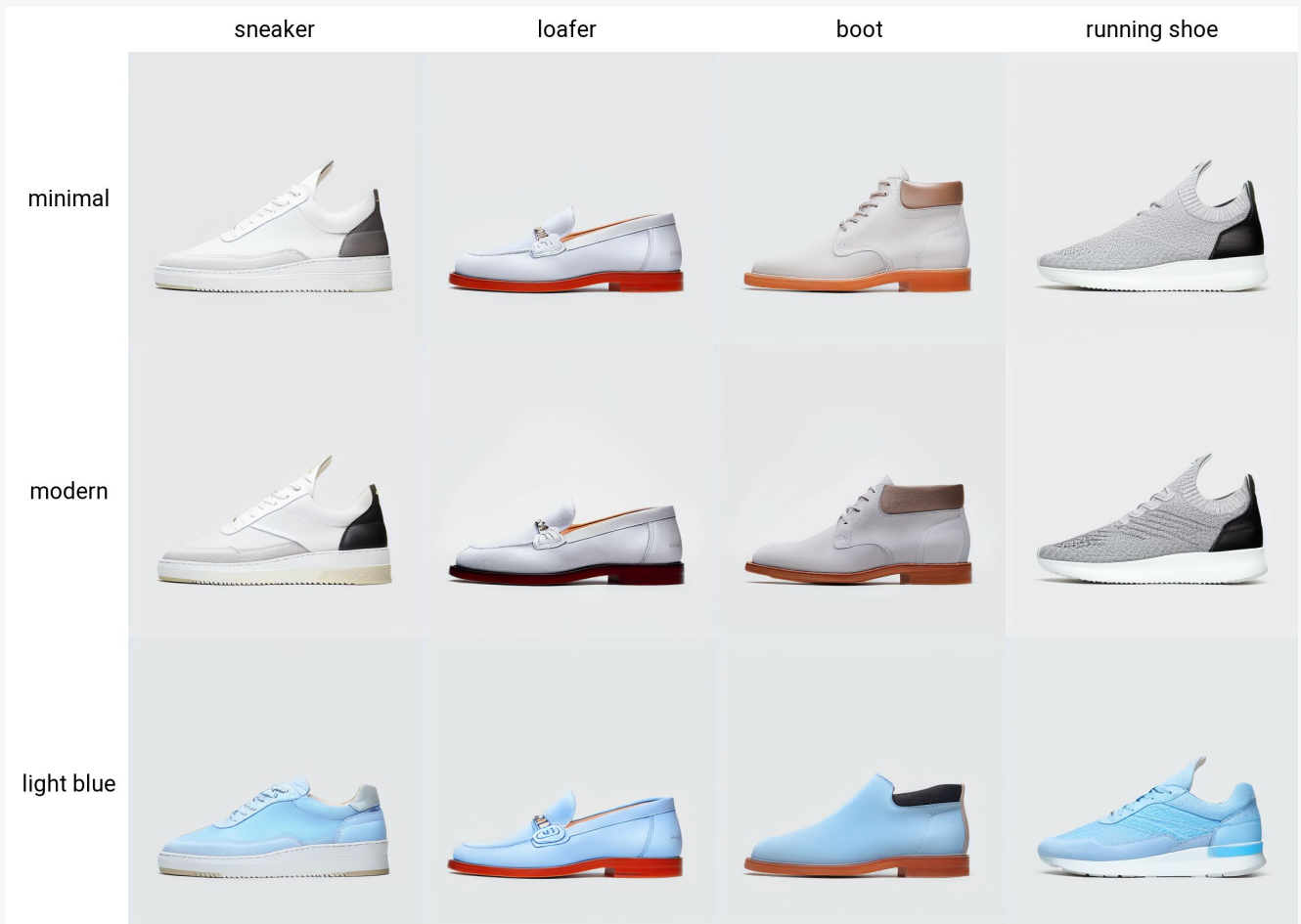


Figure 45: Different prompt combinations on the same seed with FP LoRA, no additional prompt words

### 3.3.2 IMAGE REFERENCE

#### 3.3.2.1 Composition and silhouette

Using an image reference works for controlling the output silhouette. The initial aim was to generate a photorealistic sneaker similar to the sketch input, to meet requirement 6, 7 & 10. With a low denoising value, the input is translated very literally, resulting in a sneaker sketch that consists of just black lines. With a high value on the other hand, only the composition got translated, not the linework which was the intention (see figure 4).

The next try was with a colored sketch, still the output only matched at lower denoise levels. At low levels, the images were however too literal, resulting in black lines that made them look cartoony, similar to the input sketch. Higher denoise levels reduced the influence of the color and linework, though the composition remained consistent across all levels,

which was an unexpected but positive result. All generated images are a sneaker facing left against a white (or light gray) background, which is desirable (see figure 47).

The black cartoony lines can be avoided by making them less visible in the input sketch, giving better results at a low to mid range denoise level. Through experimentation, the best results for rough silhouette, linework, and color translation were achieved with this type of input image (see figure 48). However, even better results are achieved when the input is an AI-generated image that already looks realistic (see figure 49). Particularly with a denoising value in the range of 0.3 to 0.5, the results are quite good. Interestingly, not every denoise value produces a different design, the changes seem to happen in steps rather than gradually.



Figure 46: Outputs of different denoising values, with black line sketch as input image, with FP LoRA, no prompt



Figure 47: Outputs of different denoising values, with black line sketch with color as input image, with FP LoRA, no prompt



Figure 48: Outputs of different denoising values, with colored sketch with light lines as input image, with FP LoRA, no prompt

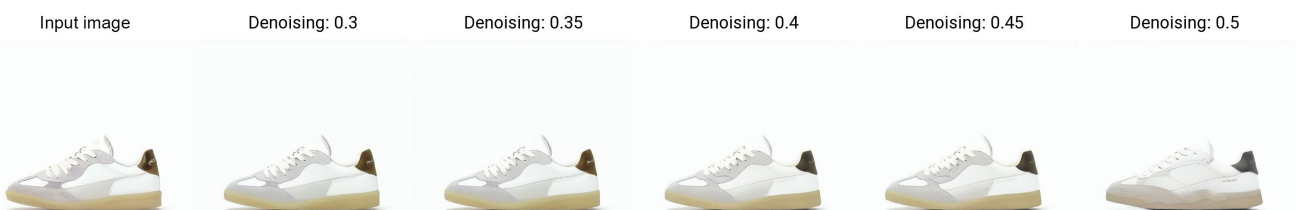


Figure 49: Outputs of different denoising values, with AI-generated image as input image, with FP LoRA, no prompt

What also works really well is inputting an image similar to what you want and sketch over it. With lower denoise, you can use a live painter node in ComfyUI as the node that acts as the reference image. For example, if the input shoe is good but needs slight adjustments (requirement 3) like and additional pull tabs or a reshaped heel counter, you can sketch these changes and run it with a lower denoise level, around 0.4, to achieve the desired result (see figure 50)

The unexpected result of a near perfect translation of the composition at a high denoise level suggested the possibility of achieving the same with just an outline sketch. This approach would allow the AI model to generate a creative output in terms of linework, which is beneficial in the early design phase, while still maintaining output consistency, which is always desirable. Without an input image, backgrounds were inconsistent, often producing multiple shoes or even legs (see figure 51). This method effectively guided the composition while allowing the AI model to be creative.

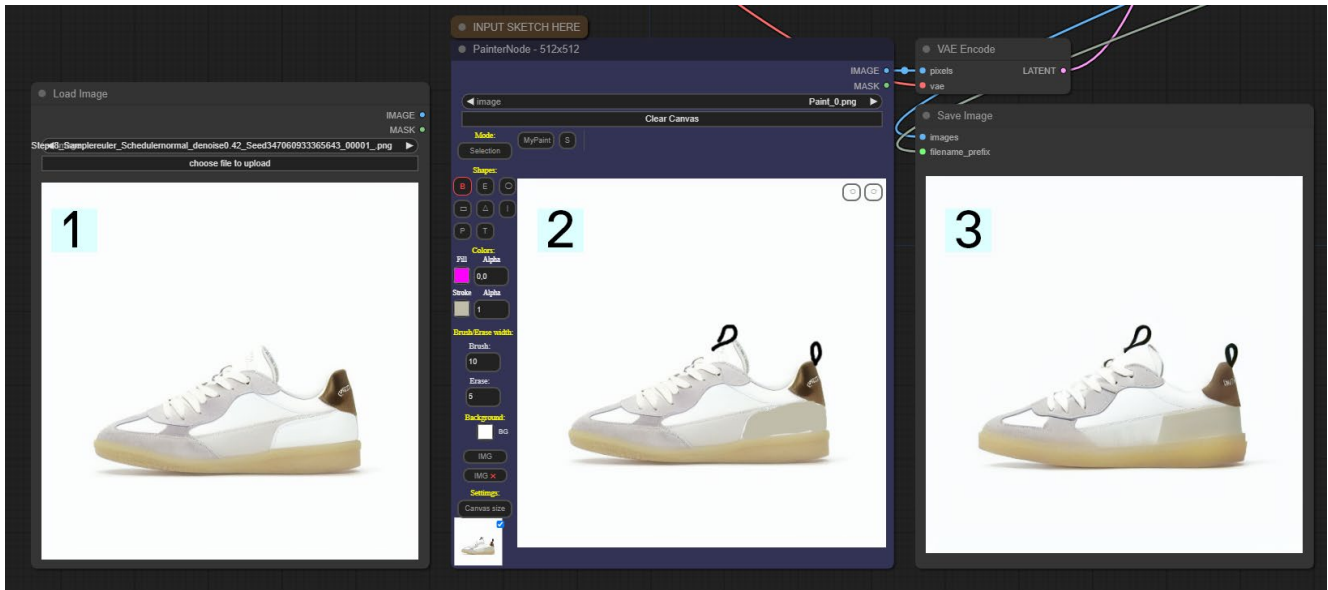


Figure 50: Input image (1), input image sketched over in the live painter node that is the input for the img2img latent (2) and output (3)



Figure 51: Outputs of different denoising values, with outline sketch as input image, also showing the same seed without input image

### 3.3.2.2 Controlling the color

Using an image reference with the image-to-image function can also help steer the colors more effectively than just a prompt. However, balancing CFG and denoising strength is important to avoid simply replicating the reference image. Finding the right balance allows for better control over the color in the final output, as shown in the figure 52.

The findings from this experiment show that with a low CFG value, the shoe appears less realistic but the colors are translated more accurately. This allows the model to be less strict in following the LoRA, resulting in more flexibility in the output. The denoising value seems to have more impact on this color accuracy.



Figure 52: Outputs of different denoising and CFG value combinations with *CAD of cruiser* as reference image for colorway, prompt: “sneaker” in combination with *Cruiser LoRA*

### 3.3.2.3 Moodboard

An image reference was also used to try to reflect a moodboard in the output design (requirement 10) This moodboard (figure 53) was chosen randomly for its nice mixture of different colors and materials, for experimental purposes. The results show that it works to some extent, but not completely. The composition of the output is more influenced by the moodboard, which clashes with the silhouette of the sneaker with a lower denoising value.

In figure 53 can be seen that the desired effect is not achieved. At high denoise levels, there is no influence on the image, while at lower denoise levels, the colors can be noticed. However, the composition is altered too much, resulting in a weird composition of the shoes. Therefore, using a moodboard as image reference does not effectively work for adhering the generated shoe to the seasonal theme.

### 3.3.2.4 Conclusion

The best use for a reference image is for controlling the composition of the image, since the composition is most influenced. For a consistent and desirable composition of a side view on a plain background, an outline sketch in combination with a high denoise value (0.9) is recommended. Another approach is to create variations of the input image using a denoise value between 0.3 and 0.5. It is important to start with an image that already looks realistic, otherwise the output will also be influenced by the sketched and cartoony look. The higher the denoise value, the more creative the outcome, while a lower value results in more similarity (RQ3). Therefore, experimenting with different denoise values is important when generating variations.



Figure 53: Outputs of different denoising values with moodboard as reference image, prompt: “shoe” in combination with *FP LoRA*



### 3.3.3 LORA FINETUNING

Most of the previous images were generated using LoRA models, which improved the quality and consistency of creating Filling Pieces shoes. Therefore, most examples use a LoRA trained on Filling Pieces shoes, which helped to meet all the output requirements (5, 6, 7 & 8). This ensured that the outputs aligned with the objective of generating shoes that fit the FP brand identity, which was hard to do with just a prompt, and tweaking the parameters accordingly. The precise outcome influence of a LoRA model is unpredictable, so the best approach is to start with default settings and then troubleshoot, refining the process with each iteration to improve the results (Ma, 2023).

LoRA is bound to the specific model it was trained on, meaning it can only be used in combination with that base model. For most images, the Stable-Diffusion v1.4 checkpoint (Rombach et al., 2021) was used as the base model, which could be done on my local laptop. For SDXL, more VRAM is needed for LoRA training, at least 12 GB. Therefore, the online service RunDiffusion (Ed, 2024) was used. While it is a paid service, it is necessary as local training for SDXL is not feasible.

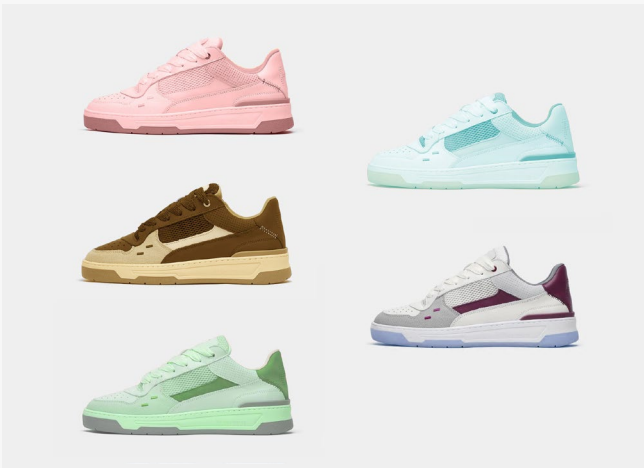


Figure 54: Selection of cruiser LoRA database

### 3.3.3.1 LoRA for Cruiser

Applying LoRA models can be useful for multiple purposes. For instance, when the aim is to consistently generate the Cruiser model with slight variations, a LoRA model can be trained exclusively on images of the Cruiser style. The key is to balance the training so it learns the features of the cruiser, but is not overtrained. The LoRA needs to stay flexible to be able to make minor adjustments in materials and linework. If this balance is achieved, the results should generate realistic shoes using the normal strength of 1.0 of the LoRA model. This strength can always be adjusted as needed to achieve the desired influence.

However, since only five variations of the Cruiser exist, additional variations needed to be made in Photoshop. These additional color variations made sure that the minimum amount of images was met and enhanced the color accuracy of the model. Even though the background was white and even in all images in the dataset, the background in the generations was not consistently white, despite being specified in the prompt. Findings from this LoRA training was that controlling colors and materials was still a challenge, because they remained somewhat random in the output.

There were only 5 colorways of the cruiser available at the time of making the LoRA model, with additional photoshopped combinations a total of 25 images was available for the database. The learning rate in combination with the LR scheduler controls how fast the model learns over time, and how this learning rate is adjusted. The network Rank and Alpha determine the size, expressiveness and adaptability of the model. The combination of these key parameters resulted in a model that generated a cruiser consistently, but was not too rigid where no other color and material options could be generated. For the final Cruiser LoRA, the parameters seen in table 1 were used.



Figure 55: Example outputs of the Cruiser LoRA model

Table 1: Key fine tuning parameters for the Cruiser LoRA model

Amount of images	25
Total steps	3750
Learning rate	0,0001
LR scheduler	Cosine with restarts
Network Rank	32
Network Alpha	16

### 3.3.3.1 LoRA for FP brand identity

For the LoRA model for generating new styles in the Filling Pieces brand identity, the selection of images had to be refined. From the 130 SKUs available on the Filling Pieces website, only those that would add unique elements to the dataset were included, with at least one colorway per style and adding additional ones only if they offered something extra in terms of color or material. Another reason for this selection was that some models, such as the Low Top would otherwise have been overrepresented in the dataset, as this style has more variations than the others. Filling Pieces produces a variety of shoe styles (see figure 56), including not only sneakers but also dress shoes like loafers, as well as boots. Each of these styles have a distinct Filling Pieces brand identity, so all styles from the current collection are included in the dataset. These align best with the current brand identity of Filling Pieces, since older models are discontinued for a reason. Each image was also captioned with BLP and complemented manually with the target style. This particular type of model tended to be overtrained more easily, possibly due to the high network alpha, that for a larger variety of styles in the dataset could lead to less creativity. However, lowering the network alpha failed to produce results consistent with the Filling Pieces brand identity. For the final FP LoRA, the parameters in table 2 were used.

Table 2: Key fine tuning parameters for the FP LoRA model

Amount of images	40
Total steps	2400
Learning rate	0,0001
LR scheduler	Cosine with restarts
Network Rank	32
Network Alpha	16

Fewer training steps were required here, because this LoRA didn't need to learn as many details as the Cruiser model, which demands higher accuracy and specificity. For this model, the focus was on learning the brand identity of Filling Pieces, which is less rigid. Higher total training steps resulted in overtraining, since the generations would more or less be exact copies of the dataset images rather than creatively generating new shoes. The combination of these key parameters resulted in a model that generated different types of shoe styles, but with a consistent brand identity.

#### Impact of LoRA strength

Increasing the strength of the FP LoRA model results in a stronger expression of the model, making the influence of the database images more apparent. As seen in figure 57, a higher LoRA strength in the LoRA model produces shoe designs that are not only more realistic, but also reflect the brand identity better, especially when a composition reference image is used.

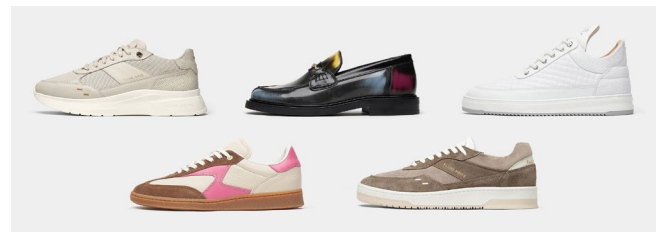


Figure 56: Selection of FP LoRA database

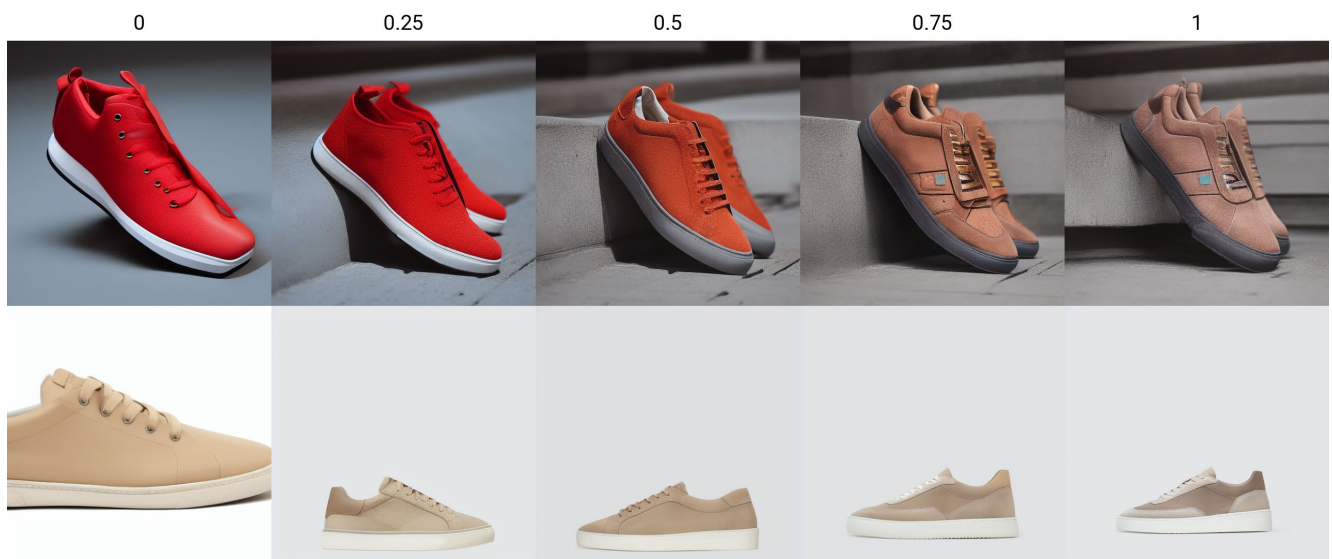


Figure 57: FP LoRA model strength values, on same seed, with prompt "sneaker". Top has no reference image, bottom has reference image of the outline sketch (figure 50)



### 3.3.3.3 LoRA for materials

A LoRA model for materials was also explored, but the results were unsuccessful since they were unpredictable. The database consisted of flat images of material textures, each captioned with the corresponding material name. When training the LoRA on these materials, the model could reproduce the flat scans of the materials (see figure 58) but failed to transfer them onto the sneaker. The the materials are not reflected in the sneaker. Sometimes a really small component or the background is textured (see figure 59). This can be explained by the fact that the model only learns what the image looks like, but lacks the nuanced understanding of how the material behaves and interacts with the structure of a shoe.

This issue could be resolved by creating a large database of real shoes made from various materials, each accurately captioned with the material name. This would allow the model to learn how materials look on a shoe, rather than just from flat images. However, making such a large and complete database is not feasible, since most new materials are never used before.

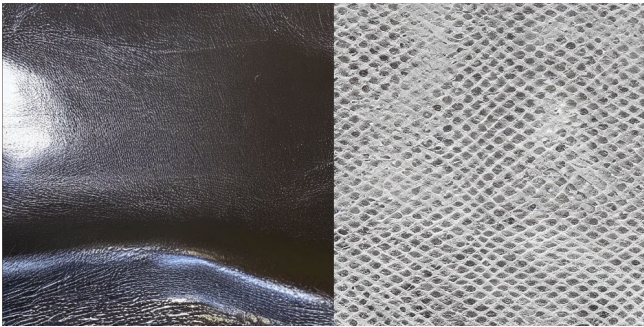


Figure 58: Flat material texture outputs



Figure 59: Most successful attempts of the material LoRA

Table 3: Key fine tuning parameters for the Thematic Moodboard LoRA model

Amount of images	30
Total steps	3480
Learning rate	0,0001
LR scheduler	Cosine with restarts
Network Rank	32
Network Alpha	16

### 3.3.3.4 LoRA for Moodboard style

Since the reference image was not effective in reflecting a moodboard, a LoRA model will be used to achieve this goal for both thematic and shoe moodboards. Using a reference image limits the influence to only the composition of the output image, whereas a LoRA model can change the image generation. To ensure the LoRA model focuses on sneakers and not other images, the strength of the thematic LoRA has to be set slightly lower than the shoe model. These LoRA models need to be used in combination with the FP LoRA, since the desired output should still incorporate the brand identity, mixed with the moodboard influence. The only disadvantage of using a LoRA model for moodboards is the lack of control, the influence of the images on the shoe design will always be subject to a degree of randomness.

For the final Thematic Moodboard LoRA, the parameters in table 3 were used. This is the only LoRA model used in this thesis that does not include shoes in the dataset. However, the same combination of key parameters was used apart from the relatively high total training steps. This was probably needed for the model to learn the key characteristics of the theme style.

To determine the influence of all the LoRA models on the output, a balance between their strengths needed to be found experimentally. This was achieved by setting the FP LoRA at a fixed strength and generating images with the same seed with varying strengths of the other LoRA models. The image below shows example outputs using this LoRA model and the influence of the LoRA model strength on the design.

A nice combination of thematic influence with the brand identity still being apparent happened at a strength of 0.5-0.6 (see image 62). It is important to note that the difference is small but noticeable because the other LoRA is dominant due to the higher strength. With a higher strength of the thematic LoRA, the image gets distorted and does not look like a realistic shoe anymore. This is probably explained by the fact that in the dataset for this LoRA model, no specific images of shoes were present. Despite this, the approach works better than using a reference image for moodboard influence.

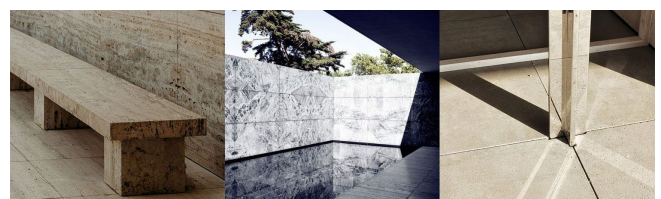


Figure 60: Selection of Thematic Moodboard LoRA database

For the final Footwear Moodboard LoRA, the parameters in table 4 were used. The footwear moodboard model did include shoes, but not in the Filling Pieces brand identity. Here it was important to capture the design language of the theme, with the same key parameters this was done successfully. But it was important to lower the strength when applying the LoRA, even though one could say that lowering the total amount of training steps would give the same result, this was not the case. Lower training steps resulted in a model that did not capture the design language of shoes inspired by modern architecture as well as this LoRA model.

The figure 63 shows example outputs using this LoRA model and the influence of the LoRA model strength on the design. Interesting things happened between strengths of 0.8 and 1.0, where the shoe transformed from a sneaker to a boot, likely due to the dataset containing one image of a boot that got copied. Another interesting thing occurred at a strength of 0.5, lower values resulted in the influence of the moodboard not being reflected.



Figure 61: Selection of Thematic Moodboard LoRA database

Table 4: Key fine tuning parameters for the Footwear Moodboard LoRA model

Amount of images	28
Total steps	3360
Learning rate	0,0001
LR scheduler	Cosine with restarts
Network Rank	32
Network Alpha	16

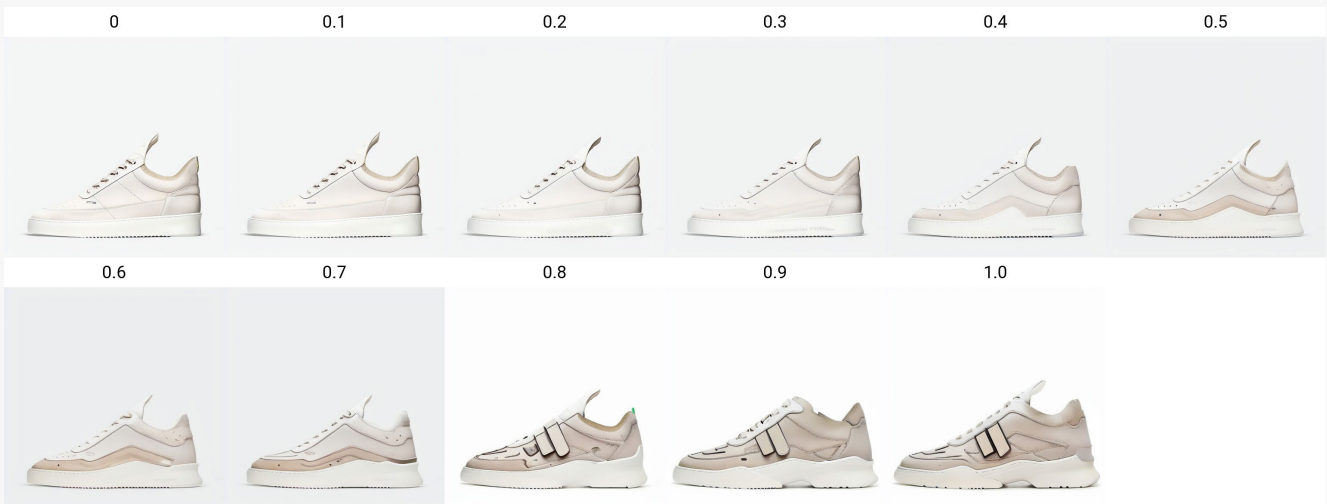


Figure 62: Different strengths of the Thematic Moodboard LoRA model, in combination with the FP LoRA model, silhouette reference image and without prompt

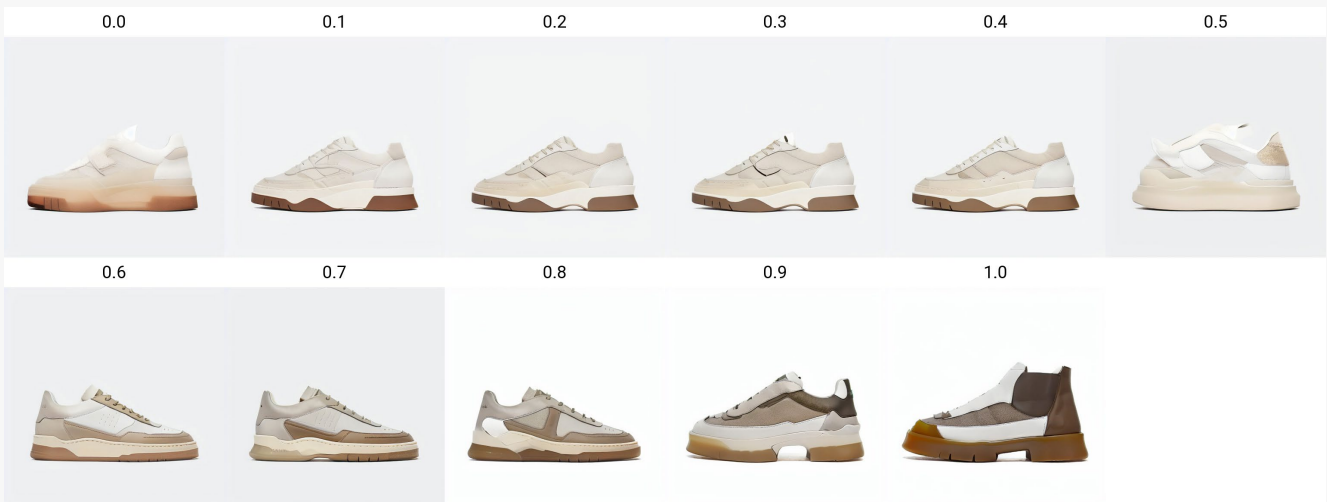


Figure 63: Different strengths of Footwear Moodboard LoRA on the same seed, in combination with FP LoRA, silhouette reference image and without prompt

Combining the three LoRA models is also possible, which requires a balanced influence from each model according to its intended purpose. Experimenting with different values and finding the right balance can help the designer incorporate moodboard references and thematic styles into the shoe design.

From these combinations, it can be seen that the thematic moodboard LoRA model tends to distort the image with higher values, as it doesn't have shoes in its database and is not trained to generate them. It primarily creates the modern architecture style, which can be incorporated at lower values without distorting the shoe. On the other hand, increasing the strength of the footwear LoRA decreases the shoe's resemblance to a Filling Pieces shoe, but the brand identity remains visible

due to the high influence of the FP LoRA model. Additionally, it's noticeable that the LoRAs affect each other. When both are in the higher range, they tend to result in a bad image more easily. The best results happen with a lower range of the thematic moodboard LoRA and a higher range of the footwear LoRA, indicated by the blue area in figure 64. These combinations effectively blend modern architecture and footwear inspiration, while still being recognizable as a Filling Pieces shoe that is not overly distorted.

### 3.3.3.5 LoRA conclusions

To conclude the LoRA training, a total of around 3000-3500 training steps was most effective for capturing the details and influence of the moodboards. A slightly lower range of around 2500 seemed optimal for capturing the style of the



Figure 64: Different combination strengths of both moodboard LoRA models in combination with the FP LoRA, composition reference image and prompt: "neutral colorway sneaker, modernism, functional". The blue area indicate the most effective combinations of LoRA models



Filling Pieces brand identity, while still maintaining flexibility. A higher amount of training steps resulted in overtraining, where the results were too rigid and not yet creative anymore. The network dimensions and alpha values of 32 and 16 respectively, worked best for all three models, as other values did not pick up the style and details of the shoes as well. The most effective value of these settings are dependent on the complexity of the subject, which in this case were all shoes, so it makes sense that they are all equal. The same applied to the learning rate and LR scheduler, other values were tried but did not get as good results, whereas the standard learning rate of 0,0001 did give good results in combination with the cosine with restarts LR scheduler.

When using the 3 LoRA models in combination with each other, it is also important to balance the strengths when making design generations. Since the thematic moodboard also existed of images that were not shoes, this model should have the lowest strength, of around 0.5-0.7, to avoid the output images from being distorted. The FP and footwear LoRA models can have a higher strength, since they are only trained on shoes. Depending on the influence of the correlating dataset the designer wants to have on the output design, he can vary with strength values between 0.6-0.95. Values of 1 should be avoided, as they seem to distort the results when used in combination with other models. Of course, it is possible to step outside these recommended ranges, but then there is less chance of getting a good result. Within these indicated ranges, the chance is highest.

### 3.4 CONTROLNET

The goal with ControlNet was to even have more control over the output, by influencing the linework and meeting requirements 7, 9 and 10. ControlNet alone produces images that are not as detailed as those generated with LoRA, in terms of materials. However, combining ControlNet with LoRA gives better results, although LoRA still tends to dominate (see figure 65). This raised the question of whether this combination is truly superior to using just LoRA. What was found was that side views were

consistently generated, without random undesirable elements like legs, as well as a consistent clean background.

It also offers the possibility of reducing the strength of the ControlNet interference, resulting in less restriction in the linework (see figure 66). This approach was used in the case study, combining the linework conditioning image of the Cruiser for ControlNet with the LoRA model trained for creating new styles.

#### 3.4.1 CONTROLNET CONCLUSION

Using ControlNet is really efficient when wanting to keep the linework of an input style consistent. The higher the model strength value is, the more similar the output linework will be to the input. When wanting to make slight variations, a value of between 0.5-0.7 is recommended. This results in an output design that is a little bit different, but still recognisable as the input style. It is however important to note that these recommendations are created based on the Cruiser, so these could be different for other styles.



Figure 65: *Input for canny preprocessor (1), ControlNet Conditioning image of linework (2), output without a LoRA model (3) and output with Cruiser LoRA and ControlNet (4)*



Figure 66: *Different ControlNet weight values, with Cruiser as conditioning image (figure 65), prompt: "Sneaker" with FP LoRA, reference image of outline silhouette*

### 3.5 VIZCOM

The Vizcom render model acts similar to the ControlNet Canny Edge model, since it renders an image that only replicates the linework from the input, rather than also the colors. The advantage however is that the user can also just input a rough sketch and get a render of a shoe in seconds. For this project however, the input is an image already, so the Vizcom refiner model is more applicable. This model generated a high-quality image that is really similar to the input image, also in terms of color (see figure 67). With a slightly lower image influence percentage, the user can also clean up some imperfections or add small details with a brush tool. With a bit of human intervention and co-design, it is possible to combine the best elements, making good generations even better and more realistic (requirement 7).

#### 3.5.1 VIZCOM CONCLUSION

When using the refiner model to upscale and refine the input image, the original colors and materials will be preserved. Starting with this model and setting the image influence to about 85-95% will make the lines smoother while maintaining accuracy. The render mode works similarly to ControlNet by only keeping the linework. This is particularly useful for adding details, as it is quick and results in high quality images, even from less precise sketches. In render mode, the materials are also higher quality and it is more detailed. Since the refiner just upscales the images, the inaccurate details of the input image can be reflected, although an advantage is that the colors match with the input. A mask mode can be used to generate only the specific details the designer wants to add. Vizcom is therefore very effective to quickly upscale the image quality and refine the concept within a few minutes.



Figure 67: The effect of different refiner models on the image quality

### 3.6 IMAGE-TO-3D AI MODEL

Experiments were done with the 3D generative AI tools to create 3D models of the Cruiser, from the 2D image outputs generated by the AI models see (figure 68). The results could be easily evaluated, since they could be compared to the shape of the real sneaker. The models work by uploading a side view image of the shoe and generating the model. Only Shap-E needed a prompt and allowed for some finetuning, since it was running on a python script. Unfortunately, the outcomes were not very promising, as the 3D meshes were low-quality and thus not suitable for practical use for development. Additionally, the meshes generated were single textured triangular meshes, making them difficult to modify for 3D development, which typically



Figure 68: 3D model outputs of different 3D generative AI tools.



requires multiple meshes for each component of the sneaker. Therefore, these models are currently only useful for communication and understanding the shape during development and production, and do not necessarily speed up the development process by eliminating the need for sampling rounds (requirement 2).

- Shap-E: The shape and texture of the shoe were recognizable but lacked accuracy and high quality. Each generation produced varying and inconsistent results.
- Alpha3D: The generated shapes were generic and not accurate. The shapes were almost identical to the real and AI images and the top view looked weird due to the mirroring of the image.
- 3D AI Studio: This tool produced very accurate shapes and high-quality textures for both input images. However, the conditioning image led to slightly less realistic shapes.

### 3.6.1 CONCLUSION

This phase will be considered an experiment and proof of concept. While the technology currently works to some extent, it is not advanced enough for 3D development purposes and integration with platforms like Emersya. Since it would still require a lot of human intervention to make a useful and applicable 3D model, 3D generative AI will not be further explored. Currently integrating it in the workflow would take too much time, which negates the benefits of saving time in the whole design and development process, so it just serves as a confirmation for future potential. Therefore, the scope of this project is also adjusted to only focus on the 2D image generation, specifically on capturing the brand identity and reflecting input from mood boards.

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## 4 VALIDATION

Testing was conducted based on intuition, with weekly sessions with Filling Pieces to discuss the output, its usefulness, and future directions. This feedback-driven approach replaced the initial plan to evaluate the intermediate version with users, which would likely only confirm existing viewpoints rather than provide new insights. These weekly sessions served as small evaluations and validations within the iterative and exploratory process.

Over time, I gained more control over the output, understood the influence of various parameters, and reevaluated solutions when tools didn't work as envisioned. This iterative learning improved the framework's effectiveness.

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## 5 CONCLUSIONS

Not all of the researched tools were effective for achieving the envisioned results (RQ1). Controlling the output accurately with just a prompt was challenging, and the standardized protocol was unsuccessful. Although a simplified version of the RAG model worked, it failed to implement specific materials into the output image.

However, the LoRA models were effective in capturing the style, especially when used in combination with each other and a reference image to ensure consistent image composition. ControlNet was also beneficial for accurately referencing linework, making all these tools useful for quick design exploration. Next to that, Vizcom was more effective in the second step, upscaling the image into a high quality design. These tools work well together, complementing each other (RQ3).

3D modeling was excluded as it did not result in the required model quality for development. This conclusion forms the foundation for the final framework workflow. It's important to note that the examples shown in this section of the report were generated during earlier iterations of the workflows, reflecting the iterative and experimental nature of this design project.

# PART 3

## FINAL DESIGN

This chapter presents the steps of the suggested AI Augmented Footwear Design Process, explaining how to practically implement each step of the AI workflow. It also shows how these steps are embodied with the AI tools researched, demonstrating the use based on a case study.

1 FINAL OVERVIEW OF THE AI AUGMENTED  
FOOTWEAR DESIGN FRAMEWORK

2 CASE DEMONSTRATION



Figure 69: Filling Pieces Low Top (*Filling Pieces, n.d.*)

# 1 FINAL OVERVIEW OF THE AI AUGMENTED FOOTWEAR DESIGN FRAMEWORK

It is important to recognize that in the traditional footwear design process, there are two distinct variations: creating new styles and updating existing ones. Both workflows however undergo the same creative phase, although the goals and design directions could be different. The outputs however remain similar for each phase, as the end goal is to create a concept that is ready for production. The only difference between the two is the way the activities are tackled. The creative phase, which is the focus of this project, is a highly visual, exploratory, and design centered phase of the whole process. This is where generative AI can significantly impact by applying the tools and methods researched.

The three steps in the current creative phase of the design process can be translated into two steps for the AI augmented design process: designing and defining (see figure 71). In this context, designing combines the sketching and CAD phases, as generative AI produces images already including colors and materials. The defining phase merges the concluding part of CAD phase and the initial part of the CMF phase, since this is where details are refined and colors finalized.

Human intervention however is still required to create the final CAD for production, as factories need this for manufacturing. Therefore there is a

small additional deliver phase that is not augmented by generative AI, before moving to the techpack phase of the current footwear design cycle.

This creative phase consists of three sub-phases in the current process. The overarching creative journey however can be divided into a divergent and convergent stage, similar to the second diamond in the classic double diamond design process (see figure 70), which is a universally accepted model that depicts the design process (Design Council, n.d.). The divergence and convergence characteristics of the classic design process are still present in the AI augmented process. The input in the beginning is however not necessarily a problem, but more a design direction, which is the starting point of creative exploration. Additionally, the output is not a solution to the problem, but a concept that fits with the design goals.

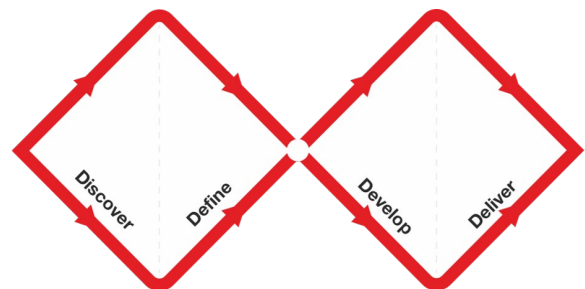


Figure 70: Traditional Double Diamond (Design Council, n.d.)

## AI AUGMENTED FOOTWEAR DESIGN PROCESS

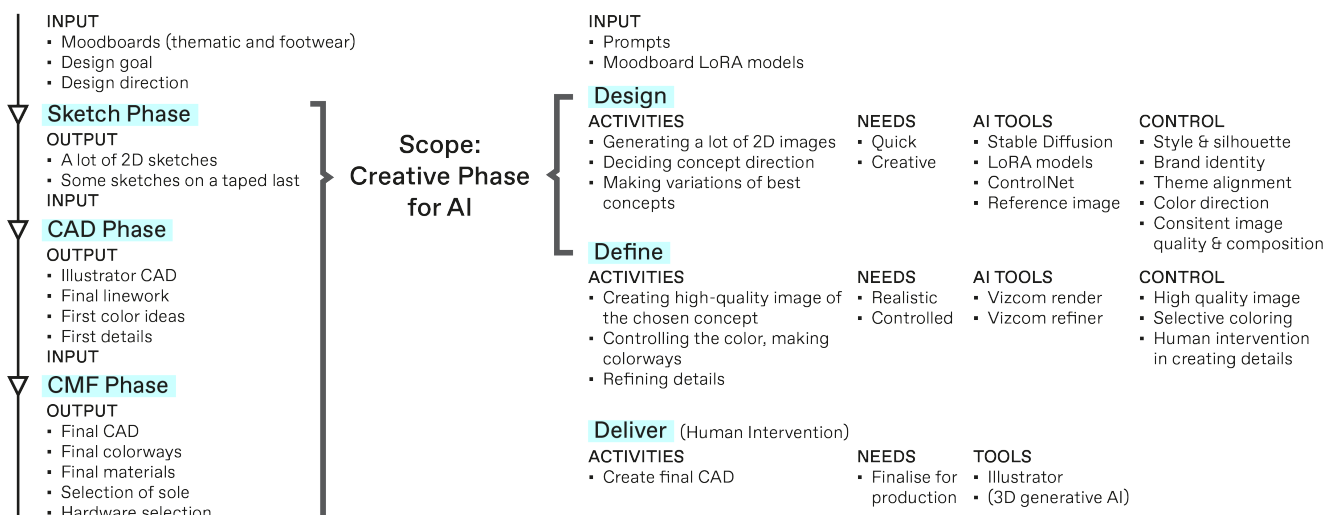


Figure 71: AI Augmented Footwear Design Process phases and activities

## 1.1 VISUAL OVERVIEW OF THE FRAMEWORK

The visual overview of the final proposed AI augmented footwear design framework can be seen in figure 73. As previously mentioned, the initial steps of the AI Augmented Footwear Design Process are different for creating new styles and updating existing ones, so they have different starting points in the complete workflow. For the designing phase, the designer can follow two AI workflows when creating new styles, having influence over the prompt and the strength of moodboard LoRAs. It is also possible to create variations of the generated images. For updating an existing style, the designer also controls the prompt and the influence of the LoRA models. Additionally, the designer can adjust the strength of the ControlNet model to determine how closely the output aligns with the original Cruiser linework.

Once the initial concept image is finished, the designer can make minor adjustments in Photoshop before moving on to the Defining phase. The next step involves using Vizcom, starting with the refiner model to achieve high quality, followed by either the render of refiner model to further add details and finalize the concept. It is also possible to create a 3D model to communicate the shape effectively, but not a necessary step for finishing the creative process.

The first phase makes use of LoRA models that ensure alignment with the Filling Pieces brand identity (requirement 6), as well as looking realistic in terms of proportions and materials (requirement 7). The balance between the strengths of the models allow for a mix between design consistency and variation, ensuring they are reliable and yet interesting (requirement 9). Additionally, the LoRA models make sure that the references from the moodboards are reflected in the final design (requirement 10).

## 1.1.1 DESIGNING

Designing is the initial phase in the workflow, characterized by creative, divergent, and rapid ideation. This phase uses inputs from moodboards to train LoRA models and generate a lot of ideas that align with the design goals. The outputs of this phase should serve as inspiration for the designer to come up with the final concepts.

### 1.1.1.1 New styles

Designing is the first phase of the AI workflow, characterized by creativity, divergence, and quick ideation. This phase uses the inputs from moodboards supported by multiple LoRA models for creating new styles. These models are based on Filling Pieces footwear styles, thematic moodboard images, and footwear moodboard images.

There are two workflows to execute in ComfyUI for the designing phase of creating new styles, the first one (see figure 72) starting with an explorative and highly divergent phase. Here, a LoRA model is used to select the styles that form the foundation of the brand identity for Filling Pieces shoes. Another LoRA model is applied for footwear moodboard shoes and thematic images to ensure alignment with the theme is visible in the concept. A reference image of a shoe outline on a white background is used, with a high denoise value to consistently produce side views on a plain background. The image generation and the LoRA models are based on the Stable Diffusion v1.4 model with the Euler sampler, to make sure that the model can quickly generate realistic images with low sampling steps. This combination of settings makes it very suitable for creative exploration of diverse design options. The prompt can also be adjusted to align with the goals of the designers, being based on the design language of the seasonal theme.

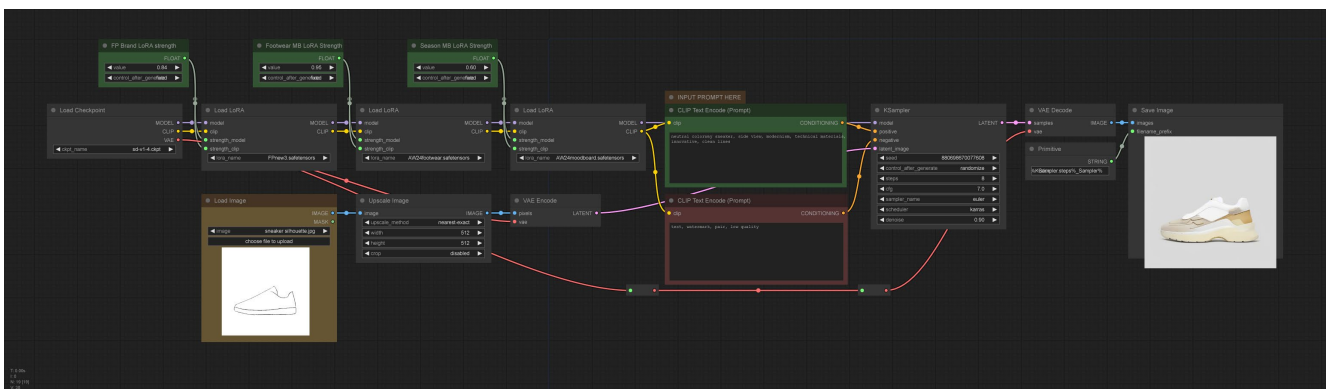


Figure 72: First ComfyUI workflow for designing new styles

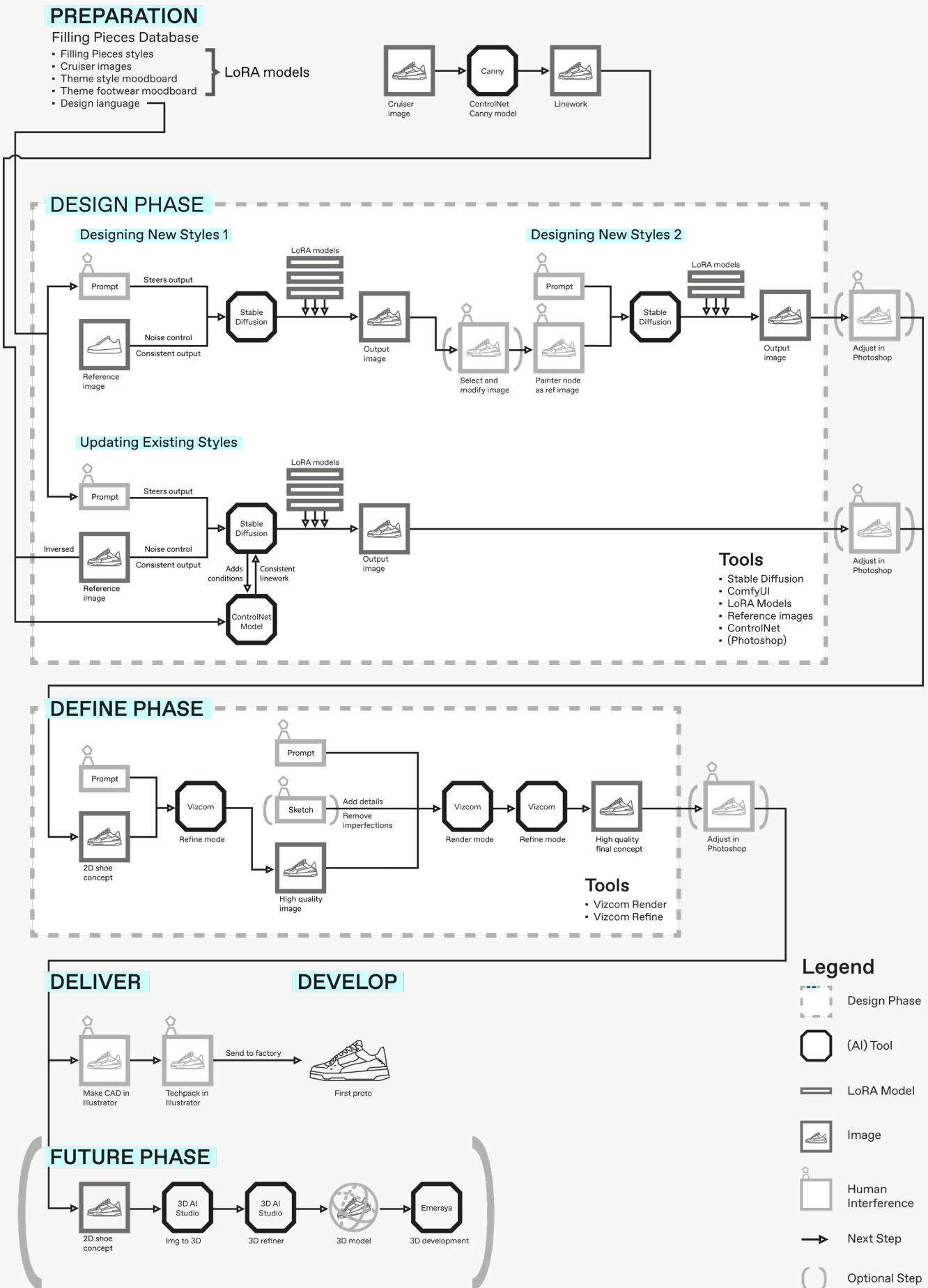


Figure 73: Visual overview of the proposed AI augmented footwear design framework



The second workflow focuses on the divergent exploration of a chosen silhouette from the first workflow (see figure 74). This image is used as a reference image that steers the generation steps of the image, to create variations. In this phase, two LoRA models are employed, the Filling Pieces styles and the footwear moodboard models, to achieve a more realistic shoe design as the output. The initial input image should already reflect the seasonal theme, otherwise it would not have been selected to continue with, so the thematic moodboard LoRA model is not necessary. This image is used in a painter node, allowing the user to also draw over the original image to create creative variations in colors and linework. The live painter node also opens up the possibility to sketch a rough silhouette as a reference image. This feature is useful when the designer has a specific vision in mind, in terms of colors or details, but also works for a rough silhouette (see figure 75). Additionally, a prompt input is required, that can be based on the design language to further guide the generation process.

In the first workflow the user has control over how much the output is influenced by the footwear moodboard styles, by adjusting the strength of that LoRA model. The composition is also controlled by using the outline sketch as reference image. For the second workflow, the general style of the silhouette is controlled, also allowing the user to sketch over it or change up the colors slightly with the painter node.

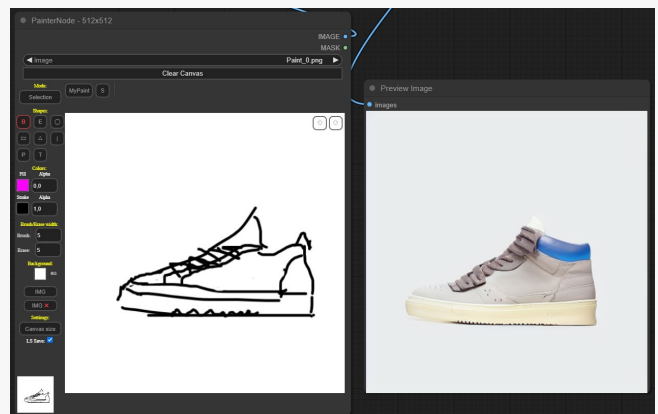


Figure 75: Live painter node silhouette sketch input (left) and generated output (right)

### 1.1.1.2 Updating the Cruiser

The same LoRA models are used for updating the Cruiser, along with an additional LoRA model trained specifically on the Cruiser. This model has learned what the Cruiser looks like, to ensure that the output will still be recognisable as a Cruiser.

For this workflow, a combination of LoRA models, a painting node as image reference and a ControlNet model are used, to make sure that the general silhouette and style of the Cruiser are maintained. This input image of the Cruiser linework is used both as a reference image with a high denoise value to create consistent compositions, as well as the input for the ControlNet Canny Edge model. For this workflow it is not desirable to generate random sneakers, since it must update an existing style. The ControlNet model strength can be adjusted to make the output more or less similar to the

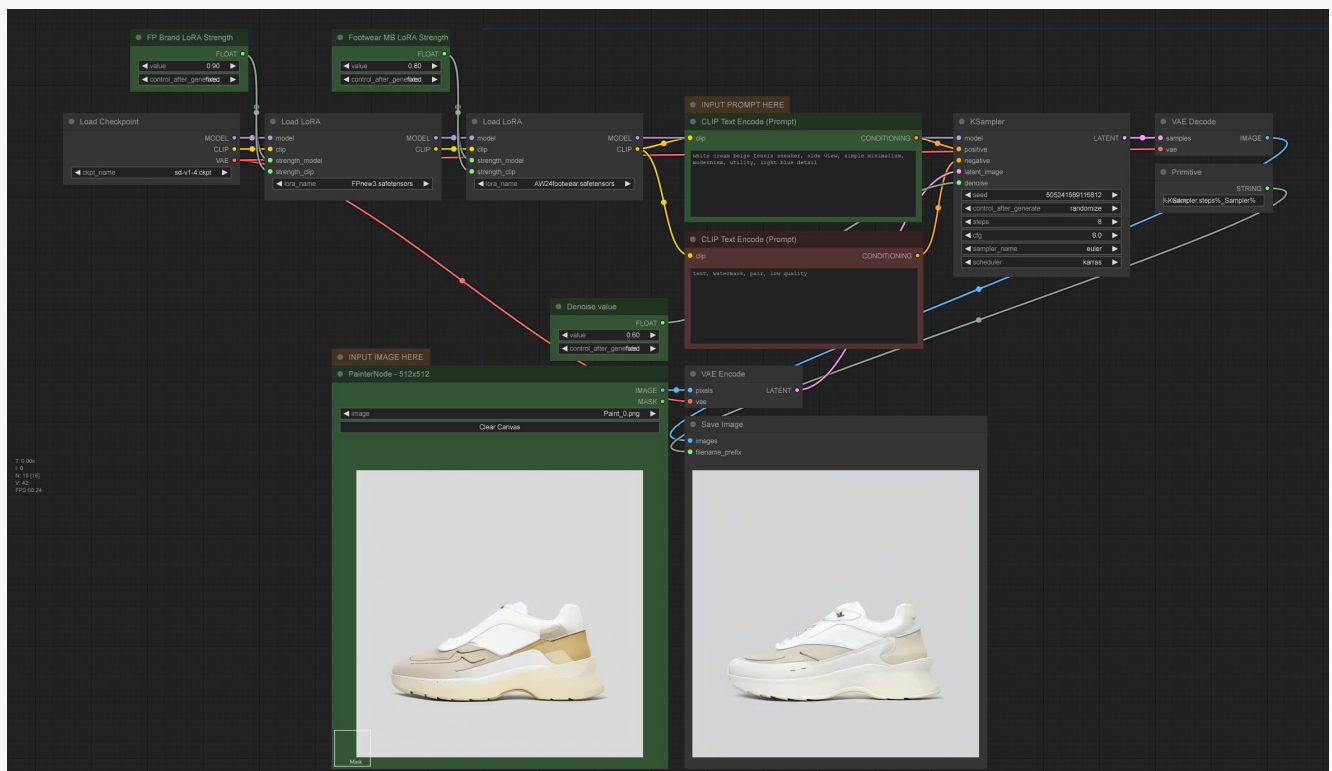


Figure 74: Second ComfyUI workflow for designing new styles

Cruiser linework. The users can also change the linework manually in the painting node that is used as input for the ControlNet Canny Edge model. This combination of ControlNet and the Cruiser LoRA model ensures that the design remains recognizable and is not changed too much, even with a lower ControlNet strength. Additionally, both other shoe LoRA models are used to explore different ideas for updating the sneaker within the constraints of the Cruiser. The output can also be guided by using a prompt.

There is control over the silhouette, since it consistently generates the Cruiser. The user can also control the strength of the ControlNet model, to adjust the degree of similarity to the original Cruiser style. Additionally, with the prompt the user can have some control over the colors, though the results may be somewhat random.

### 1.1.1.3 ComfyUI

The ComfyUI GUI looks very complex, but with its limited graphical customization options, it is still designed to be as easy to use as possible. The nodes with values that need to be adjusted are colored, where the green ones have the most impact. The yellow (reference image) and red (negative prompt) nodes are optional to change, since they do not have a great influence when changed. The gray nodes should be left as is, as those values are determined to be the most optimal through the earlier experimentation.

The file output name will include the values of the settings in the green nodes, as well as the prompt used. This allows users to retrieve and reuse the combinations when they find a particularly successful outcome, to make sure that these are not lost during exploration.

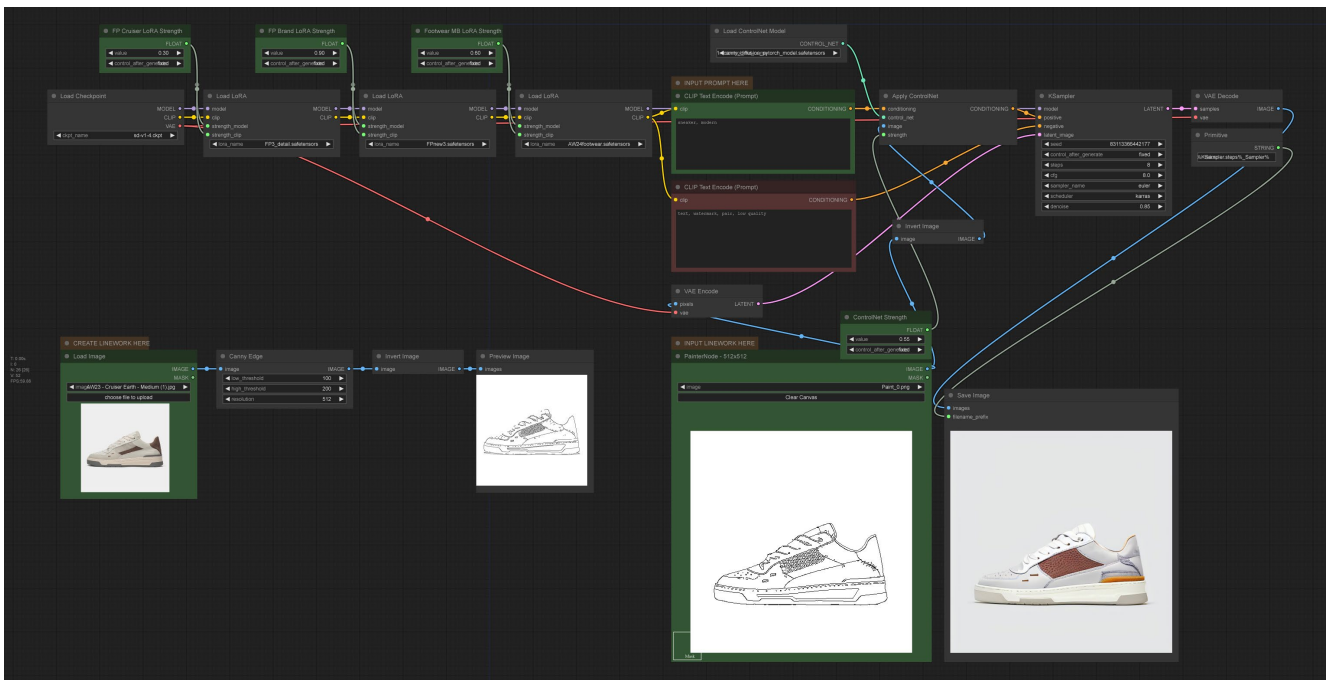


Figure 76: ComfyUI workflow for updating existing styles

### 1.1.2 DEFINING

For the defining phase, the Vizcom refiner model will be used with the input image being the image created in the designing phase. This tool allows for defining and making slight adjustments layer by layer, similar to the Photoshop UI. Start by upscaling the image to achieve higher quality, then selectively adjust all panels, details, hardware, and other elements as needed. The goal is however to minimize human intervention while maintaining control over the final result, only making changes to correct any imperfections, rather than making adjustments to change the design. The designing phase is the same for creating new styles and updating existing ones.

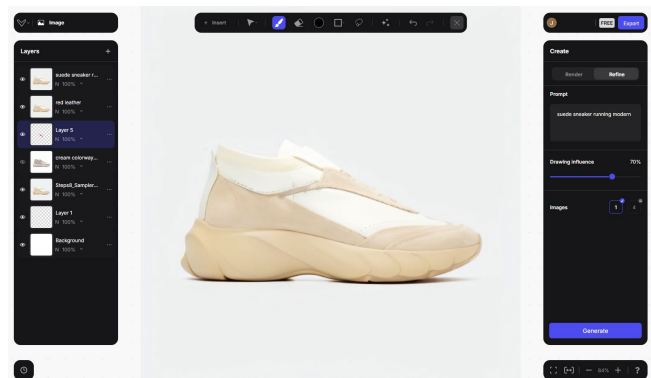


Figure 77: Vizcom UI, refiner model selected

# 2 CASE DEMONSTRATION

To demonstrate the functionality and quality of the AI-augmented Design Framework, a demonstration was done using the final proposed version of the framework and workflows. The results presented in Part 2 were generated with previous iterations and were created without a clear goal of what the output should look like. This case demonstration shows what the tools are capable of when designing with a clear design brief, it thus follows the whole workflow of the proposed framework as seen in figure 73.

First, the design brief is explained with the moodboards for the LoRA models. Then, both assignments, updating the Cruiser and designing a new style, are executed in both the designing and defining phases. Finally, 3D models are created as a proof of concept. This process can be seen in figure 78.

## 2.1 DESIGN BRIEF

The design brief for the case study involves creating a new silhouette and updating the Cruiser for the AW24 season. Since the designs for this season are already finished and being produced, these releases can be compared to the AI generated designs. This case study aims to test and demonstrate the design process, since it has a clear design direction. By focusing on this specific seasonal theme and referencing it in the design, the influence of moodboards and inspirations can be evaluated for how effectively they translate into the final designs.

### 2.1.1 UNITED BY DESIGN - MODERN ARCHITECTURE

The AW24 season theme is “United by Design,” inspired by modern architecture. It emphasizes modernism and experimentation, aligning perfectly with this experimental and AI oriented design approach. The design language features core colors with pop accents, including black, white, and neutral tones. It incorporates geometric forms and abstract shapes, with clean linework and simple, geometric forms. The principles of “form follows function” and “less is more” are central, with the focus on minimalism, utility and quality. This is realized by using new and innovative technical materials.

Modern architecture has significantly influenced product and fashion design with its clean lines and functionalist approach. It has inspired designers

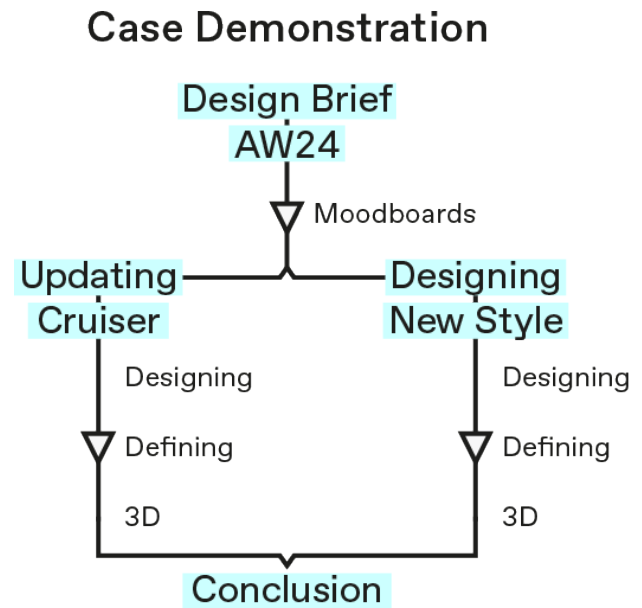


Figure 78: Case demonstration structure

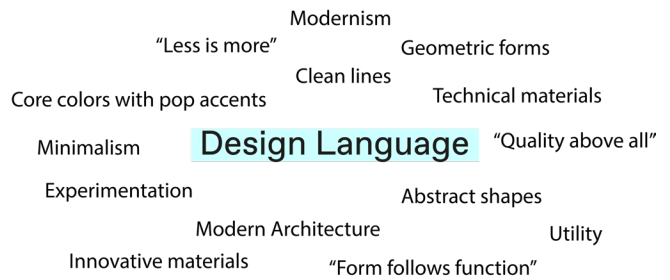


Figure 79: Mindmap of the Design Language, words that relate to the theme

to experiment with and develop new materials. This design style rejects predetermined rules, it focuses on freedom of expression. This aligns with the AI augmented design approach, as it also represents the rejection of the current design process. Furthermore, freedom of expression in the context of AI can be interpreted as the randomness that is inherent with AI models.

The words that were used as input prompts for the generated image are seen in the mindmap of the design language (see figure 79), influencing the appearance of the output. They align with the theme, ensuring the overall style of the output image remains consistent and as desired.

The images in the moodboard in figure 80 formed the database for the Thematic Moodboard LoRA model, which guided the output style to align with the Modern Architecture theme in terms of colors, linework and overall aesthetic.



The AW24 moodboard initially contained only three shoes, so additional design references needed to be added for training a LoRA model. The selection of these additions was based on the original 3 shoes and alignment with the rest of the theme, and can be seen in figure 81.

Those are images are included in the database for the AW24 footwear LoRA model, guiding the designs toward silhouettes that align more closely with the theme. They matched the colors design language of the theme, being modern yet experimental in terms of materials and linework.



Figure 80: Thematic moodboard images used for the Thematic Moodboard LoRA model

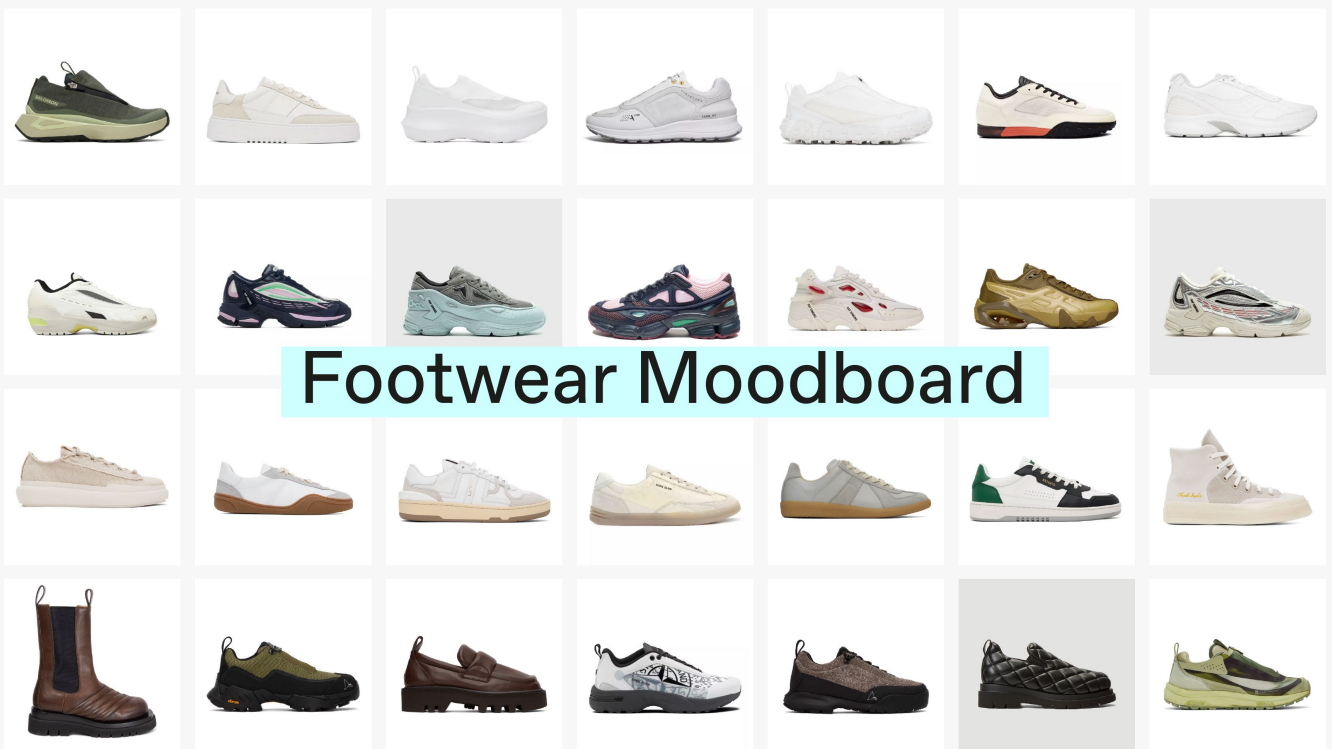


Figure 81: Footwear moodboard images used for the AW24 Footwear LoRA model



## 2.2 IDEATION CRUISER UPDATE

A lot of variations of the Cruiser were generated by playing around with the strength of the Cruiser LoRA model and ControlNet model, which influenced the degree of similarity to the original linework. The words “sneaker” and “modern” were used in the prompt to keep it simple and allow for more creativity from the AI model. The eight shoes in figure 82 were cherry-picked since they all had something interesting and had varying amounts of difference to the original style.

Some variations featured only minor changes, while others had notable adjustments in linework, patterns, and materials. The three most interesting designs from these were selected and slightly refined in Photoshop for more visual clarity, by removing the imperfections (see figure 83).

Concept 1 is just a new colorway that aligns with the theme, in a cream monochrome design with an orange accent. Concept 2 stood out due to the use of a canvas material, a simpler pattern, and a unicolored sole, making it more cost-effective. Concept 3 offers a ‘light’ version of the upper, yet maintaining enough similarity to the original to remain recognizable.

The final concept will combine the colorway of concept 1 with the design of concept 3. This concept is very interesting in terms of development, since it is a simplified version of the Cruiser upper. The original style has a quite complex design with many different panels and materials, which makes it expensive to produce. Therefore, it is interesting to explore a more simple and accessible approach to this style that is still relevant to the theme of AW24 and fits within the brand identity.



Figure 82: Selection of 8 cherry-picked generated Cruiser designs

1

2

3



Figure 83: The 3 most interesting AI generated Cruiser concepts

### 2.2.1 DEFINING DETAILS

The colors were edited in Photoshop and the whole concept was refined with Vizcom to achieve a higher resolution. Additionally, some parts, such as the collar, required some more selective refining with Vizcom due to imperfections in the initial generation. The final concept is a successful update of the Cruiser style that demonstrates the effectiveness of the proposed AI framework. This revised design process shows that experimenting with different redesigns can be really experimental, yet result in tangible and realistic designs. The final concept is a very concrete example of what a cost-effective version of the Cruiser could look like.

In 3D AI Studio, the final defined image with the background removed was used as input for the AI software to create a 3D model, afterwards the mesh was refined with the same tool. The result, which serves as a proof of concept, shows that the shape is quite accurate. However, some details like the laces, eyestay and vamp are unrealistic. This can be explained by the fact that only a side view is used.



Figure 84: *Final AI generated Cruiser concept, retouched in Photoshop (left) and final high quality concept refined with Vizcom (right)*



Figure 85: *Final generated 3D models, draft version (left) and refined version (right)*

## 2.3 IDEATION NEW STYLE

### 2.3.1 GENERATING DESIGNS

First, various prompts were tested in the first workflow to determine which ones produced the best designs. This involved exploring the influence of specific words from the design language on the output images. Additionally, the right balance between the strengths of the three different LoRA models needed to be found.

During this exploration and once the balance was found, numerous shoes were generated (see figure 86) and used as input images for the second AI workflow, to make a final selection of a few interesting designs for further exploration. In the end, the prompt was: “neutral colorway sneaker, side view, modernism, functional technical materials, innovative, clean lines.” These words were derived from the design language mind map and seemed to give the most desirable results.

These concepts all have certain aspects that align with the theme, the brand identity, or just look aesthetically appealing. For example, one shoe features a sole variation inspired by the Jet Runner style and has a stitch-and-turn seam, which gives it a luxurious feel. Some soles have an interesting arch, and add to the functionalist design approach. Additionally, all color combinations align with the natural tones of the theme. Some shoes also have an interesting play of materials, the last shoe seems to have a mesh upper with a welded TPU overlay, which is really technical.

Not all shoes have realistic proportions, and sometimes the soles did not match the upper. To address this, combinations between uppers and soles were made and adjusted with Photoshop. This led to the creation of three concepts in figure 87 that were interesting to develop further.

Concept 3 is going to be defined further, since it is the most futuristic and innovative concept of the 3 and aligns best with the seasonal theme in terms of aesthetics. Concept 1 does not fully capture the FP brand identity, while the upper of Concept 2 on the other hand is not experimental enough. According to the Filling Pieces team, Concept 3 is the most aesthetically appealing and clearly shows an interesting influence of the AI models, while it could still be a Filling Pieces shoe. It is also the most interesting balance of technical and innovative materials, showing the harmony between form and function.



Figure 86: Selection of 8 cherry-picked generated new style designs

### 2.3.2 GENERATING VARIATIONS

When using the concept image as the input for the second workflow, variations of this style were created, as seen in figure 88. To maintain consistency, the same prompt used for the first generations was used, but the strengths of the LoRA models were adjusted to either increase or decrease the influence from the Filling Pieces brand identity and the footwear inspiration from the moodboard. Next to that, a higher denoising value was used to get more creative variations, but not too high to ensure the silhouette of the output remained roughly similar. Ultimately, this process served as inspiration. With only minor adjustments, the concept was ready to be refined in the next phase to finalize the design.

1



2



3



Figure 87: *The 3 most interesting AI generated new style concepts*



Figure 88: *Example variations generated by workflow 2, with concept 3 as input*



### 2.3.3 DEFINING DETAILS

Being visionary and innovative, this new design direction targets a specific market segment, providing a good design idea for the AW24 season. This concept is valuable for the design department to guide and inspire their creative process. To address a small imperfection in the sole, an orange shank was added in Vizcom to create a color pop, similar to the Cruiser concept. This was the only human intervention in the AI augmented design process for this concept.

In 3D AI Studio, the final defined image with the background removed was used as input for the AI software to create a 3D model, afterwards the mesh was refined with the same tool. The result shows that the shape can be generated quite realistically. Some details like the lacing system are not correctly translated however.



Figure 89: *Final high quality concept retouched and refined with Vizcom*



Figure 90: *Final generated 3D models, draft version (left) and refined version (right)*

## 2.4 CONCLUSION

The generated concepts (see figure 91) successfully reflect the Filling Pieces brand identity and theme of the AW24 season (RQ5), with a functional and minimal aesthetic in terms of linework, and a technical and innovative approach with the materials and lacing system. The update of the Cruiser is also successful, featuring a more minimalistic approach while effectively using colors that align with the modern architecture theme. The generation of the images was very fast, as it took about 12-16 seconds per image. This is very beneficial for the process, as the designer does not have to spend time waiting for the designs (RQ4). With more computational power, generation could be even faster, which would open the possibility to generate multiple designs simultaneously.

The design process was significantly accelerated, since there was no need to create rough sketches and the process jumped right into more concrete design concepts. In one day, two designs, with high-quality images in addition to a rough 3D model were produced. These designs were nearly complete without any human intervention, only adding more branding and refining some details would be improvements to make. However, the goal was to minimize human intervention, which was successfully achieved.



Figure 91: *Final AI generated and refined concepts*

# PART 4

## DESIGN EVALUATION

The workflows were specifically built for Filling Pieces, with the intention that the designer can use it to create effective results. In this part of the report, the focus is only on the designing phase of creating new styles, meaning only the first two ComfyUI workflows are used (see figure 72 & 74). This was a conscious choice, to make the evaluation process less complex, since the designer required explanation on how to use the tools. If all outputs were to be evaluated, it would be a very long evaluation process.

1 EXPLORATION ON MEASURING  
PERFORMANCE  
2 METHODOLOGY

3 RESULTS  
4 DISCUSSION  
5 CONCLUSION



Figure 92: Filling Pieces SS25 showroom (Filling Pieces, n.d.)

# 1 EXPLORATION ON MEASURING PERFORMANCE

## 1.1 MEASURING PERFORMANCE

The performance can either be measured by the quality of the output, or the quality of the creative process. Since idea quality also reflects the whole creative process, measuring the entire process gives a better view of the framework's impact. The AI-generated outcomes are always subject to some degree of randomness, so it is not sufficient to solely focus on the outcome quality.

Human designers produce rough sketches and technical drawings, while the AI generates photorealistic images, making direct comparisons difficult. Success should be measured by quantifiable metrics like design speed, visual communication usefulness, and process efficiency, rather than directly comparing outputs. These measurements relate to the indirect benefits, such as saving time and costs in the process. Comparing the quality of the design process itself, including creativity and divergent thinking for example, offers a better measure than comparing outcomes directly. It's also important to consider how well the ideas align with the design goals, balancing both divergent and convergent thinking.

## 1.2 MEASURING THE CREATIVE PROCESS

Since each creative process is unique, its quality and efficiency is also dependent on the context. There is no universal approach to a design process, only a broad and fundamental outline that has to be adjusted according to the context, which also

applies to the evaluation of the process. Each design context requires a specific evaluation method based on the most important criteria for the corresponding context (Gabriel et al., 2016).

Creativity is often linked to divergent thinking when examining the creative process, typically measured by the Alternative Uses Test (AUT). In this test, participants have to come up with as many creative and novel uses as possible for a common object (like a brick) within a fixed amount of time. The total number of ideas and the originality of ideas are rated to measure their creativity (Hass, 2017).

While this test is a standard for assessing divergent thinking, it doesn't fully represent general creativity as it ignores the usefulness and feasibility of ideas, making it less applicable to real-world problem solving. Kudrowitz and Dippo (2013) therefore suggest that an improvement to the AUT is to limit the number of ideas participants can generate. This constraint would likely encourage them to focus on presenting more novel and useful ideas.

Verhaegen et al. (2013) created a high-level overview of different metrics of creativeness of ideas and ideation methods, based on multiple studies (see figure 93). These metrics allow for a more complete evaluation, focusing not only on the number of ideas generated but also on their diversity, originality, and practicality. By dissecting these metrics, the evaluation of the creative process is more detailed and nuanced, which makes it more suitable for evaluating the design process.

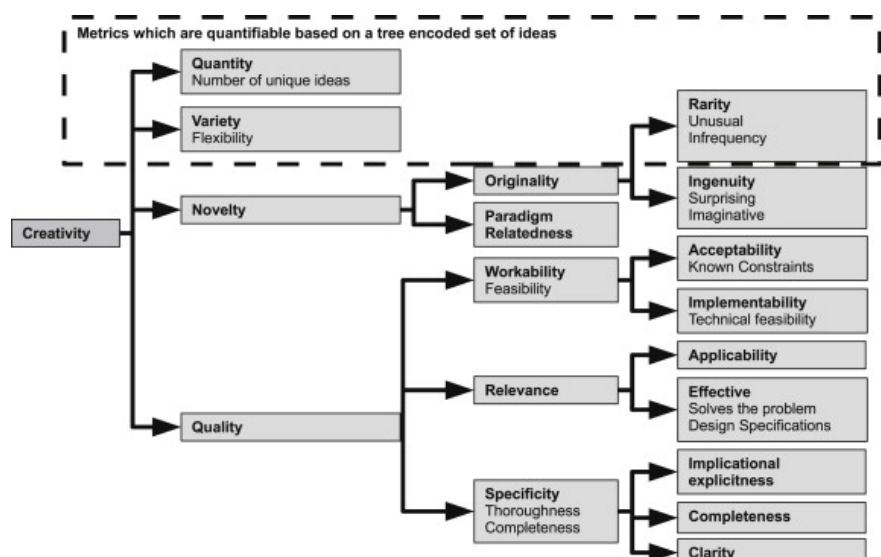


Figure 93: High-level overview of the creativity metrics (Verhaegen et al., 2013)



It is important to evaluate not only the process but also the application of that process in terms of the quality of the outcome. The quality of the outcome should be assessed for its value, both aesthetic and functional. Aesthetic value can be measured by novelty and complexity, which have proven to be good indicators of outcome quality for GAN models (Yuan et al., 2023).

There is a Wundt curve correlation between the likability of a design and its novelty and complexity. This means there's a sweet spot: designs with too little or too much novelty have a low value, while those with moderate novelty and complexity are more valued. This balance maximizes the perceived aesthetic value, or hedonic value, of the outcome (Sbai et al., 2018), which is also supported by the MAYA (Most Advanced, Yet Acceptable) principle (Honda et al., 2022).

Only three of the suggested metrics are quantifiable: the quantity, variety, and rarity. But variety and rarity require a large sample size as they are calculated in comparison to responses of other participants. The remaining metrics are subjective, based on individual interpretations and judgments. Since it is hard to objectively measure creativity, it is crucial to ensure that the subjective metrics are thoroughly and systematically evaluated, to ensure reliable results. They should be clearly explained, so the participants understand exactly what they

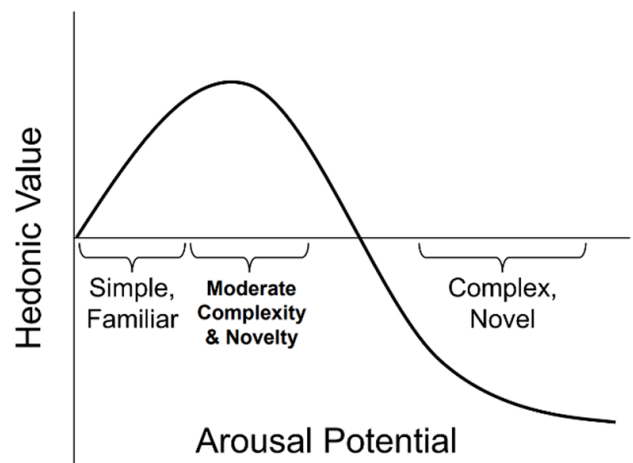


Figure 94: Wundt curve (Honda et al., 2022)

are assessing, to reduce personal interpretation. Additionally, a larger sample size increases the validity of the results by reducing the impact of outliers and random variations.

For final evaluation, the following performance metrics for the context of generative AI-augmented footwear design are suggested in figure 95 (RQ4). Note that variety is not included, as the creative process outcomes are sketches and images rather than ideas, making it difficult to quantify. In footwear design in the realm of fashion, the focus is on aesthetic needs rather than problem-solving. Additionally, relevance as part of quality is reframed as alignment to the design goal. This translates to how well the concept or sketch aligns with the initial design goal and seasonal theme. Finally, usefulness is both part of process efficiency, as well as specificity that determines the usefulness in terms of visual communication of the outcome. These metrics give a complete picture of the performance of the proposed framework, both for the quality of the process and its outcome.

There is a clear distinction between the metrics used to assess the process and the outcome, so these were evaluated differently. The quality of the process was assessed through a user test, that is inherently qualitative. During this first phase of the evaluation, all outcome-related metrics were therefore also qualitatively evaluated. To also gather quantitative data, the second phase of the evaluation solely focused on the quality of the outcome, done through an online survey. It is important to note that the intended goal could not have been evaluated in the survey, as it is only clear to the designer that created the output what his personal design intent was. In conclusion, the metrics highlighted in blue are the measures that measure the performance of a creative process of both the outcomes and the process itself.

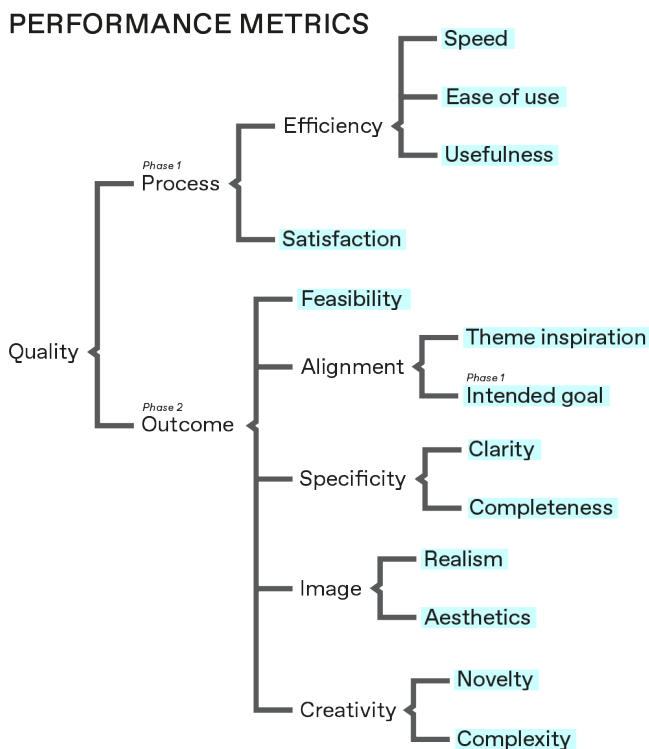


Figure 95: Performance measurement metrics; highlighted blue words are the ones that will be questioned and evaluated specifically.

# 2 METHODOLOGY

The goal of the final test is to assess the effectiveness of the process and outcome of the proposed AI framework in two phases. In the first phase, the focus will be on qualitative results, evaluating the effectiveness of the AI augmented process and the interaction with the AI tools. This was done with the Footwear Designer of Filling Pieces, to get the most thorough understanding of the quality of the brand specific AI workflows that are proposed. Ideally, the user test would have been done with multiple designers, but they lack the understanding of Filling Pieces identity. The final version of the framework and workflows were used, the same version with which the case demonstration had been done.

The outputs of the first phase will be used for the second phase, where quantitative data is gathered to evaluate the quality of the outputs, benchmarking the AI generated designs against traditionally made designs. This was done through a survey with a large number of participants, to test if the requirements for the output designs are met.

A pilot test was conducted with an IDE student that has design experience and academic knowledge about assessing designed products and systems (see figure 96). The pilot test provided critical feedback, which led to slight improvements in the methodology of user testing. Since the interface and user experience was not developed, because the focus was primarily on the functionality and performance, it was important to give a demonstration of how the tools work.

The evaluation with the user test will only focus on the creation of new styles, rather than updating existing ones, due to time constraints and the project scope. Since the workflows are relatively similar, it can be assumed that the results will be comparable for both workflows. Additionally, the defining phase with Vizcom is not included in the evaluation as it was not designed as part of this project, but rather an existing tool integrated in the overall framework. Comparing the use of Vizcom to the traditional process would also require the designer to create a complete CAD model, which is a time-consuming task and therefore not feasible.

## 2.1 PHASE 1: QUALITATIVE ASSESSMENT

The first phase, which is the user test, was conducted with the footwear designer from Filling Pieces (N=1). The workflow is specifically tailored to Filling Pieces, since the LoRA models are trained on the brand's data. Since reflecting the brand identity was one of the objectives, this can only effectively be measured if the designer has experience in designing for the Filling Pieces.

This participant will also be the end-user of the proposed framework. By conducting the user test with him, valuable insights were gained into his opinions on what works well and what needs improvement. The goal is to determine whether he would actually use and implement the framework, which was discovered through this assessment. Since both of our preferred languages were Dutch, the test was conducted in Dutch. The session was audio-recorded, and the participant was asked to think aloud to capture their thoughts, ensuring the best qualitative understanding.



Figure 96: *Pilot test*

### 2.1.1 Method user test

A general overview of the user test process can be seen in figure 97. The user test began with an introduction where the goals of the study and the project overview were explained. Some background information was asked to get an understanding of his professional experience, such as his design and footwear experience, as well as familiarity with AI tools.

Next, a detailed explanation of the design brief was given. The task was to design a new functional footwear style, both with and without the AI framework. The brief specifically was to design it for the AW24 collection, inspired by the seasonal theme: United by Design - Modern Architecture. Moodboards were shown to provide context and visual inspiration. He was given the opportunity to briefly do a warm-up exercise to get ready for the test. To get a comprehensive understanding of his thought process, he was instructed to think aloud during the tasks to capture his thoughts and reasoning.

#### 2.1.1.1 Traditional design task (without AI)

The traditional design task was divided into two parts, the first task being to make rough explorative and divergent sketches for 5 minutes. The goal here was to come up with a lot of ideas where rapid ideation was encouraged. Before going to the next part, he was asked to select the best sketch to refine. The next step was to refine this sketch for 5 minutes into a more definite and complete concept design. Following this process, the participant was asked to provide feedback on the process and outcome, based on a semi-structured set of questions (see appendix D).

In the pilot test, the participant, a design student that was not very experienced with footwear, used iPad sketching to define the design. He stated that 5 minutes was sufficient, however, after the user test with the Filling Pieces designer, it became clear that 5 minutes for defining the design was too short. The difference in quality between the CAD created by the designer in 5 minutes and an AI-generated image was too obvious (see chapter 3.1.2, figure 100). It was also not representative of his skills and the quality of the work he normally does. Therefore, the control design was changed to a CAD design made without time constraints that he had created previously for the AW24 season.

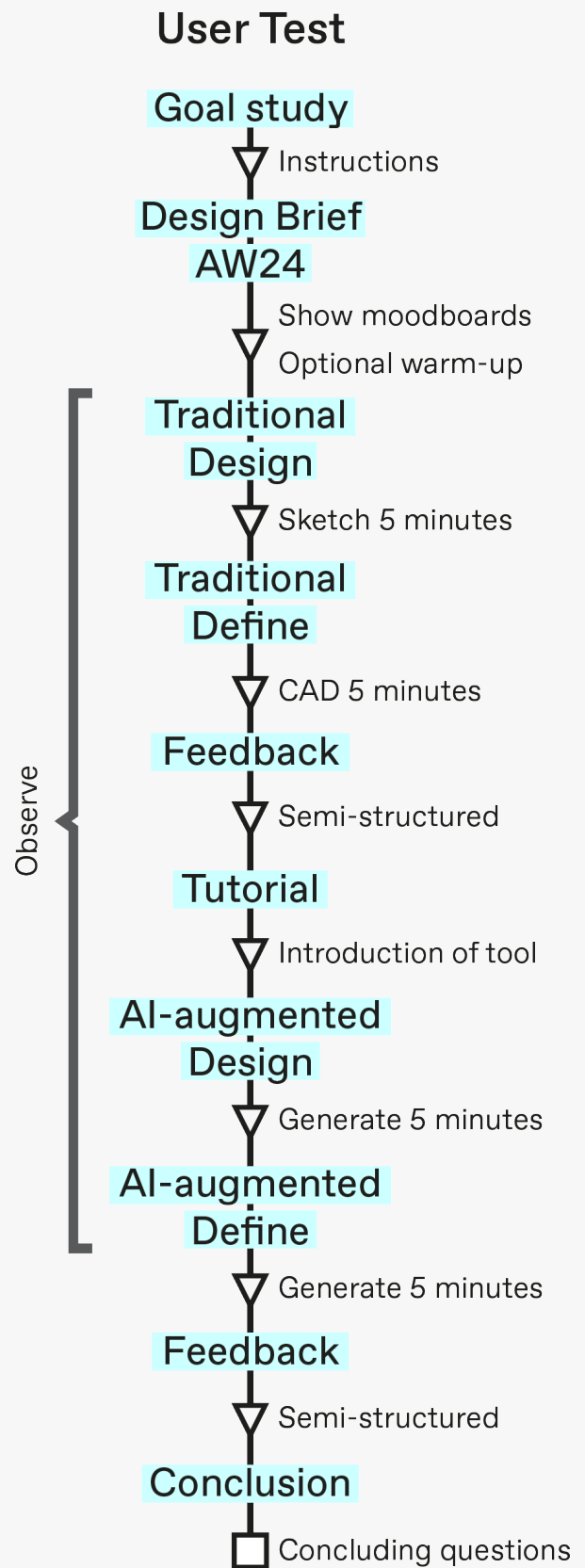


Figure 97: Overview of the user test process

### 2.1.1.2 AI-Augmented design task (with AI)

Before starting the user test with the proposed AI framework, an introductory tutorial had to be given to explain what values parameters could be adjusted and what their influence was. The participant was instructed to only change the values of the green nodes, which had the most significant impact on the output design. The prompt had to be based on the design language and project goal of the theme, with the LoRA strengths adjusted according to desired influence of the moodboard, within the ranges that were identified to be optimal according to earlier experimentation. Next to that, it was explained that multiple prompts could be queued without affecting overall speed, and that the settings used in the AI tool were found in the file name of the output for reference.

The participant was allowed to ask questions on the use of the framework, since the goal was to assess the effectiveness and quality of the framework, not the interface and design of the tool.

The only change made after the pilot test was the addition of recommended ranges for each value of the green nodes (see figure 98). To make the workflow a bit more user friendly, this visual cue was added to the interface. No changes were made to the parameters or the design of the framework itself however.

The AI-augmented design task was also divided into two parts, similar to the traditional design process. In the first part, the participant had to spend 5 minutes exploring designs using the first explorative workflow. Again, he was asked to select the best design to create variations on and refine it into a more complete concept. Following these tasks, he was asked to provide feedback on the process and outcome, based on the same set of questions.

To conclude the user test, additional questions were asked to gain deeper insights. These questions were not only based on semi-structured question format (see appendix D), but also based on observations made during the use. These concluding questions aimed to capture the participant's perceptions, experiences and acceptance of the AI tools used in the design process.

## 2.2 PHASE 2: QUANTITATIVE ASSESSMENT

For the second phase, the qualitative evaluation, a survey was distributed to a group that included people with experience in the footwear industry, as well as people with design experience. This selection was made to ensure that participants were familiar with the context, to obtain valid responses. In total, an amount of 37 respondents (N=37) answered the survey. The whole survey can be found in appendix E.

The goal was to gather quantitative results on the quality of the outcomes of the user test, comparing designs made with the AI workflow with CADs made for AW24, which had the same design brief. This assessment would determine whether the design requirements were met. A Likert scale is used to rate the performance metrics, providing a quick and relatively easy way to analyze data from the qualitative questions. Rating responses on a scale from 1 to 7, with each response option labeled, has been proven to lower response bias and increase consistency in answers (Weijters et al., 2010).

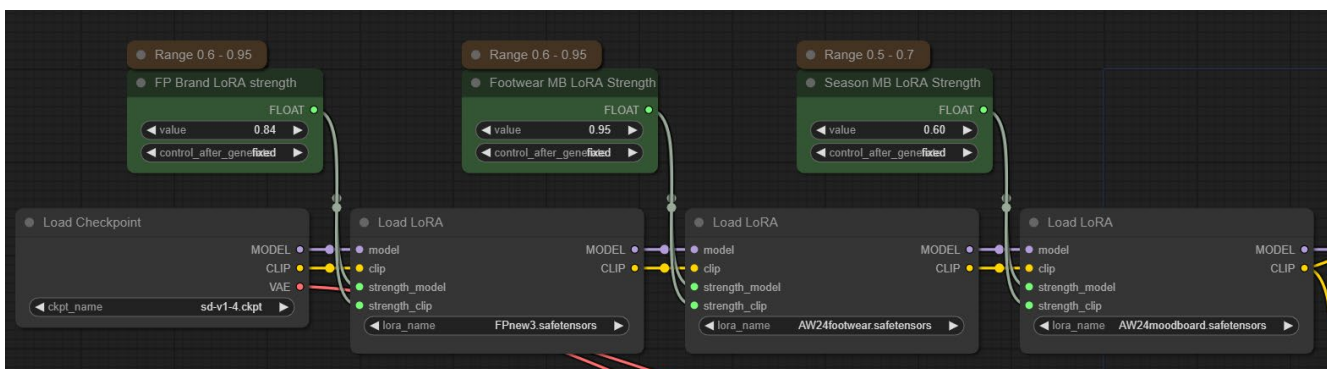


Figure 98: Addition of the recommended value ranges



### 2.2.1 METHOD SURVEY

The evaluation survey began with an introduction explaining the goal of the study and providing an overview of the project, without mentioning Filling Pieces. Participants were asked to provide data on their design experience, experience in the footwear industry, and familiarity with AI tools. This information would be used to contextualize their responses and ensure a relevant and informed evaluation.

The survey showed the design outputs from the user test, both traditional and AI-generated, side by side. This allowed participants to directly compare the different design methods, without naming which design was created using which method. Participants had to rate the designs on the selected metrics using an online survey to determine the quality of the design outputs. The metrics were rated on a fully labeled Likert scale from 1 to 7, with 1 being the lowest (e.g. very unrealistic), 4 being neutral, and 7 being the highest (e.g. very realistic).

After this rating section, it was named how the two designs were made. To gain a comprehensive understanding of the participants' perspectives on AI in design, additional questions were included that provided room for general comments and suggestions for improvement. Participants were also asked if they could identify the brand the designs were made for, to see if they could recognize the Filling Pieces brand identity.

### 2.3 DATA ANALYSIS

The interview data, as well as the written answers from the survey were thematically analyzed, to find commonalities in the answers. SPSS was used to digitally analyze the collected numerical survey data. To measure the statistical significance of the results, various statistical tests were conducted.

Independent t-tests were conducted to compare the means of the Likert scale ratings for the performance metrics of design A and B. A chi-square test was performed to analyze the design preference and the perception of what brand the designs were made for. To determine the significance of the differences, p-values were calculated. Results were considered significant with a p-value < 0.05.

The analysis was also conducted separately for participants with and without experience in the footwear industry. The threshold was set at the novice level (less than one year of experience), with novices, students and those with no experience grouped together. Participants with experience classified as beginners (1-3 years of experience) or higher were included in the experienced group.

This study uses a mixed design approach to assess the differences within and between subjects. The main focus is to compare the differences between design A and B, traditional versus AI-generated designs, within the same participants. Additionally, the study looks at the differences in their ratings of the metrics between participants divided into two groups: experienced versus non-experienced in the footwear industry.

# 3 RESULTS

The designer that did the user test has more experience in developing designs into final products, rather than executing the sketching process itself. Overall, he has about 3 to 4 years of design experience, with 2 to 3 years specifically within the footwear industry. Next to that, he did have some experience with AI tools like ChatGPT and Dall-E and uses them occasionally. His initial perception was that they are not yet suitable for professional use because they do not understand the design language of Filling Pieces.

Out of the 37 survey respondents, there were 13 respondents out of a total of 37 who had at least 1 year of experience in the footwear industry. Additionally, all respondents stated that at least at some experience with AI tools. Responses of the survey were rated on a 1-7 Likert scale, where 1 indicates the lowest and 7 the highest level. The detailed participant demographics are summarized in Table 5.

Table 5: Survey participant demographics

Variable	Item	N	%
<b>Age</b>	18-24	17	45,9
	25-29	12	32,4
	30-39	7	18,9
	40-49	1	2,7
	50+	0	0
<b>Experience as a designer</b>	No experience	5	13,5
	Student	14	37,8
	Novice (less than one year)	0	0
	Beginner (1-3 years)	6	16,2
	Intermediate (4-6 years)	8	21,6
	Advanced (7+ years)	4	10,8
<b>Experience in footwear industry</b>	No experience	18	48,6
	Student	3	8,1
	Novice (less than one year)	3	8,1
	Beginner (1-3 years)	3	8,1
	Intermediate (4-6 years)	7	18,9
	Advanced (7+ years)	3	8,1
<b>Familiarity with generative AI for images</b>	Not familiar at all	0	0
	Slightly familiar (I've heard of them but never used them)	2	5,4
	Somewhat familiar (I've used them a few times)	12	32,4
	Moderately familiar (I use them occasionally)	13	35,1
	Very familiar (I use them regularly and am well-versed in their capabilities)	9	24,3
	Expert (I have in-depth knowledge and extensive experience using them in various projects)	1	2,7
	<b>Total</b>		<b>37</b>

### 3.1 FOOTWEAR DESIGN RESULTS

#### 3.1.1 TRADITIONAL DESIGN PROCESS

In 5 minutes, the designer made 4 rough sketches of shoes for the design brief (see figure 99), which is 0.8 per minute on average. He used underlays to sketch over the silhouettes, his preferred method of working.

He tried to convey the theme through clean lines and hardware such as big eyelets in his sketches. He mentioned that he did not spend much time on the soles, as they require a large investment, so he focused on the upper. His sketches included a mix of footwear styles, reflecting the theme consistently.

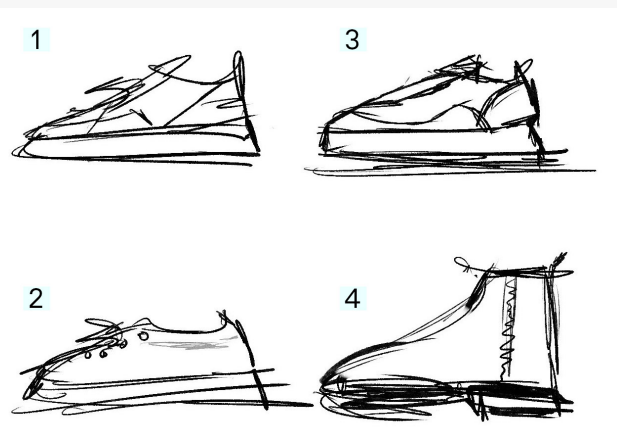


Figure 99: *Rough sketches the designer created in 5 minutes*

#### 3.1.2 TRADITIONAL DEFINE PROCESS

He chose sketch 2, the dress shoe, to define further in Adobe Illustrator, as he saw the most potential in this idea. Since it was far from complete and he had no clear vision of the final look, he just started doing something. However, completing this process within just 5 minutes was unrealistic, as he typically spends about 30 minutes per design. So given the time constraint, the end result does not really reflect his skills (see figure 100).

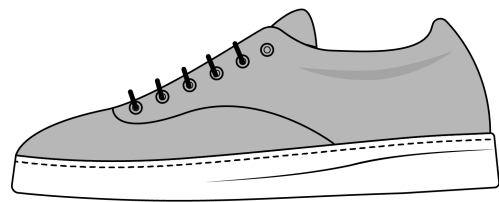


Figure 100: *CAD the designer created in 5 minutes*

If he had 30 minutes, the outcome would have most likely been significantly better. An example of a complete CAD he created in about 30 minutes can be seen in figure 101, which is a good example of what he is capable of. Since this is more representative of his skills, it was used for the comparison in Phase 2 of the final evaluation, rather than the 5-minute CAD as shown in figure 100.



Figure 101: *CAD made by the designer for AW24*

#### 3.1.3 AI DESIGN PROCESS

Using the AI workflow, he created a total of 10 initial concepts in 5 minutes, an average of 2 concepts per minute. He began by reviewing the theme moodboards to craft a prompt for the desired shoe design. Aiming for a more formal shoe, he initially used a prompt for a dress sneaker to maintain some sneaker influence. The results were mostly sneakers with a hint of dress shoe elements, as seen in figure 102.

To increase the influence of the brand identity, he increased the LoRA value and experimented with different descriptive words for the prompt. The final concept he chose was a dress shoe upper on a sneaker sole, which he described as a creative interpretation by the AI. He used the prompt: “neutral dress sneaker, side view, clean, classic materials, basic lines.”

#### 3.1.4 AI DEFINE PROCESS

He used that image as the input for the second phase of AI, spending 5 minutes to create 16 variations, averaging 3.2 concepts per minute. His intention was to blend the sneaker and dress shoe upper with a dress shoe sole, so he adjusted the prompt to “dress shoe...”. However, the sole design did not really change, only slight variations of the upper were generated. To produce more creative variations, he consciously increased the denoise value outside of the recommended range, to change the overall silhouette and hope for a result that looked more like a dress shoe.

Despite his efforts, changing and adjusting the sole did not work as intended. He wanted a dress shoe sole, but the sneaker sole in the input image prevented this, which he became aware of after trying it a few times.

Though the final design turned out to be an interesting blend of a dress shoe-like sneaker, he still would have wanted to see the effect of a more formal sole. He understood that he would have needed to change the sole in Photoshop first, but it was too late to do so. For the final image, the designer used the prompt “colorful dress shoe, side view, clean, innovative materials, basic lines, dress shoe sole”. He mentioned that 5 minutes was a short time to fully understand the capabilities of the AI tools. Nonetheless, he found the output result to be very inspiring.

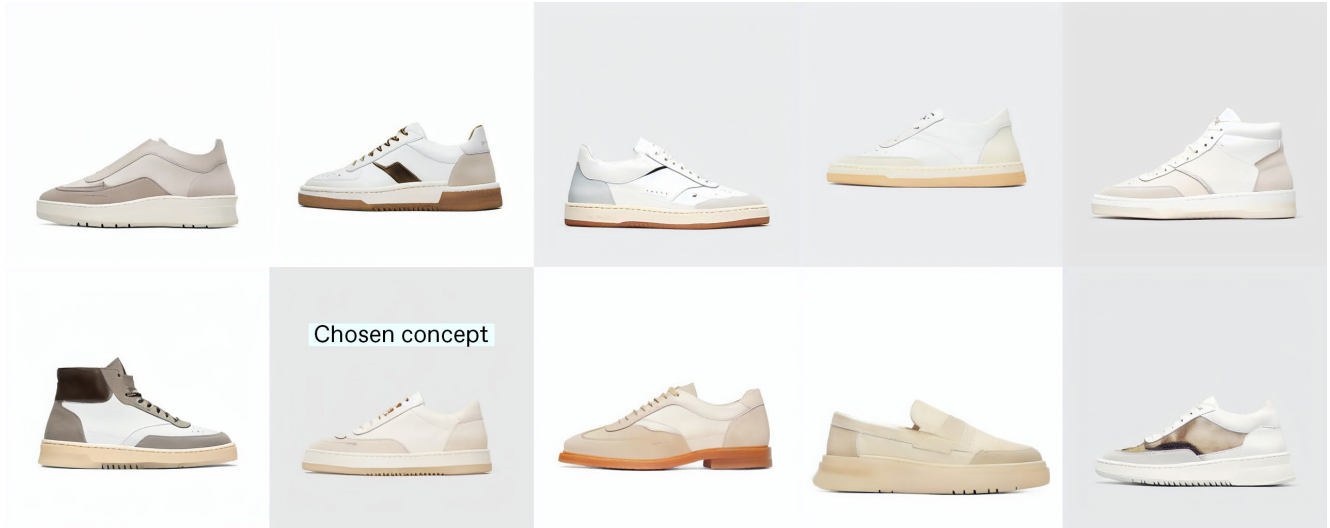


Figure 102: *First AI concepts made by the designer in 5 minutes with the AI workflow*

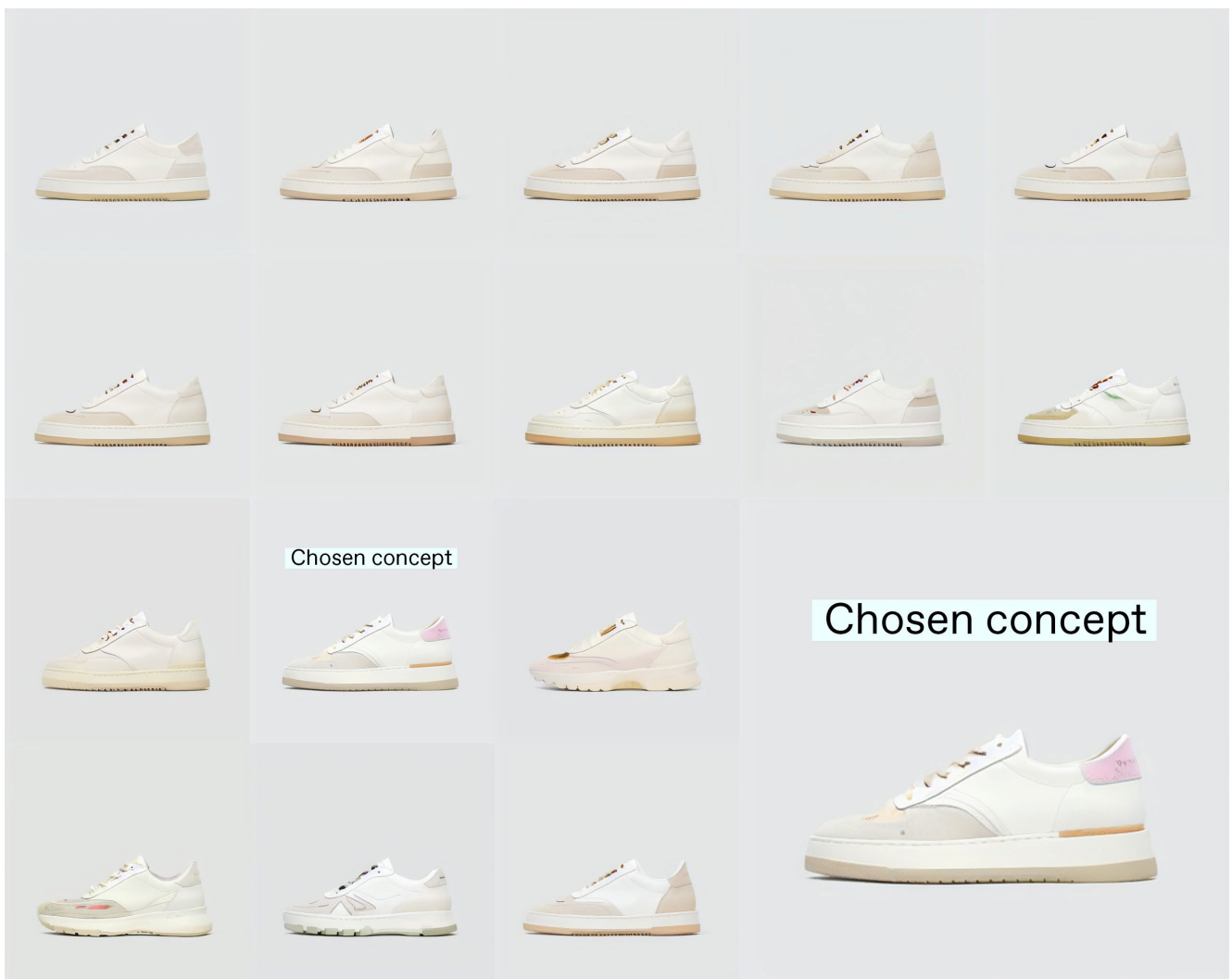


Figure 103: *Defined AI concepts made by the designer in 5 minutes with the AI workflow*



## 3.2 PERFORMANCE METRICS

### 3.2.1 QUALITY OF PROCESS

#### 3.2.1.1 Speed

In 5 minutes, the designer made 4 rough sketches for the design brief (see figure 99), which is 0.8 per minute on average. Normally, it takes him approximately 30 minutes to create a CAD.

Using the first AI workflow, he generated a total of 10 initial concepts in 5 minutes, averaging 2 concepts per minute. In the second phase of the AI process, he spent 5 minutes creating 16 variations, averaging 3.2 concepts per minute.

The AI workflow is faster, generating more concepts per unit of time. For ideation, the AI workflow was 150% faster than the traditional method in generating design ideas. For the defining workflow however, the outcomes are different and not directly comparable. It cannot be evaluated on the speed of generation alone.

As quoted by the designer: “it is not a finished concept immediately” and “you still need an illustrator variant (CAD) in the end to develop the shoe, with material references before it’s a finished concept. There’s a lot more behind it than just creating the AI image.”

With a sample size of N=1, these results cannot be considered statistically significant and are also not generalizable.

#### 3.2.1.2 Ease of use

The designer found the AI process very easy to use initially, but mentioned that he needed more time to understand all capabilities of the tool, such as changing specific components. He stated: “I kept the prompt basic for now, but realized that there is

more possible than what I did in these 5 minutes.” This suggests that it requires time and experience to understand how to use the full potential of the AI workflows.

#### 3.2.1.3 Usefulness

The designer found the AI process efficient for inspiration and to speed up idea generation. He also emphasized that traditional methods are still necessary, as AI tools and traditional processes serve different goals. But for exploring design variations, the tool is valuable since he quoted: “You can explore with it, if you want it to look a certain way you can make many variations”.

#### 3.2.1.4 Satisfaction

The designer was impressed by the AI tool: “Very surprising how it works with the references, very cool.” However, he noted some small mistakes that require refinement, which can be tricky.

Despite the effectiveness, he felt a bit disconnected from the creation process, as he did not feel like it was his own idea since he did not really make it himself. This suggests that while the AI tool works well, it may lack a sense of personal ownership in the design process.

#### 3.2.1.5 Creativity

The designer found the AI tool to be creative, as it allowed him to see possibilities and explore shoe design in new ways. This suggests that the AI tool enhances creativity by offering new perspectives and opportunities for design exploration.



Design A



Design B

Figure 104: Design A and B as presented in the survey

### 3.2.2 QUALITY OF OUTCOME

The performance metrics to assess the quality were measured by presenting design A and B side by side in a survey, as shown in figure 104.

Figure 105 shows the visualization of survey responses for the performance metrics, comparing designs A and B. The data is also divided by the level of footwear experience of the participants.

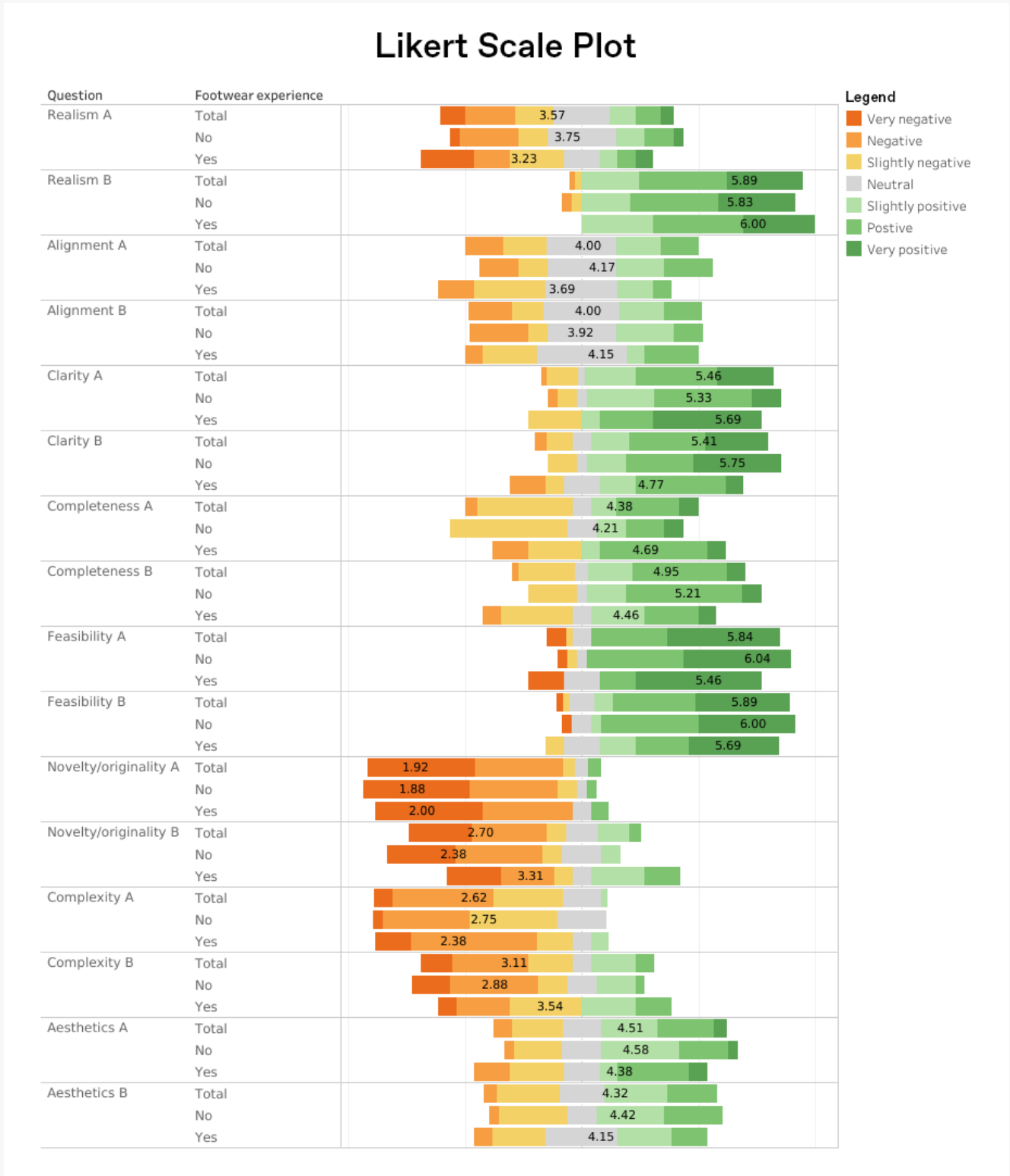


Figure 105: Plot of all Likert scale metrics

### 3.2.2.1 Realism

For the realism of the outputs, design B was rated higher with an average rating of 5.89, compared to design A, which received an average rating of 3.57. This difference was found to be statistically significant ( $p = 9.13e-8$ ).

### 3.2.2.2 Alignment Theme

For the alignment with the theme, both designs A and B received an average rating of 4.00, with a p-value of 1.0, indicating no significant difference. The designer confirmed the neutrality however, as he mentioned that the output somewhat aligned with the theme, but he would have preferred to see it with a different sole, suggesting that it also did not perfectly match his intended goal.

### 3.2.2.3 Alignment Brand Identity

The other intended goal was to make it in the brand identity of Filling Pieces. The designer said that the designs aligned well with the brand identity, since some components looked somewhat similar to other styles, like the heel tab and the sole. It was not perfect yet however, since he was missing the branding with logos to make it a complete Filling Pieces shoe.

From the survey results, Filling Pieces was identified as one of the brands by 18 out of the 37 respondents. Other notable brands mentioned were Reebok with 7 times and Adidas with 5 times. A word cloud showing all brands mentioned is shown in Figure 106. The finding that Filling Pieces was the most frequently mentioned brand is statistically significant ( $p = 2.74e-13$ ).

### 3.2.2.4 Clarity

For the clarity of the designs, meaning how clear it is to see what each part represents, no significant difference was measured ( $p = 0.88$ ). Design A was rated 5.40 on average, and design B received an average rating of 5.41.

For participants with no experience in footwear, design A received an average rating of 5.33, while design B was rated higher with an average of 5.75 ( $p = 0.273$ ). For experienced participants, design A was rated higher with an average of 5.69 compared to design B with an average rating of 4.77 ( $p = 0.202$ ).

Although these differences are also not statistically significant, they suggest that the perception of clarity is based on their level of experience in the footwear industry. Experienced participants rated design A as more, while participants without experience rated design B as more clear.

The designer commented that the AI out was very clear, he only mentioned that the nose area was a bit unclear, since the materials overlapped.

### 3.2.2.5 Completeness

The completeness of the designs, defined as whether there are any missing elements, resulted in no significant differences for the total number of participants. Design A received an average rating of 4.38, while design B received a higher average rating of 4.95, with a p-value of 0.068.

For participants with no experience, the difference was significant, design A received an average rating of 4.21, while design B was rated higher at 5.21 ( $p = 0.001$ ).

For experienced participants, Design A had an average rating of 4.69 compared to Design B's 4.46, with a p-value of 0.741, indicating no significant difference.

These results show a significant difference in completeness ratings for participants without experience, who found design B to be more complete. However, there was no significant difference in ratings for the total responses and only experienced participants.



Figure 106: Wordcloud of mentioned brands

The designer mentioned that the output was quite complete: “Just a bit blurry at the front, you need to fill it in a bit yourself. Also the branding is missing.”

### 3.2.2.6 Feasibility to Produce

For the feasibility to produce the designs, A received an average rating of 5.84, while design B received a slightly higher average rating of 5.89 ( $p = 0.827$ ).

For participants with no experience, design A received an average rating of 6.04, while design B was rated at 6.00 ( $p = 0.814$ ). For experienced participants, design A had an average rating of 5.46 compared to the average of 5.69 of design B ( $p = 0.721$ ). Although the differences are not statistically significant, the experienced group showed a slight preference for design B.

The experienced group, likely more familiar with factory requirements and manufacturing limitations, mentioned that traditional spec drawings (which are included in tech packs) are much clearer and probably preferred by factories. This suggests that AI generated images still need to be accompanied by a tech pack necessary for clear and complete communication, to ensure feasibility in production.

### 3.2.2.7 Novelty / Originality

Design B was rated higher on novelty and originality, with an average of 2.70, while design A was rated 1.92 on average ( $p = 0.009$ ). While the overall results show a significant difference, indicating that Design B is more novel and original, both designs were still perceived as quite familiar to respondents.

### 3.2.2.8 Complexity

The complexity of the designs was assessed, with design A receiving an average rating of 2.62 and design B receiving a higher average rating of 3.11. This difference has a very strong trend towards statistical significance ( $p = 0.054$ ), but it cannot be claimed.



### 3.2.2.9 Aesthetic Value

Design A received a higher average rating of 4.51 for aesthetic value, compared to the average of 4.32 for design B. This difference was not statistically significant ( $p = 0.5511$ ), however, when asked which design was preferred overall in another question, 25 participants preferred design A (see figure 107). This preference was statistically significant ( $p = 0.033$ ), indicating that overall people liked design A more.

The aesthetic value was also analyzed using the Wundt curve to see if the findings match with the literature. This analysis initially averaged the values of novelty and complexity, as arousal potential in the Wundt curve is dependent on both metrics (Honda et al., 2022). The points in the scatter plot are far apart, as seen in figure 108. The trend line shows an upward trend, stabilizes, and then goes up again.

It looks like there is a relationship between novelty/complexity and aesthetic value, but the data is insufficient to achieve a significant result ( $p = 0.45$ ), likely due the wide distribution of the points. The confidence bands, indicated by the lighter gray lines above and below the trend line, also show more deviation at the beginning and end of

the trend line. This indicates that at those points the relationship between the metrics is even less significant.

When only plotting aesthetic value against just novelty, as done in previous research on AI-generated images by Sbaji et al. (2018), the graph in figure 109 is created.

Again, there seems to be a relationship between novelty and aesthetic value, but the data is too limited to get a significant result ( $p = 0.90$ ). Also, the deviation in the confidence bands is very high at lower and higher levels of novelty.

Which design do you prefer overall?

37 responses

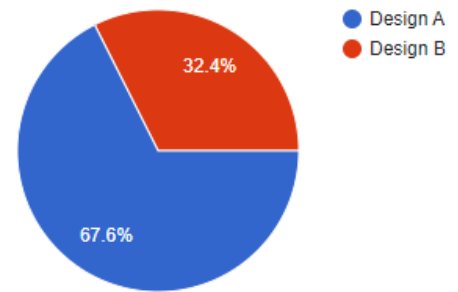


Figure 107: Design preference

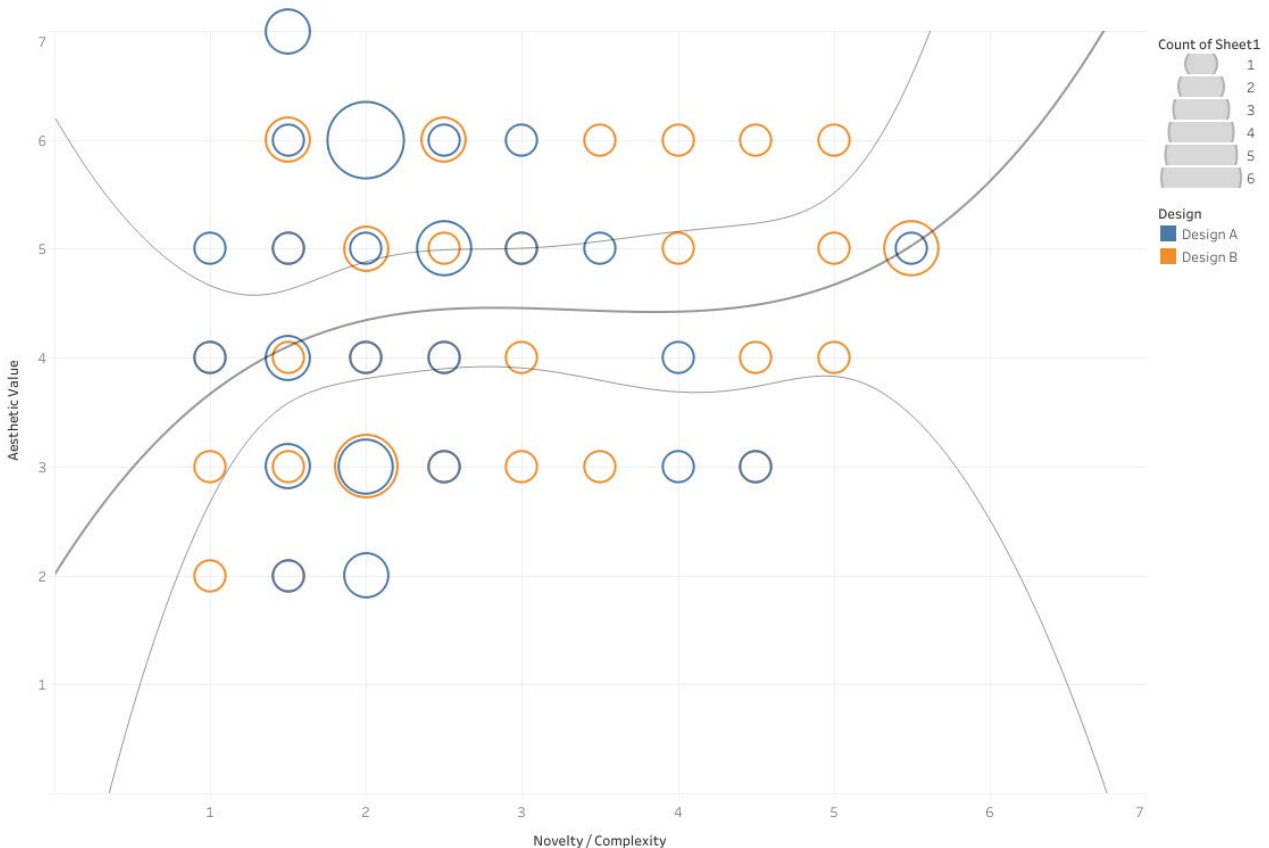


Figure 108: Scatterplot of aesthetic value and average of novelty and complexity

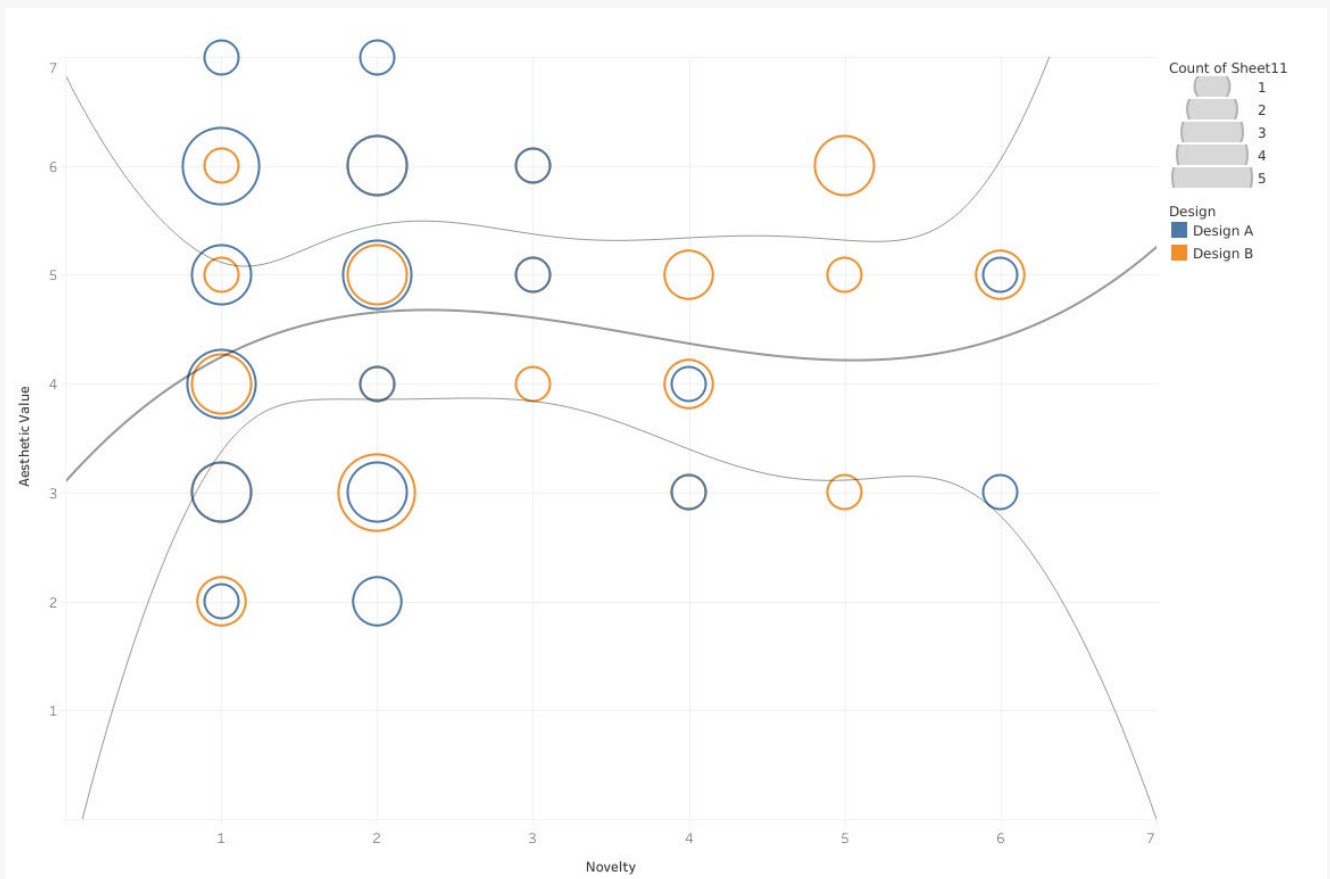


Figure 109: Scatterplot of aesthetic value and novelty

# 4 DISCUSSION

The primary objective of the user test was to evaluate the effectiveness of the process and outcome of the proposed AI framework that was designed to enhance the creative process of footwear design for Filling Pieces, and ultimately make that part of the product creation process more efficient in terms of time and cost. The findings indicate that these objectives were met to varying degrees on the multiple assessed metrics, and the impact on the creativity was notable. The AI framework did not only speed up the generation of design concepts but also resulted in higher levels of novelty and originality, enhancing the creative output significantly. However, some objectives, such as clarity, completeness and feasibility of designs were not fully met, indicating room for improvement.

## 4.1 PROCESS EFFICIENCY: SPEED, EASE OF USE & USEFULNESS

Through the user test, it was found that using the AI framework in the design process increased the speed of idea and concept creation, which means that the creative process can be completed faster and the time-to-market shortened consequentially. This was supported by the survey results, as many of the comments were in line with the description of the tool as “a design and ideation acceleration tool.” Even though the workflows were made to be purely functional and lacked an optimized UI, the designer found it to be easy to use and very useful. The designer was surprised with the effectiveness of the tool and the new possibilities and perspectives it presented for footwear design, suggesting that it enhances the creative exploration during the process.

## 4.2 CREATIVITY

Creativity in design is a combination of novelty, originality and complexity. The AI-generated design scored higher on these metrics, suggesting that the proposed AI framework can be a powerful tool for enhancing the creativity of the output footwear designs. The survey comments however still highlight the need for human creativity in the process to get a meaningful result. This suggests that the framework is seen as a tool complementing the process and not a substitution of the designer.

## 4.3 OUTCOME IMAGE QUALITY: AESTHETICS AND REALISM

Higher novelty, originality and complexity do not necessarily mean that the design is more aesthetically pleasing. The Wundt curve (Honda et al., 2022) explains that for the most optimal aesthetic value, a balance between the metrics needs to be found. Design A was perceived to be more aesthetically appealing than the AI generated design. This suggests that the AI generated designs can be too complex, leading to a lower aesthetic value.

Nevertheless, design B was perceived as more realistic, as it resembled a real image more closely than the technical drawing. This can be particularly helpful in convincing stakeholders without a design or technical background, as photos are more accessible and easier to understand how complex shapes would manifest in reality before actually being produced.

## 4.4 OUTCOME FEASIBILITY AND SPECIFICITY: COMPLETENESS & CLARITY

Photorealistic images do however not automatically mean that the designs are feasible to produce or supportive in the communication with the factory. Factories do have the technical people that can interpret technical drawings, which remain the most effective way to communicate detailed design specifications for production. While the result was not significant, the CAD design was perceived to be more clear and complete than the AI generated concept by participants with footwear experience, as it “avoids room for interpretation [by the factory], since the AI image seemed incomplete” and “some AI-generated footwear designs still need some post-production work.” This suggests that AI-generated designs are less feasible for production compared to technical drawings, a finding that did not align with the survey results, although these were not statistically significant. Therefore, any conclusions drawn would be speculative.

Elements that were missing include details such as stitch lines, construction, and branding application, as well as more broad aspects like proportions, product performance, and sustainability.

Additionally, the image sometimes lacks clarity and completeness due to errors in the design, this happens often in the laces similar to the way human hands are often weirdly displayed in AI-generated images. This happens because the AI framework still lacks a nuanced understanding of how these concepts physically work, it generates outputs based on just training data and visual patterns.

The outcomes of the traditional and AI-augmented creative phase are distinctly different, making it challenging to compare them in every aspect. The findings indicate that for communicating the design with the factory, a translation step into a technical drawing is necessary when moving the concept to production. An AI image should thus always be complemented by a technical drawing for manufacturing purposes. This finding suggests a complementary relationship where AI supports the creative process, and human designers enhance and complete the designs.

For development, technical drawings are needed that cannot be generated by AI. Before the concept is ready for production, human intervention is necessary to convert the concept into an Illustrator CAD with accurate linework. It is important to factor in the time required for this translation when considering the speed of the AI design process, since it was assumed that the outcomes of the creative phase of the footwear design process would be equal in their use. This finding actually stresses the importance of the deliver phase, which makes the AI generated concepts ready for production, like the technical drawing. This suggests that creating production ready design concepts cannot be done without human intervention. Nevertheless, the idea generation is still accelerated, so the fact that the translation step is needed does not make this benefit insignificant.

#### 4.5 ALIGNMENT

These improvements are only beneficial when the output matches the intended design goal, in this case reflecting the brand identity and theme of the season. The findings showed similar performance for the traditional and AI generated designs, suggesting that the designer can produce aligned concepts as effectively with and without the AI framework. Furthermore, the brand identity of Filling Pieces was recognized multiple times in the survey, meaning that the style of the brand was successfully reflected in the design.

However, this finding could be biased, as at least 11 out of the 37 respondents were aware of my internship at Filling Pieces, which could have affected their responses. Although some respondents who recognized the brand were unbiased, as I did not know them personally, not all respondents provided their names. This makes it challenging to assess to what extent this bias influenced these results.

#### 4.6 LIMITATIONS

One of the limitations of this user test was the assessment of only one AI-generated design with one CAD. The AI-generated design was created in just 10 minutes total, while it was the first interaction of the designer with the tool. The CAD on the other hand was developed in a longer and more iterative process, and ended up to be one of that season's best-selling styles. These differences may have had an impact on the results, as they were not made under similar circumstances. Moreover, the difference between the two designs was bigger than initially expected, since the AI generated design was a lot more incomplete for development than anticipated. This implies that the two designs may not have been the best ones to compare, given that the traditional CAD was considerably more developed in the process already.

Furthermore, the study was done with only one designer, who was not yet familiar with generative AI tools. This was the only feasible approach, as the participant needed to understand the design language and brand identity of Filling Pieces. In addition, the tool also has a learning curve, so ideally the designer would have been given a more extensive tutorial and practice period. These points limit the generalizability of the findings.

The subjective nature of design makes it challenging to quantify the quality. While Likert scales are one way to objectify these subjective assessments, they are still dependent on the personal preferences of the participants. Methods such as Neural Image Assessment offer a data-driven way to measure the aesthetics of AI-generated images. This approach was however outside the scope of this project due to computational limitations, since it requires intermediate results of the generation process that were not available (Talebi & Milanfar, 2018).



## 4.7 ETHICAL CONSIDERATIONS

The user test and survey data revealed that some participants have ethical concerns when it comes to AI generated design. Authenticity of the designs is one of the key issues, as the tools are trained on pre-existing images, which raises questions about originality and intellectual property, as well as the risk of unintentional copying. This, in combination with the lack of ownership that the designer felt, could lead to a reduced perceived value of their creative work and potentially impact their motivation. It is not uncommon that these concerns arise with a new technology like AI, as all innovations require the adaptation that rarely happens without friction. Most common causes are that people naturally resist change because it takes effort and they have a desire to stick to the status quo (Schonthal & Euchner, 2022).

# 5 CONCLUSION

In conclusion, the user test demonstrated that the proposed AI framework can effectively speed up the creative phase of the footwear design process, making it more efficient and enhancing creativity to produce more novel and original concepts (RQ1 & 5). However, it also showed that the capabilities of the AI tools are limited in terms of clarity, completeness and producing feasible designs compared to the traditional process. While the realistic images do support the communication of the design to some stakeholders, they are not as effective and detailed as traditional technical drawings when handing over the design to the factory. From these findings, it can be concluded that AI-generated designs should be complemented by technical drawings to ensure that the concepts are clearly communicated and feasible to produce. This means that the relationship between the AI framework and human designers is complementary, the AI workflows support and enhance the creative process, but it is still a tool that requires human intervention to get to a complete end product ready for production (RQ3).

# PART 5

## THESIS CONCLUSIONS

To reflect back, the overall goal of this thesis was to innovate the footwear design process of Filling Pieces with generative AI, aiming to address multiple challenges and opportunities. The objectives were to improve efficiency by reducing time-to-market and costs, enhance creativity, and to capture the brand identity in the designs. Additionally, the project aimed to evaluate the integration of the proposed AI framework AI into the current process and assess its impact and effectiveness.

1 GENERAL DISCUSSION

2 GENERAL CONCLUSION

3 PERSONAL REFLECTION



Figure 110: Filling Pieces Flagship store (*Filling Pieces, n.d.*)

# 1 GENERAL DISUCSSION

## 1.1 SUMMARY OF KEY FINDINGS

The key findings indicate that the AI framework significantly speeds up the design process and enhances creativity. However, there are limitations in the clarity, completeness, and production feasibility with the AI-generated designs. To address these limitations, AI outputs should be supplemented with traditional technical drawings to be useful for the factory. To achieve the most effective results, the relationship between AI and human designers should be complementary, leveraging the strengths of both.

## 1.2 PROJECT RELEVANCE

Both the case study and the user test demonstrate that it is feasible to use the proposed AI framework, since they both demonstrate that designers are able to effectively create footwear design concepts with it. Using the AI framework has shown to be valuable for Filling Pieces on multiple aspects. Applying it on another season will only require new LoRA models to finetune the LDM for the moodboards, to make sure that the outputs align with the theme. Training those models is relatively simple, since experimentation on the parameters to achieve desirable outcomes has already been done, demonstrating that it is feasible.

In terms of desirability, the designer has expressed his satisfaction with the AI workflows and indicated that he would want to use it in the early stages of the design process. The findings from the test indicate that the tools enhance efficiency and creativity, being beneficial to the design process. This means that it adds significant value for the Filling Pieces team, next to offering a new perspective on the application of AI tools, being a valuable outcome for both the footwear industry and the domain of AI.

The framework is designed to be applicable for every season when making new LoRA models, providing long-term value. Even if additional functions will be added, the core structure of the proposed framework stays the same, ensuring its viability. ComfyUI was also used because of its adaptability, supporting the integration of new innovative tools.

## 1.3 THEORETICAL CONTRIBUTIONS

The application of LoRA models for brand-driven generative AI design is a new theoretical contribution, as fine tuning LDMs on a brand identity is something not yet discussed in literature. This thesis demonstrates how this approach can not only generate creative and novel designs, but also designs aligning with the brand identity of Filling Pieces. This represents an innovative method for consistently merging a brand identity with AI-generated design.

## 1.4 GENERALIZABILITY

The generalizability of this framework is somewhat limited. The user test study only compared one design by a single designer, for a single brand. This thesis argues that using LoRA models are effective for capturing the brand identity in generating footwear designs. It should however be kept in mind that Filling Pieces is a well-established brand that has built up its strong brand identity in over 15 years. The effectiveness for brands with smaller collections and less distinct design languages is uncertain, therefore it cannot be validated that the AI framework has a broader applicability within the footwear industry outside of Filling Pieces.

## 1.5 GENERAL LIMITATIONS OF THE THESIS

It is important to consider that some of the generated pictures in this thesis report are cherry picked, which may create a biased perception of the consistency of quality of the outputs. Not all generated images were of the same quality, sometimes the results were really distorted as seen in figure 111.



Figure 111: *Examples of distorted generations*



Another limitation is the learning curve that the AI tools have, it takes time to master them. Since I have trained, optimized and most importantly extensively used the workflows, I am most familiar with its functionality and capabilities. For users who were not involved in this process, using the tools can be more challenging. As a consequence, the results produced by the designer may differ in quality from those in the case study demonstration.

A lack of precise control is another limitation of the AI framework. While unexpected outcomes are especially valuable during the early stages of diverging and exploring ideas, having precise control becomes desirable later in the process when defining and finalizing a concept. In this phase, you want to tailor the design to specific stylistic needs like colors, shapes and linework. However, AI-generated results are always somewhat random. For instance, colors may not match exactly and when modifying a single line, other lines may be affected as well. Additionally, upscaling the image to add details can sometimes distort the linework. This lack of control and precision can sometimes be frustrating when the designer has a clear end goal in mind.

When the complexity of the idea the designer has is greater than what can be described in a prompt, there will be a misalignment between the image information and the prompt information, described by the crooked bow tie effect. The image generation process can be visualized as a bow tie, where the idea is narrowed down by the prompt. Words are only so limited in what they describe about a design, since images are richer in information than words. When generative AI is used for inspiration, both sides are equally rich, even though they have different formats (see bow tie A in figure 112). But when it is used for a final design, it is challenging to represent the richness and complexity of the idea completely in a prompt, resulting in an image that might not be the same level of richness and accuracy, hence the crooked bow tie (B) as seen in figure 112 (Verheijden & Funk, 2023).

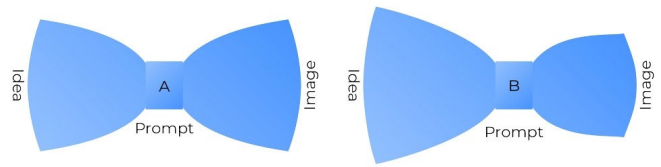


Figure 112: *Crooked bow tie effect (Verheijden & Funk, 2023)*

## 1.6 ROLE OF THE DESIGNER

Based on my understanding, AI will not fully replace the role of designers in the future. For that to happen, a technological breakthrough has to take place where AI gains the ability to imitate emotional cognition, which is the characteristic that sets humans apart from algorithms. The technology should be viewed as a tool rather than an autonomous creator, as it can enhance the creative process without replacing the designer's role in shaping the final outcome.

This reflects the perspective of the designer from the user test, AI is seen as a valuable aid rather than a replacement, with its current role being to support and immediately visualize what you think. However it is likely that the responsibilities of designers do shift with the integration of AI, to a more anticipatory, problem-setting and decision-making role (Mortati, 2022).

## 1.7 RECOMMENDED IMPLEMENTATION

In the current state of the proposed AI framework, it is recommended to primarily position it as an inspirational tool for the beginning stages of the footwear design process of Filling Pieces. During this exploratory phase, when a lot of ideas are divergently being generated, the goal of the AI tools is not to produce perfect and complete designs. Instead, it will offer fresh perspectives and potential design directions for the team that might otherwise remain unexplored. As the designer also noted, "I would use it in the inspiration phase, the first phase of design before developing and working it out." Especially in the beginning of the design phase, when the new seasonal theme is just decided, it is recommended that the designer collaborates with the creative director to create moodboards and consequently train the LoRA models.



Figure 113: *Implementation of the framework, Design and Define are AI augmented phases, Deliver is with human intervention*

This AI-oriented approach opens up quick creative exploration early in the design phase, allowing for a broad range of possibilities, before the definitive design direction of the footwear styles has been set, to increase the creativity of the process and speed up early ideation.

While the initial goal for the AI-oriented framework was to generate production-ready final designs, it was anticipated that human intervention would still be necessary in this process. The findings confirmed this expectation, but also revealed that the AI-generated designs needed more refinement than predicted. The findings showed that it was neither desirable nor feasible for the AI tools to generate production-ready final designs, due to the limitations of the tools. Therefore, the personal touch of designers is still important, to refine the design and add details and adjustments into a technical drawing to deliver the concept and make it ready for production. As the designer highlighted, “It won’t necessarily replace the illustrator process, as they are different tools with different goals.” The recommendation is to not yet make the AI tools autonomous, the outputs must always still be checked and given a human touch in terms of design and detailing, and finally translated into a technical file for production.

This means that the recommended implementation of the tools and workflows will follow the proposed AI framework, but the deliver phase is emphasized, considering that human intervention is necessary in the process, as seen in figure 113. After preparation, the AI tools of the framework make the design and define phase more efficient and do not require human intervention, although the personal touch of designers might improve the quality of the designs even more. The deliver phase refers to the responsibility of the designer to make technical drawings in Illustrator, preparing the design for development and production. Implementing this framework offers both advantages and challenges, as it changes the traditional workflow and requires designers to adapt to a new process. This is similar to the adoption of the first digital design tools like Photoshop and Illustrator some years ago. Such innovations always take time to get adapted to, but it is wise to start using these tools as soon as possible and be an early adapter in developing new skills and staying competitive.

## 1.8 FUTURE WORK

The proposed framework is beneficial to use in the footwear design process for Filling Pieces, but there are still opportunities for improvement or further research and development, in terms of quality and functionality of the framework.

### 1.8.1 IMPROVE QUALITY

First of all, investing in upgrading computational resources will open up the possibility to increase both the amount of images generated, as well as their quality. A better VRAM can handle a bigger batch size, so multiple images can be generated simultaneously, which increases efficiency in terms of speed of design creation. Next to that, SDXL can be used to get higher definition images, which increases the image quality metric. Both modifications would enhance the usability of the framework, without changing the overall structure of the workflow.

Additional experimentation with LoRA settings is still possible, as the current values might not be the most optimal, due to computational limitations as well as time restriction. Furthermore, a larger image database might potentially result in more creative and novel results. For this project, the experimentation has only been done with one image dataset per LoRA model. The addition or removal of some of the images could lead to better results, in terms of novelty, complexity and overall aesthetics of the generated images.

## 1.8.2 ADDITIONAL FUNCTIONS

To further broaden the usefulness of the framework for the Filling Pieces design team, it can be extended beyond footwear. Additional LoRA models can be trained on the ready-to-wear collection as well, split up in different clothing categories for example. By leveraging the same thematic moodboard LoRA model, but applying different categorical models (e.g. jackets or pants), the same design language can be captured for these different pieces of clothing to create a coherent collection.

The current framework operates in two phases using different tools, and lacks an integrated UI. Developing this UI was beyond the scope of this project, but future work could focus on creating a standalone, user-centered application. ComfyUI is quite complex to use, so it would be beneficial to make it more user-friendly. It is possible to do this, as ComfyUI supports interaction with an API ([Comfyanonymous], n.d.).

Further research could also explore full control of the generation process through Segformer, a semantic segmentation model, although this requires a very large dataset. With this model, the algorithm can learn to segment all individual components and learn their corresponding names (Cornille & Rogge, 2022). This opens up the possibility to create precise control over generating the individual components of a shoe via just a prompt. It does demand a lot of training data and computational resources, but might be really valuable for updating existing sneaker styles, since it could lead to more complete outputs. Some experimentation was done to prepare the data (see figure 114), but the training did not give any usable results due to the database probably being too small for such a complex subject as a shoe.

Future research should also focus on improving the AI 3D modeling accuracy by allowing the upload of multiple views, as well as enabling the generation of 3D models with multiple components rather than a single mesh. Relying on a single side view often leads to inaccuracies, which can be mitigated by incorporating multiple perspectives into the modeling process. Furthermore, the multi-mesh generation would make the models compatible with 3D development softwares. This process would enable the creation of models that can actually replace physical samples, potentially reducing sample production and associated costs.

The ideal scenario would be if the material information could be retrieved from a dataset, making the whole framework also data-driven, which initially was one of the requirements. The approach to use a RAG model to incorporate this data was not successful, but it might be possible in the future. Especially if all suppliers would create 3D textures of their materials, then they can be integrated into the 3D model, for the most realistic digital representation of the shoe.

The last opportunity for future research is about integrating quantitative tools and market and sales data into a feedback loop within the AI framework. It would be beneficial to integrate a continuous refinement of the AI models, using quantitative assessment to enhance the quality of the outputs. By doing this, the generated design would align better with both the aesthetic preferences, as well as the market and consumer needs.



Figure 114: Prepared segmentation training dataset for the Cruiser

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# 2 GENERAL CONCLUSION

This thesis project explores the integration of innovative generative AI into the footwear design process at Filling Pieces, and argues that such integration can significantly enhance efficiency by speeding up the idea generation process and creativity in terms of generating more novel designs. By applying Stable Diffusion in combination with LoRA fine-tuning, this thesis not only demonstrates the effectiveness of these AI technologies on a design brief but also assesses the results from a user test conducted with a designer from Filling Pieces. It was hypothesized that integrating generative AI tools into the footwear design process could significantly enhance the quality of the process and outcome on multiple metrics for the Filling Pieces team. This hypothesis was partially accepted, since the user test and survey results on the proposed AI framework successfully resulted in significant improvements in some of the metrics. However, not all findings were significant, so the hypothesis is not fully accepted.

During the synthesis of the project, the structure of the framework changed several times to focus only on the most important requirements. The aim was to create a functional MVP rather than a full-fledged application, meaning that some of the requirements were neglected due to the scope of the project. These adjustments quickly validated the core functionality of the AI tools, to make sure that all AI tools in the framework were working properly.

ComfyUI was used to create adaptable workflows that used Stable Diffusion as the main generative AI tool that helps to optimize the initial ideation phase. Multiple LoRA models were used to fine tune the Stable Diffusion model to make sure that the outputs align with the theme, as well as with the brand identity of Filling Pieces. This approach is a new contribution to the literature, as using a LoRA model for a brand-driven design has not been explored yet. Reference images were used to steer the generation process, to make sure that the output was consistent, desirable and relevant. ControlNet added an extra layer of control that was used to consistently generate the linework of a chosen shoe silhouette, making it more specific. Lastly, Vizcom was used for the refinement of the designs, since its outputs are high quality and they allow for the addition of details in the later stages of design.

One of the key challenges that was faced was the lack of specificity of AI models, since they are trained on a large database and therefore produce really generic designs, which was tackled by fine tuning LoRA models. But by adding a lot of additional models, the next challenge arose. Integrating multiple different AI models into one cohesive workflow was done with ComfyUI, to make adaptable workflows in one overview. These results show that the integration of AI tools in the process is beneficial on multiple metrics, but they also indicate that they must still be complemented by a traditional technical drawing made by the designer to ensure that the design is feasible to produce, in terms of completeness and clarity, since AI tools can make mistakes or produce unrealistic designs.

To compare the traditional and AI-augmented design processes, performance metrics were made for both the quality of the process and the outcome. The quality of the process is measured by the satisfaction of the designer, as well as its efficiency in terms of speed, ease of use and usefulness. The quality of the outcomes was measured on several criteria: feasibility for manufacturing, alignment with the theme and design goals, clarity and completeness of the design, realism and aesthetic value of the image, and creativity in terms of novelty and complexity. Likert scales were used to quantitatively evaluate these subjective metrics. The quality of the AI-augmented design process showed significant improvements in terms of speed and creativity, compared to the traditional process.

If the AI framework will be implemented by Filling Pieces, it will have a significant impact on the design and development cycle. The design phase saw increased efficiency due to faster ideation and iteration, and enhanced creativity resulting in more diverse and novel design concepts. But prior to this, the model needs to be fine tuned on the moodboards on the theme. So the recommended change in the design processes of the Filling Pieces team requires some preparation, but it will benefit the process in the long run. The deliver phase however remains mostly unchanged, as technical drawings are still necessary. Next to that, the 3D development component was used only as a proof of concept, since the AI technology was not yet ready for practical application with 3D development tools, so the reliance on physical prototypes was not reduced.

In conclusion, integrating AI into the footwear design process at Filling Pieces showed significant improvements in enhancing creativity and efficiency. However, it has notable limitations in clarity, completeness, and production feasibility. To address these, AI-generated designs should be accompanied by detailed technical drawings to ensure clarity and precision for manufacturing. This implies that the relationship between AI tools and human designers should be complementary, leveraging the strengths of both for the best results.



# 3 PERSONAL REFLECTION

Reflecting on this thesis project, I have expanded my knowledge of the footwear industry, particularly in design and development, though the experience went in a different direction than initially expected. While the project was primarily focused on the application of AI in the footwear design process, I delved deeper into the training and integration of different algorithms than anticipated. Nonetheless, I learned a lot throughout this individual graduation project as I was mentored well in all areas.

While the exploration into 3D modeling was somewhat limited due to current technological constraints and the scope of the project, I did at least find it fascinating to dip my toes into this field. In the end, the project did not include creating full 3D models of shoe concepts, but it was still an opportunity to demonstrate my proficiency in footwear design for a brand, which I consider a significant achievement.

Overall, this project provided a unique chance to showcase my proficiency in footwear design while simultaneously exploring the innovative potential of generative AI. I gained valuable insights and built a lot of new connections within the industry. But most importantly, I had a lot of fun along the way. I am proud of the progress I have made and the contributions I have added to the domain of generative AI and the footwear industry, and I look forward to now more confidently applying my expertise into future projects.

*- Joram Steen*

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# THANK YOU

BY JORAM STEEN

# APPENDIX

## Appendix A

### Exploratory Interview Guide

#### Informed consent

- Hi [name interviewee], before I begin, do you give consent to use the data for my graduation project?

#### Intro

The aim of this project is to design and create a 3D-AI oriented framework that can enhance the design and development processes for the Filling Pieces team. The goal for the framework is to train it on Filling Pieces footwear, so it can generate a concept (potentially also in 3D) that fits the brand identity from just a text input. To validate the framework, it will be applied to a redesign project of the Cruiser style.

#### Background & general questions

- How would you describe your role within Filling Pieces?
- What methods and tools do you use in your workflow?
  - Why use those specific tools?
- What is your personal and professional experience with AI tools?
  - How do you feel about it?

#### Current process and way of working

##### Design specific

- What are the drivers/motivations behind creation of new concepts and why?
  - What are the boundaries or requirements that you set for a design?
- How do you get inspired and where do you get your inspiration from?
- To what extent do you rely on your intuition when it comes to designing a new style?
  - How subjective do you feel your design process is?
  - In what ways do you want to incorporate your personal touch?

##### Development specific

- What explains the need for multiple sample rounds? What flaws or imperfections cause this?
- What aspects of the design are important to communicate with the factory?
  - Which errors or flaws are the most common?
- What is the motivation behind the changes, are they purely aesthetic?
- When is a proto/sample good enough to make it into final production to be sold?



## General

- What are the current pain points and challenges that you encounter in your process?
  - In what ways do you try to negate these flaws and try to optimize your workflow?
  - Which human errors happen sometimes in the process?
- What features and capabilities would you like to see in the AI framework?
- Are there any functionalities you believe to be essential for the success of the framework?
- To what extent do you wish to have human control over the process?
  - What are the boundaries, in which situation would you feel like you have no control at all and when would you feel like you have too much control?
- What is the desired end-result of the AI framework?
- What boxes does the end-result need to check in order for it to be complete to start the sampling process?

## Perception of the outcome of the AI framework

- How do you feel about acceptance of AI generated designs in general?
- What challenges do you envision in transitioning to an AI oriented workflow?
- What are your expectations of an AI oriented workflow? What are your concerns or how do you think that it can benefit you personally?
- What would be the most desirable that the AI framework could generate?
  - What are some aspects that it needs to have, or nice to have?

## Performance measurements

### Process

- What factors make a design process good?
  - When do you feel like your process was successful?
- Do you measure your performance and success?
  - How (would you do it)?
- In order to objectively assess the quality of the framework compared to the performance of a designer performing the design process, it needs to be compared on a set of metrics. How would you objectively measure the quality of a design process?
  - What makes a good designer stand out from bad ones?

### Concept

- What determines the readiness of a concept to move into production?
  - How can this be influenced?
- In order to objectively assess the quality of the generated concept compared to a human-made concept, it needs to be compared on a set of metrics. How would you objectively measure the quality of a concept?
  - What makes a good concept stand out from bad ones?
- What factors determine how commercial a product is?

- How can you translate a very visionary style into a more commercial one?
- How do you make a “boring” product more sexy?
- Why do some colorways and material combinations work better than others?

# Appendix B

## Thematic Analysis Exploratory Interview

### Interviewees

The expertises of the interviewees within the company and industry are as follows:

- Responsible for all touchpoints that customers experience with Filling Pieces, including design, development, and other creative aspects. His vision on the outcome is crucial for the project's success.
- Responsible for designing ready-to-wear and footwear concepts, including creating the seasonal themes for the collections. His expertise is in building and researching the toolboxes and moodboards for the design department to use as references and directional ideas.
- Responsible for serving as the bridge between design and production. His knowledge of development and production processes provides insights into the practical implementation of the framework and the scope of the project.
- Responsible for managing the entire sampling and production processes in the factories, from the first prototype to the final distribution in stores. His expertise include conducting cost analyses, negotiating contracts and sourcing materials.

### Design

#### Design process

- Start with sketches on paper, next make technical drawings on Illustrator, also try to sketch on a last to see how design translates to 3D. Make material and color variations on illustrator. Make a techpack with Bolden. Make a prototype, make changes in prototype for second round. Make multiple samples to try different colors and materials. Make a final sample round to sell the samples. Sell the samples to retailers.
- You work data driven as well, what worked well last season, what colorways determine the next season. Need to be specific.
- Sketching is the first step for creating a new silhouette. Then making a quick proto with available materials, stock fabrics for sustainability and speed, of course some benchmarking of what parts are leather and mesh. On a 2D sketch, an example compared with Formula 1, on paper and computer design can be good, but correlation of how it works on the circuit in real life is not always 1:1. Testing and simulation with scale models in wind tunnels for example, translation is not always 1:1. But whether it is good or beautiful is a gut feeling, subjective.
- Process is like a funnel, in the beginning loose ends and lots of inspiration, in the end you cut down to the needs and requirements for a nice collection.

- Existing silhouettes need to be further developed so that they continue to exist, ensure continuity, continuous updates for existence. From the design department there's often resistance, because it is less creative, but certainly important for commercial purposes.
- Aesthetics is a design choice. Technical construction is an evaluation from the factory, sometimes comments from design perspectives, but mostly subjective from the designer eye of aesthetics, or what is popular in the market.

#### Summary:

The whole process starts with the theme of the collection, that is communicated through moodboards and references for inspiration to steer the design direction. Sketching begins on paper and later with Procreate on iPad, followed by 3D translation by sketching on a taped last. Technical drawings in Illustrator are made to make mockups of color and material options, both based on aesthetic intuition as well as data based on successful past seasons. Creating a techpack, that serves as a blueprint for the design, is crucial for prototyping, which mitigates the difference between a 2D sketch and a real shoe. The design process evolves from loose inspiration to focused requirements and needs for the collection, like a funnel where you cut down on ideas.

#### Design tools and methods

- Adobe packages, illustrator and photoshop. Presentations in Keynote. Worktools, such as Monday to keep track of styles, Trend forecasting, and sales data to use for the design process.
- The factories work in flats, 2D, tech packs that serve as blueprints for the design
- New silhouettes sketching on Procreate on iPad, color options in illustrator. The very first phase is on paper, quick.
- Also masking tape on the last, for the upper. Using clay to shape the sole in 3D.
- Begin is manual, more and more digital tools to the final design, next step is 3D, but they don't do that yet
- Tools, illustrator and lots of photoshop. To make examples of what it could look like. Bolden ERP system to make tech packs. Swatch cards for material selection, from material conventions.
- For proto, sampling and production methods are quality procedures, a toolbox on Monday where they can check the materials. Different guidelines that they follow.

#### Summary:

The current tools and methods that are used for the design are mainly manual, but there's a gradual shift towards digitalization. The next step in that transition is the use of AI and 3D modeling, which is currently achieved for the upper through sketching on a last covered with masking tape, and sculpting clay for the sole. Although digital mockups for material and color selection are part of the process, the process is still reliant on physical swatch cards since the mockups lack realism. This traditional 2D approach is driven by the factory's dependence on 2D tech packs. Additionally, it has proven successful over time and is deeply ingrained in their operational procedures.

## Design inspiration

- Inspiration from everywhere, bridge the gap between people, cultures and disciplines in the broadest sense. Disciplines are in the art universe, creative disciplines. It is a people driven brand, elements from cultures and themes. From their point of view these themes give strength to the brand.
- Design based on colors they see, also based on the theme of the collection. Cost price and materials, bring multiple ideas together.
- Theme defines the graphics more for the t-shirts, and the directions for marketing activations, art direction shoots and events. More clear, interesting and good the theme is, the easier it is for the whole team to execute. Should sound good within the brand DNA, but also find a new unexpected community.
- Core DNA for the brand, innovation, creativity, comfort, quality (also responsibility and sustainability) 4 pillars. Should be complete in order to be successful.

### Summary:

The brand embraces diverse inspirations to unite people, cultures, and creative disciplines. These elements form the theme of the collection and give strength to the brand. The designs are based on colors and references that stem from the inspiration source, aiming to fit within the brand's DNA, but also finding a new unexpected community. Core values that are essential for its success include innovation, creativity, comfort, quality, responsibility, and sustainability.

## Material

- New materials always need to be tested, especially natural materials like leather. Since every skin is different, some are softer and crease more, some are thicker or thinner, some are sturdier. So you won't know how the shoe will qualitatively act with that leather, but you can frame it in advance by using materials you understand because you used them before. So in that way you can objectify it.

### Summary:

Testing new materials, especially natural ones like leather, is essential due to the variability in material properties. Prior experience with similar materials helps in anticipating the quality and behavior of the material on a shoe.

## Development

- Proto rounds are for new silhouettes, 2-3 rounds to make sure that the design is finished. Different factors influence this, sometimes the shape is not good, sometimes it is the fit, sometimes the design isn't it yet, so small design changes (purely aesthetic). But shape is dependent on the last. Sometimes new sole, which means new last and also a changing shape.
- For a new pair, you always need 2-3 pairs before you go to production. Always is a moment that you need the human touch before it goes to production.



- Sampling rounds 2-3 is of existing silhouettes, in new color and material options.

#### Summary:

Proto rounds are for the creation of new silhouettes, typically requiring 2-3 rounds to finalize the design. Various factors influence this process, including shape and fit that are dependent on the last, but also aesthetic and structural design adjustments. Before production, it's usual to have 2-3 prototyping rounds for a new design, the adjustments require human input before finalizing production. Sampling rounds, on the other hand, focus on existing silhouettes in new color and material variations.

### Development process

- Addition of reference images for communication in tech pack. First proto rounds are very broad, don't expect the shoe to be perfect after the first proto, so try out what works and doesn't, in terms of materials what it could look like. They do give the shape of the last of the models they want to make. Important that the shoe fits the brand identity, hard to leave to the factory, but in the design comments make it more clear to the factory.
- Factory always follows the reference that is bound to the panels on the techpack, they don't follow the mock up image, but the reference in the techpack. Mockup is supportive, but reference is leading.
- Development takes half a year, and can be shorter sometimes. Start with prototyping, fitting, material sourcing, price wise, always timeline for production around 8 weeks plus 2 weeks shipments. Sometimes it can be faster, if you have less proto rounds and less samples.
- Usually the best is 2 proto rounds. Always some flaws, the shape of the shoe, the last is not good yet. Always try new materials on proto, see how it will look already for a sample round. Changes are logos, fitting, side panel small adjustments. Always happens, the main issue is the materials, may not be commercial enough, means that you need to remake everything again. Changes are mostly aesthetic, changes in fitting is how the shoe feels and fits around the foot.
- Development team gives advice to the design team to make the product better, cheaper or better construction, higher quality or easier for production to make. Supportive role to design, not changing it to make it more beautiful. It is good if the designer knows the rules and has the knowledge of production. So that you can design with the rules in mind. Prevent unnecessary changes, less changes is better. But there are always some changes, but the better the professional designer is, the less changes are necessary. Technical issues are mostly avoided then. Junior designer is seen, takes more time because he does not have the experience and expertise of the construction rules and limitations.

#### Summary:

Tech packs also include reference images for communication. Initial proto rounds are exploratory, aiming to test materials and shape. Factories always follow the techpack references instead of the mockups, they need to be clear to get a result that fits within the brand identity.

Clear communication with comments on the design are key for this. Development typically spans six months, with prototyping, fitting, material sourcing, and the production timeline. Ideally, two proto rounds are sufficient, focusing on aesthetic and fitting adjustments. The development team advises on cost-effectiveness, quality, and production ease, supporting the design team in making decisions. The designer's familiarity with production rules and limitations minimizes unnecessary changes, avoiding technical issues.

## Perspective on AI

- AI is the future, extremely important to understand and understand how to use AI. Has no knowledge himself, but important to have that expertise and knowledge in team
- Data on market sales, what colors, which styles sell well, what kind of silhouettes, what kind of leathers and materials, which soles. That can be trained, but AI shouldn't be the opponent of the creative process.
- Some chatGPT experience, dall-e images, but the feeling that is not that advanced yet. It knows what the brand is, but it doesn't know the brand design language.
- Big challenge, AI can make it to 70%, human touch is always needed to make it a 100% complete concept.
- Acceptance not there yet, he hasn't seen a useful proposal yet in terms of readiness. But it is about the key ingredients that you give it, educate it, the more information you give, the better the results are.
- Interesting to start with something really weird, then bring human touch of individuals, but AI as starting point. But realized if you type random and general things, it will generate rubbish and generic designs. So I need to filter the information to create something that is actually valuable.
- Creative industry is safe for AI to take over the jobs, because you always need the clients to know exactly what they want which will never happen. Always hard to say really clearly what they need to do. Can be a really valuable part of the process, but will never be able to be replaced completely.
- AI is very recent, right now it is interesting, and should be a way to be applicable. But the brand doesn't work traditionally, already up front so new tools are important to consider to move forward. Did do trials already with chatGPT out of curiosity but not more than that.

### Summary:

AI will be a big part of footwear design in the future, so having the expertise of understanding the applications and how to effectively use it within the team is important for the brand. While AI can support design decisions, it should not be the opponent of the creative process. It should rather supplement the process by having input data that includes market sales, color preferences, style trends, material choices and more to be trained on predicting what works and what doesn't. Human designers are still needed to incorporate the brand identity into the design, this is something that AI currently cannot do well yet. Next to that, clients often cannot accurately describe their needs, so communicating this to AI is another hurdle for which humans are necessary. However, having a weird and fuzzy starting point and refining it with AI can also

help the humans to understand their needs more clearly in the process. The filtering of information is essential in this complex communication process, to ensure results that match the goal well.

## Flaws and limitations

- Only problem is that it is fed by humans, you have the digital framework, but it has to be trained and fed by sources that are fed by humans. So humans are really important. Data is also really important, but data is not always the truth in the creative process.
- Creativity flows from culture, how people feel and act, that feeling is translated to design, AI doesn't understand culture and how people think. Process should be a combination, a yin yang, with AI and humans to also have culture and creativity also etc.
- Use AI for inspiration for techniques, or logos, not 1:1 copy but as a means of inspiration, because it's not 100% there yet. Results do not always match with what you expect it to generate.
- AI is cool, but it is not complete yet, and still makes some errors. Will always need to be a human eye or human touch within the process.
- Trick is to not expect good end results, but try with keywords to create an interesting starting point. Shift the focus from the end result to the process. Take the focus and expectations away, to only support the process with interesting approaches and starting points.

### Summary:

AI still relies on human input for its data, which is valuable, but does not always reflect the truth in the creative process. Creativity is nuanced and something human, since it stems from culture, behavior and emotions. So an effective approach would be a balance between AI and human creativity, like yin and yang. Rather than expecting perfect results, AI should be used as a means of inspiration and divergence. Shifting the focus away from the end result, but to the process itself will ensure proper expectation management and the right supportive and collaborative balance in the process.

## Envisioned benefits

- With Illustrator you can also apply AI to make colorways, generate color options, Adobe Firefly.
- Only tool I use is chatGPT. I need to write a lot. Can help save some time, but realize that you need to be very clear in the briefing to get the result that you want, otherwise it becomes really generic. If you understand that, you can get the result you want.
- Did try Midjourney with a friend that works at the experimental department of Nike. But did not try it himself because he didn't want to spend the money. Took a lot of time to get the image he really wanted, that explained the idea the best, could be helpful, but the images were very literal and on the aesthetic side lacking. But could be helpful for commercial clients to explain the very literal approach.
- AI can bring ideas, but you always need to look into the market and what it needs, also to the brand identity, since the brand has a really unique identity different from what is seen in the market.
- Creative people can envision what suede looks like on a flat translated to real life. But the commercial team does not have that skill. Hopefully AI can help with that. Hopefully AI will be that good, that you need way less samples. For sales only have 1 color option in real life to show, but then have more versions digitally on the screen presentation with all details, so the retailers can buy. Process is one of the big parts, but also saving costs and time is why the brand looks into AI. More sustainable as a company.
- Generate lots of options, to determine what directions work and do not work. Save time in the process. Much more help than asking the framework to design from scratch. Always build on existing products that are available.

### Summary:

If the design brief is clear, AI can save a lot of time in the process. However, unclear instructions lead to generic or overall bad results. Although creative people can visualize what materials would look like in real life from flat mockups, commercial teams may lack this skill, this is a gap that AI can bridge. This could lead to a reduced need for physical samples, which helps in the sales process by showcasing digital renders of the shoe to retailers, next to only one physical sample. The brand's interest in AI is driven by a desire to enhance processes, save costs, and promote sustainability, by building on the existing products and brand identity.

## Envisioned and desired use of AI in the process

- The AI framework needs to be the senior person in the team with a voice, but not of bigger importance than the people in the team with certain values and a vision. So, it needs to help to create a vision, but not 100% taking the lead. So a team member.
- As long as the human is involved in the company and in the process, will never feel like AI is too much in control. All people in the team are stubborn and have their own vision, that makes the AI tool probably not take over 100%. If it will be really successful, that will prove that the process needs to shift. But the quality of individuals in the team is paramount, and needs to be valued, so AI will never dominate in the process.

- Testing with new technologies is always good, doesn't always mean it does not work. Always learn from it, maybe some outcome has potential
- In the first phase, it would be nice if input is small and output is broad and lots of options for inspiration. But later in the process, it would be nice to have more input and the result is the way you imagined it to be.
- Future work will be combination of techpack and AI as supporting tool
- The decisions in terms of material use is what you want to control in a way, the nuance on how to translate references should stay human. What will help is generating lots of options, how this would look in materials, to visualize certain ideas. Also in terms of line and detail usage as reference, to use that approach to your design. Merge existing things to add to design. Means of inspiration. Cannot invent new things, everything has been done already. Just take things and put them in your world and change them accordingly, give them new spins to it.
- In terms of design, humans only needed to pick colors and only very small adjustments. But for translating it to production, you always need a human because the AI will not develop a last for example. Involves human work, also to translate it to production. Human nuances also needed to translate the design to CAD cutting the patterns. What works and what does not work.

#### Summary:

The AI framework should be considered as a member of the, contributing to the process but not outweighing human input, visions and values. In the first phase of the process AI will provide inspiration, lots of design options and color and material combinations. But the human nuances, creativity and critical decision-making will refine and translate the concepts to production, by creating the tech packs. Testing new technologies is valuable for learning and potentially leading to unexpected outcomes.

#### Desired end result of the framework

- Strategically, it needs to be fed by sales data what does and doesn't work. By sales team and ecom and merchandising. Needs to be fed with data that they see. That will result in better briefing for the AI framework. AI will be a good solution, for combination or past data, personal taste of the brand, somewhere in between is the sweet spot of what needs to be made, AI good solution. So on the one hand you are innovative enough, relevant enough, but on the other hand also commercially successful. A good balance between the two is the sweet spot. But the sales data is from the past, the brand started with something that wasn't there yet and that is how they became successful. Need to go out of my comfort zone to be successful. If only listened to data, never made a patch loafer, even though that was really successful. Innovative part is essential, not sure if it can come from AI.



- Hope that it helps the brand to visualize ideas, give advice on designs that the team itself does not see, create more freedom and time to focus on creative aspects that do not come from the tool.
- Ideal scenario, fabric suppliers that hopefully have the 3D textures of their articles. Would be really nice if the models also know what the consumption of the material is per shoe. So that they know how much square meters they use, and incorporate it with the price. Let's say no material waste, know exactly what the component will cost (with safety factor of course), and also incorporate the lead times of the material. Already know from the options that the AI model make, know the price and lead times with it, next to the 3D model have the data , know what it will cost, also tier pricing (if 800 this price, but 8000 what is the price difference) because now the pricing is always afterwards, so hard to keep into account. MOQ, suppliers, margin retail price, delivery times. That type of informed decision making will really help the design process.
- This is the inspiration shoe, now how would this look for a shoe that would be of our brand. There will be recognizable details. If that could be achieved, base it on a reference and translate to the brand, that would be good. Not start from zero, add info to an existing product, that would lead to a better result. If start from zero, either very literally or completely off. The more concrete you want to be the better it becomes, so have a clear design brief and description of what you want.
- Ideal would be only one batch of samples for each collection. Proto, check the colors and materials, only 1 sample round with multiple colors, then move to production.

#### Summary:

Strategically feeding the AI framework with sales data from various sources like the sales team, e-commerce, and merchandising enhances its effectiveness. This will lead to a balance between innovation and commercial success, which is crucial for a brand's success. Ideally, suppliers would offer 3D textures, material properties, MOQ lead times and prices, to facilitate the input of the AI model. Using existing products and clear design briefs in combination with data-driven decisions by AI will lead to optimal results. The ultimate goal is to aim for only one batch of samples for each collection to streamline the production process.

## Performance measurement

### What makes a design process good

- Experience, time, education in fashion design is what determines the gut feeling for making certain decisions, rather than always using tools and methods.
- Which factors make a design process successful, enough moodboards with color and material inspiration, enough design inspiration, good range plan that will set the goals clearly what is needed. The final collection needs to reflect the moodboards. Enough input that gets translated and reflected in output.
- Success is individual, the design process is based on prototyping. You can draw for a year, but at one point you need to see it in real life physically to decide whether it's good.

## Summary:

In fashion design, decision-making often relies on intuition developed through experience, time, and education, rather than only using tools and methods. A successful design process is determined by several factors: good moodboards with color and material inspiration, enough design inspiration and a good range plan to set goals. The collection should reflect the moodboards, the references need to be translated to the design. Success in design is subjective and the process also revolves around prototyping, good sketches do not always translate to a successful shoe.

## What makes a shoe design good

- Gut feeling also depends if it is good enough, need to feel material with hand in order to assess quality. Also reliant on data, but always check the last step with my own feelings. Data like GSM proves quality and sets boundaries, if not up to standards excludes options. But does not mean that every material that does tick the box is the quality that you can feel with your hands, what the brand wants. If it doesn't feel good, they don't use it. Like Dries van Noten, every fabric of his show always passes through his hands first. They also apply this at the brand, taking notes of the details.
- Gut feeling and board decides when it is ready to be sampled.
- How the market will react is in data, to determine whether it is commercially successful, but this is after launch. Phase before that, data tells that pink shoes for men don't sell well. Data driven, so they don't do that. Black shoes with white laces also don't work according to data, even if the design looks nice on paper.
- Not really methods for deciding whether a design and construction is good, mostly gut feeling.
- Best-sellers determine what works well in the market.
- It is really personal and subjective what determines whether the design looks cool and is complete.
- How to measure comfort is to try it on, let different people try it on with different feet. Walk on it and make comments about the fit. No perfect way to test it. The more people that test it, the better. All the evaluations can determine whether it is good or not.
- Factory rules are guidelines for construction, technical advice that are true when designing a shoe. Each factory has a modeler, for starting with the last, ergonomic look of the fit and translating it to a last. Shape of the shoe what the designer wants. After that all components of the shoe that are produced are designed in a CAD system. Specific measures for some parts of the shoe, per size, are different but need to be within range to be comfortable. Also gluing, when and where to glue the sole, based on testing and experience. Stitching also, footbed also. Lots of ways and rules of construction of the shoe, for productions. Design influences the construction. Sometimes the design is perfect, but in order for productions the design needs to be adjusted.
- Also the amount of attention and press and posts on social media make up for the success of a shoe. Visionary styles are evaluated differently, they also have massive marketing value next to only commercially. These products move down the pyramid, move from early adopters to the mass later. Always need to innovate so you always

have products that feed to the top, that make up for the circle of products. To stay relevant. Need to feed innovation but also be commercial. Sometimes you also need to wait for your wave, not always possible to stay relevant each year. Sometimes you need to float, when it is your wave, you can surf.

#### Summary:

The material quality is not only determined by its properties, the tactile feeling and the designer's gut feeling also play a role in assessing whether the material aligns with the brand's standards. The behavior of the material plays a big role in the perception of the quality of the shoe. The design and construction quality are mostly subjectively evaluated, by assessing the fit and comfort through wear-testing, and aesthetics through feedback from the team. Factory guidelines and technical advice can steer the direction of the construction, sometimes requiring design adjustments to ensure production feasibility. The commercial success of the design can be measured by market reactions, driven by sales data post-launch. Marketing and social media presence play a key role in achieving this success, especially with visionary styles that have considerable marketing value.

### Commerciality of a shoe

- Commercial is how accessible the shoe is to the main public. Conventional is more plain materials, not too crazy. Tonal colors, not too much happening at once. Trend maven is trend sensitive regarding colors and materials. Visionary is more crazy with materials and colors. But commerciality is also dependent on the model, combined with colors and materials, but the way you can express and color block is also dependent on the model.
- Commercial leather and suede is commercial, the normal materials. But also dependent on the silhouette and the amount and balance within the silhouette between materials.
- Factors that determine what is commercial, how many orders retailers make. How the market reacts, what big names celebrities want the shoe. Difficult to extract from data beforehand.
- Depends, there's different processes for the core commercial collection and the more visionary out of comfort collection, what you wouldn't expect. Higher tier products. Different process for the different perspectives on the collection. For the visionary you really work with a theme, tell a story about the theme. Core collection you work more with data, this material and color worked really well. Feedback from the past season and feedback from the retailers. Different approaches for the two segments, one is the retail market and the trends on top of the pyramids. A lot of market understanding in combination with design. Lots of factors that determine the product.

#### Summary:

Commercial shoe designs aim for accessibility with plain materials and tonal colors, while more visionary styles are more trend-sensitive. Success depends on factors like retailer orders, market reactions, and celebrity endorsements, making predictions challenging. Core commercial and visionary collections follow different processes, either driven by sales and market data or focusing on storytelling and thematic exploration. Market understanding and design expertise are crucial for both segments.

## How to benchmark/compare design/process

- Time, if it takes 15 minutes for humans to make 1 good colorway, but AI makes 10 in 5 minutes of which 1 is good. Then it is an improvement.
- Objective ways to measure, measure if a factory can do something with it, if it clears up the communication. Less questions and ambiguities (uncertainties) from the factory.
- See that the input really gets mirrored in the model
- That the factory can work with it, doesn't need to be perfect, but as long as it supports the techpack in the communication of the comments.
- Also sufficient if it gives more clarity, even if it is only the shape. So does it give more information, does it make more information available that was not there yet previously.
- Saves time, saves costs, more sustainable, less samples. If the communication works better with the AI visuals.

### Summary:

Using AI to generate multiple designs in a fraction of the time humans take can be considered an improvement, even if only one out of ten is satisfactory. Objective measurements of success include improved factory communication, reduced uncertainties, and clearer reflection of input in the model. The visuals don't need to be perfect, they should rather support the tech packs and communication with the factory. Even if it just provides clarity on just the shape or gives additional information that was previously not available, it adds value by saving time and costs, making the process more sustainable and reducing the need for multiple samples.

## Requirements and features

### Requirements that it needs to have

- For a new style, it would be nice if you can see the shape, realistically. Also finishes and details.
- Needs to look like a real shoe, realistic. So that you can sell from the image or model, also from the merchandising aspect. Make decisions for the collection based on the model
- Also the 3D model needs to be realistic, and input gets translated
- Apply different materials and colors, as well as the structure of the materials that you use. To get a better proper idea of what the shoe will look like visually. That would be important so it looks realistic.
- The generated image needs to be realistic enough to be sold to retailers, depending on the readiness of retailers as well. If it is good enough, supplement the physical sample, then it works. Reason to exist. Gut feeling does it look good, data does it sell well.
- The generated image needs to look very realistic. Because color options can be made easily in 2D flat with illustrator. But also needs to look 3D and realistic, with textures of meshes for example, not get that in flat illustrations. In real life and 3D some materials look different that are not visible in 2D. The difference between real life and 3D renders needs to be as small as possible.

### Summary:

In order for the image to be useful, it needs to look realistic, both in shape and proportions, but also in material finishes and detailing. The more realistic it looks, the more effective it can be in communication and decision-making for all departments. The output should also accurately represent the given input, regarding the shoe's materials, colors, and structure for a proper visual understanding. There should be minimal differences between the digital and physical appearance, so the digital version can serve as a reliable counterpart to the physical sample when selling to retailers.

### Features that would be nice to implement

- Features would like to be seen in terms of proportions and lasts, would be interesting if that could be achieved. Different angles and positions of the shoe, to determine what it looks like. Also the actual dimensions incorporated into the design. Because sometimes it looks different on the screen than it is. Also generate tech pack information with the image, rough dimensions indications. Would help to tape up the shoe and give it to the factory to make a first proto, then already much closer to the result that you want.
- Logo implementation would also be nice, which logo would be best and what measurements. Also know how many logos for which shoes. Generate it with logos. Luxury less logos, commercial too logos. AI can give advice on the logos. Style of the logo is also important, difference between logo embossed, print embroidery etc.
- Would be cool if the AI follows the references, or the other way around, that it can make the references that follow the mockup.
- Would be nice to use inspiration photos as reference, not necessarily shoes or clothing. Would be nice if that can be used to generate a shoe that fits within the brand identity. Or would be nice to generate an upper for an existing sole, with keywords to steer the design.
- Also would be nice if it can envision what different sizes would look like, how the scale influences the design and how it would look. If the size of the patterns scales well, because this can go wrong if moving up to bigger sizes. Base is the design, but also the scale of the sole and the modeling of the CAD patterns is needed to scale the design to other sizes of the shoe. Human impact on adjusting the modeling of the scale of the shoe.

### Summary:

It would also be valuable to include features such as proportions, last information and different viewpoints as outputs. Incorporating actual dimensions also adds to a higher consistency between the digital representation and physical reality. For the development and production process, it would be beneficial if tech pack information could be generated, as well as envisioning the scaling for different sizes. For the design, it would also be nice if logo implementation could be added, including considerations for the type and style of logos to serve as a guidance. Moreover, it would be nice if design could be generated from references and photos unrelated to shoes, that would create concepts that align with brand identity.



## Challenges and pain points

- Challenges in transition, but it will save time for the team.

## Communication

- Human errors can be typos in the techpack, an old model in the presentation that wasn't removed from the techpack report. Communication error, factory interprets comments differently than intended. Mitigate it by adding as many details as possible, as well as reference images of what you envision.
- Challenge is that you need to be really clear when you want a prototype, because you only get 2 chances to make it good so only 1 chance to make changes, 2 rounds to give comments before it is the SMS for sales to sell. To get good results, a lot of material and detail testing, more than drawing. But also spending a lot of time in the factory to make the prototypes, to get a perfect result.
- What does the brief look like for the AI program? But this can also help the design team to dive more into the exact keywords for the program. Sometimes it is a bit shallow, but when the team is forced to think better about what they actually want. So works in both ways, thinking about briefing the program also makes the vision for the team more clear. Become way more aware yourself as a team about what you want, and the program will get a better end-result. Have to know what you don't know and what you are struggling with.
- You have to know what you want, because you need to be really specific from the beginning in what you ask. It is not always the case that the design brief is clear.

## Summary:

Human errors in tech packs, such as typos, and communication errors with factories can lead to misinterpretations and challenges in production. To mitigate production issues, detailed design comments and reference images should be provided. Getting prototypes right is crucial, since there is usually only time for two chances for revisions before the product needs to be sold. To get good results, material and detail testing is really important, which can be best done by spending time in the factories to make the prototypes. Clear briefing is essential for the factory as well as the AI programs to ensure accurate outcomes. So it's important as a designer to understand exactly what you want the output to be, to avoid confusion and errors in the process.

## Concept creation

- Used to have technical designers who were quick with sketching on Procreate, could do a lot of options and design iterations, but now they are lacking the ability to explore different lines, aesthetics, proportions, shapes and colors. Figure out yes or no's way faster back than. Now everything in illustrator is not as fast anymore. It can be done technically but at a different speed and level. Concept wise easier if you can iterate quickly and can immediately see a result. With RTW they still have it, easier to try a lot of things in a relatively short time.
- Mitigate is by focusing on the things they want to try. Edit options, be more aware and selective with ideas and processes, in a way this is also a positive thing. Not lingering

and working for days on a design and a lot of directions and ideas, it brings focus. Make clear what you want and focus.

#### Summary:

The brand used to have a technical designer who could quickly explore design options with Procreate, but now they are lacking the ability to explore small adjustments in linework, aesthetics, proportions, shapes and colors. Now they do everything in Illustrator, which slows down the process. To mitigate this challenge, they bring more focus to specific ideas, to becoming more efficient and selective in their approach. This brings clarity and prevents lingering on multiple design directions.

### Market and trends

- Challenge is brand identity and making it fit with the market needs, can be based on data. AI can help with it according to data and resources available to the tool. Sometimes the study process is very quick now, AI can do it more extensively.
- Another pain point is not knowing how the target audience moves, what they wear and what they want.
- Fashion is cycles, now the Y2K era is popular. Clothing style with wide pants is what we see now, not at the peak because it is at the fast fashion chains. Now you see that people are tired of sneakers and moving more to dress shoes and loafers, more neat but comfortable. You need to read the audience. There are trend forecasters, could be correct, everyone listens since they are big forecasters so everyone moves. If they really see it or are the cause, are the driver. Hard to see where the market is in 2 years. They look at it, they are really big and proven to be correct, but because everyone looks at it, they become mono-cookie. So not unique and if you follow it you could be too late.
- Needing different AI framework, data driven updates for core collection, commercial shoes. Making the money and working with the market data. And the other is creating a theme collection with references and translating them into products.

#### Summary:

One of the challenges of fashion design is aligning products with the brand identity and the market developments. Understanding the fashion cycles and reading your target audience can be done by analyzing trend forecasters, but this might lead to the risk of not being unique. However, it is important to keep up with the changing market so you don't fall behind. To address these challenges, two frameworks are needed: one for data-driven updates for the core commercial collection, and one for creating more innovative, theme-based collections to stay relevant.

### Fashion timelines

- Problem is that fashion moves really fast, what you can consult today, does not mean that in 3-4 months it has not changed, this is the time you have to make proto, samples and move to production. Development to production is half a year, and goes really fast sometimes. Always take into account the timeline for the sales team to sell the shoe.

- Timelines. Receiving a collection to receive the first batch of samples, always needs to make a second batch of samples. Second batch always sells more, so it is more important. 9 months after the factory receives the tech pack, the shoes hit the market. Receiving techpack, sampling, selling shoes and receiving order, production, that takes 9 months.
- Pain points challenge is time. The sales team asks for a model, but after 2 proto rounds sometimes it is not ready to sell, even though sales wants to sell it to retailers already. That leads to time trouble. Either sell a shoe that is not finished yet, or move it to the next season with the risk that you are too late or the trend is over. How to mitigate it is for the sales team to let design and development know early what models they want. To Design and development to give as many detailed comments as possible, so that the factory doesn't leave things open for interpretation and makes the shoe as good as possible.
- Pain points in the design process. Work really in advance, which color and style are relevant in 1,5 years? Everything you design is shooting in the dark in some sense, difficult. Can be solved with AI because it is data driven, but with points from the past. Future is unknown and can change.

#### Summary:

Keeping up with the dynamic and trend-sensitive fashion industry is challenging when considering the lengthy long development to production timeline of footwear. Delays in the design and development process can lead to time constraints for the sales team, who may push for unfinished models to be sold to retailers or face the risk of missing trends completely. To mitigate these issues, early communication between sales and design teams is crucial, but designing for the future will always remain a shot in the dark. Providing clear and detailed design feedback is also critical to avoid uncertainties for the factory.

## General

- For a good collection, you need to add to the commercial part, but also stay relevant. It is always a balance. You need the fresh blood, to send to influencers, they want new shoes. You need winners that bring the money in, but also need fresh blood to stay relevant and keep it interesting. To bring consumers into the world of the brand. That is important for a brand.

#### Summary:

Maintaining a balance between innovation to remain relevant and commercial products to generate revenue is important for a brand's success.

# Appendix C

## List of requirements

The bold requirements are the most important for Filling Pieces, so those are the ones that will be focused on for this project.

### Requirements of framework

- The framework needs to seamlessly integrate into existing design and development workflow.
  - The framework should be user-friendly and easy to use for the team.
  - **The framework should be easy to implement into the current workflow of the Filling Pieces team, even for those with minimal technical expertise, it should be able to be used by dummies.**
- **The framework should optimize cost-effectiveness and speed up the design process, by reducing the reliance on prototyping and sampling rounds and ultimately shortening the time-to-market of new footwear styles**
  - The framework should save money in the process, by relying less on the production of physical samples.
- The framework should be able to run locally, on the own computers of the users to avoid privacy issues.
- The framework must rapidly produce outputs, with brief processing times for both briefing and generation stages, facilitating rapid iteration and inspiring creativity.
- The framework should offer options for customization, and flexibility to adapt to varying design requirements
  - The user should be able to only customize specific indicated parts (for example only change the upper and keep the sole design).
  - **The framework should allow designers to change individual design elements (parts, elements, patterns or details of the design) to facilitate small design updates on existing styles.**
- The framework should have a feedback mechanism, to subtly change or iterate on the generated design.
- **The framework should enhance creativity, by inspiring creative exploration.**
  - This could be assessed through user feedback, their level of engagement and the diversity and novelty of generated designs.
- **The framework should apply sales data and material toolbox information into the design input, to ensure data-driven design outputs.**
  - It should work with input from the Monday material toolbox spreadsheet.
    - This information should be used to set design boundaries for the output generation.
    - The outputs should comply with the requirements set by the user.
    - The framework should be linked with BOM information, material costs etc.

- The framework should enable integration with internal sales data, allowing the generative AI framework to utilize sales-driven data.
- The framework should lead to a higher quality design process and improved design outcomes.
- The framework should improve communication with stakeholders by providing tools that facilitate decision-making and enhance clarity through visual communication of ideas and concepts.
- **The output generations should consistently align with the design aesthetics and brand identity of Filling Pieces, as well as being relevant to the theme of the season**
- The framework must be compatible with existing tools like Illustrator, Photoshop, and Procreate to supplement rather than change the design process, minimizing friction in adoption and workflow changes.
- The use of the framework should require minimal human intervention and additions to achieve completeness, meaning that all necessary components are included without the need for manual adjustments.
- The framework should be scalable to accommodate a wide range of footwear styles, ensuring versatility for multiple styles and contexts.

#### Requirements for the output generations (2D):

- **The generated image should be visually realistic, it should resemble the real-world outcome as closely as possible, to support visual communication**
  - The proportions should be realistic, it should look like a real shoe (and not like a clown shoe).
  - **The output should be feasible to produce, it should not be an unrealistic design in terms of manufacturing.**
  - The materials should reflect the way they look in reality.
  - The details of the generated images should also be realistic.
- The differences between the digital and physical appearance should be minimal.
- **The generated images should appropriately reflect the references that are used as input.**
- The generated design should be comprehensive in terms of the total concept, meaning that it includes all elements for a completely developed concept.
- There should be a good balance between consistency and variation between the generated images, they should resemble each other to be reliable, yet vary enough to be interesting.
- **There should be a good balance between consistency and variation between the generated images, they should resemble each other to be reliable, yet vary enough to be interesting.**

#### Design requirements for creating new styles:

- The output design should reflect the influence of input shoes, but not be a direct copy.
  - It should be measurably different in 7 areas.
- The output design should reflect the design aesthetics of non-shoe reference photos.



- There should be a clear distinction between conventional and visionary styles.

#### Design requirements for updating existing styles:

- The references from the moodboard should be accurately reflected in the output generation.
- The linework of the design should not be changed in the output.
- Small changes in design elements such as color, material, and logo placement should be facilitated by the framework.

#### Requirements for the output generations (3D):

- The shape of the output 3D model should be accurate and realistic.
- The output 3D model should serve as a guideline for the final shape, to help the production process.
- The shape of the output 3D model should follow the shape of the last.
- The design of the 2D input should be maintained in the design of the output 3D model.
- The files should be compatible to work with.

#### Wishes (additional)

- The framework should enable the application of logo implementation, different logos in different styles.
- The framework should be able to generate tech pack information, such as last information and dimensions.
- The framework should be able to generate different viewing angles, such as a top view.
- The user should be able to tweak different parameters to customize the design.
- The output designs should align with manufacturing processes and capabilities, to ensure a smooth design to production process.
- A design library with pre-existing design elements, templates and assets should be integrated into the framework,
- The framework should accommodate market data, style trends from the market and market demands accurately and in real-time.

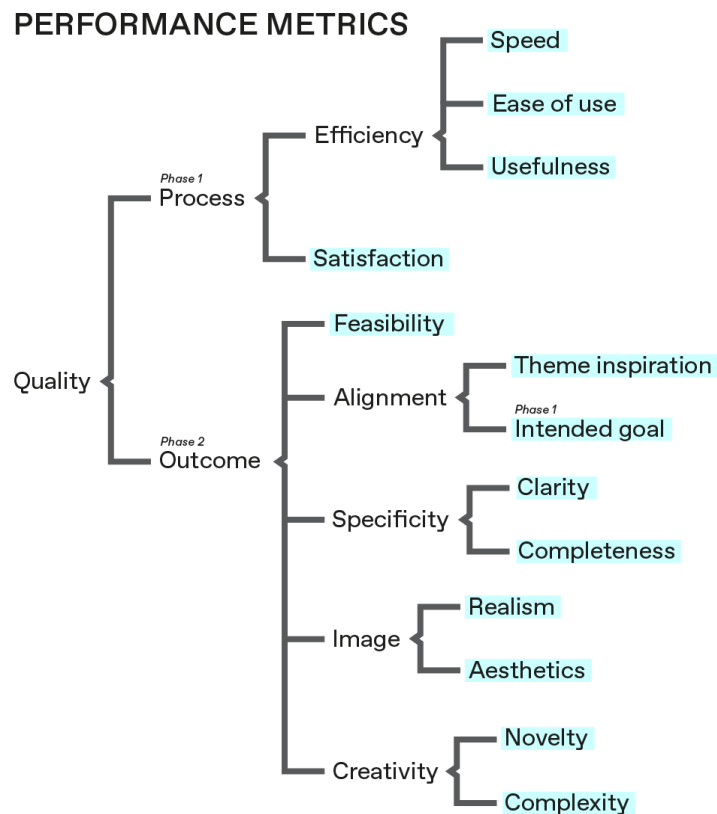
# Appendix D

## Final User Test Procedure

### Goal

The goal of the final test is to assess the effectiveness of the process and outcome of the proposed AI framework in two phases. In the first phase, the focus will be on qualitative results, evaluating the effectiveness of the AI augmented process and the interaction with the AI tools. This will be done with the Footwear Designer of Filling Pieces, to get the most thorough understanding of the quality of the brand specific AI workflows that are proposed. The outputs of the first phase will be used for the second phase, where quantitative data is gathered to evaluate the quality of the outputs, comparing the traditionally made designs with AI generated designs. This will be done through a survey with a large number of participants, to test if the requirements for the output designs are met.

### Metrics:



# Phase 1: Qualitative Assessment

The first phase, which is the user test, was conducted with the footwear designer from Filling Pieces (N=1). The workflow is specifically tailored to Filling Pieces, since the LoRA models are trained on the brand's data. Since reflecting the brand identity was one of the objectives, this can only effectively be measured if the designer has experience in designing for the Filling Pieces.

This participant will also be the end-user of the proposed framework. By conducting the user test with him, valuable insights were gained into his opinions on what works well and what needs improvement. The goal is to determine whether he would actually use and implement the framework, which was discovered through this assessment. Since both of our preferred languages were Dutch, the test was conducted in Dutch. The session was audio-recorded, and the participant was asked to think aloud to capture their thoughts, ensuring the best qualitative understanding.

## Method

The user test began with an introduction where the goals of the study and the project overview were explained. Some background information was asked to get an understanding of his professional experience, such as his design and footwear experience, as well as familiarity with AI tools.

Next, a detailed explanation of the design brief was given. The task was to design a new functional footwear style, both with and without the AI framework. The brief specifically was to design it for the AW24 collection, inspired by the seasonal theme: United by Design - Modern Architecture. Moodboards were shown to provide context and visual inspiration. He was given the opportunity to briefly do a warm-up exercise to get ready for the test. To get a comprehensive understanding of his thought process, he was instructed to think aloud during the tasks to capture his thoughts and reasoning.

### Traditional design task (without AI)

The traditional design task was divided into two parts, the first task being to make rough explorative and divergent sketches for 5 minutes. The goal here was to come up with a lot of ideas where rapid ideation was encouraged. Before going to the next part, he was asked to select the best sketch to refine. The next step was to refine this sketch for 5 minutes into a more definite and complete concept design. Following this process, the participant was asked to provide feedback on the process and outcome, based on a semi-structured set of questions.

## AI-Augmented design task (with AI)

Before starting the user test with the proposed AI framework, an introductory tutorial had to be given to explain what values parameters could be adjusted and what their influence was. The participant was instructed to only change the values of the green nodes, which had the most significant impact on the output design. The prompt had to be based on the design language and project goal of the theme, with the LoRA strengths adjusted according to desired influence of the moodboard, within the ranges that were identified to be optimal according to earlier experimentation. Next to that, it was explained that multiple prompts could be queued without affecting overall speed, and that the settings used in the AI tool were found in the file name of the output for reference.

The AI-augmented design task was also divided into two parts, similar to the traditional design process. In the first part, the participant had to spend 5 minutes exploring designs using the first explorative workflow. Again, he was asked to select the best design to create variations on and refine it into a complete concept. Following these tasks, he was asked to provide feedback on the process and outcome, based on the same set of questions.

To conclude the user test, additional questions were asked to gain deeper insights. These questions were not only based on semi-structured question format, but also based on observations made during the use. These concluding questions aimed to capture the participant's perceptions, experiences and acceptance of the AI tools used in the design process.

## Procedure + notes:

- Introduction
  - I will explain the goal of the study and the project overview
  - I will collect data on years of design experience and footwear an FP (Ivo)
    - Design experience
      - *More experience in developing rough designs into final designs, not really a lot of experience in the first phase of design. Would say about 3 to 4 years of experience.*
    - Footwear industry experience
      - *About 2 to 3 years of experience in the footwear industry*
    - Familiarity AI tools
      - *ChatGPT and Dall-E, but does not really work yet for professional use, because it does not know the design language of FP*
  - He can do a warm-up exercise if he wants to
- Explain design brief (with slides)
  - Explain case study and theme, design new functional style for AW24 theme
  - Explain theme, inspired by modern architecture
  - Show the moodboards
  - Explain that he should think out loud
- Traditional design task (without AI)

- Task 1, 5 minutes to make rough sketches
- Constrain the time
- Now select the top 1 design
- Task 2, refine the best design (5 minutes)
- Constrain the time
- Rate the output design on a 1-5 scale, also the process how it went (questions below)
- Explain AI tool
  - Explain parameters that have most influence
    - Is able to change the values in the green nodes, do not touch the rest, explain influence of the green nodes
    - Prompt based on design language and goal
    - LoRA strengths based on influence of that moodboard
    - Also explain that can queue multiple prompts, does not affect speed, just have to wait
    - Explain that settings used are found in the file name, so you can look them back
  - How to import images
  - Where export images are
- AI augmented design task (with AI)
  - Task 1, 5 minutes to make lot of generations
  - Constrain the time
  - Now select the top 3 designs
  - Task 2, refine the best design (5 or 10 minutes)
  - Constrain the time
  - Rate the output design on a 1-5 scale, also the process how it went (same questions)
- Ask more qualitative questions
  - → see additional questions
  - Observe in the meantime

# Questions

## Process Evaluation

1. How useful did you find the process in terms of coming to a final concept, and why?
  - a. *For inspiration, it is not a finished concept immediately, but it's mostly for inspiration, options, and style variations. You can explore with it. You want it to look a certain way and make many versions. Very useful for inspiration by making many versions of that shoe. But you still need an illustrator variant in the end to develop, with material references before it's a finished concept. There's a lot more behind it than just creating the AI image. Very positive about what it can do and the ideas it provides.*
2. How easy was the tool to use, and why?
  - a. *Very easy, you need to work with it longer to fully understand how everything works, for example, changing the sole or material or color. Understand which prompt to use or if you need to adjust the input image. Kept it basic now, but realizes there is more possible than what he did in those 5 minutes.*
3. To what extent do you feel that the tool made the design process more efficient, and why?
  - a. *Definitely efficient for inspiration. It makes it faster to get ideas. It takes time to decide which to develop and make accurate. Also, because the image is a shoe, but in the traditional process, you also use reference photos of real shoes. It won't necessarily replace the illustrator process, as they are different tools with different goals. So, it's also difficult to really compare.*
4. How satisfied are you with the overall use of the tool, and why?
  - a. *Very surprising how it works with the references, very cool. There are always small things that are not entirely correct, a few small mistakes, which is not a big deal but makes it tricky because it needs to be refined. But the tool works well, even when you change the values and prompt you see what it does.*

## Output Evaluation

1. How creative do you feel the output is?
  - a. *Yes it is creative, it allows you to see possibilities in a different way, explore what can be done with a shoe in a different way.*
2. How novel/original do you think the design is?
  - a. *Yes, it's not necessarily that you think of a shoe and then fill it in, just the general concept of a dress shoe for example, but the results in a very different way than you would have thought beforehand. You wouldn't come up with it yourself, a creative perspective on how you can look at a shoe.*
3. How complex do you think the design is?
  - a. *Not necessarily complex, still recognizable. Because of the values and prompt probably because of how it was described.*
4. How well does the output align with the goal of the theme?



- a. *Somewhat aligns with the theme, would have preferred to see it with a different sole though.*
- 5. How well does the output align with your intended goal?
  - a. *A different sole would have been preferred. But it wasn't necessarily the illustrator version that he made either, would have liked to see it.*
- 6. How well does the output align with the Filling Pieces brand identity?
  - a. *Quite a lot, with the heel tab and the downstrap. The sole has something of a Cruiser. Matches quite a lot. What's missing is the branding with logos.*
- 7. How clear do you think the design is? Can you easily see what each part represents?
  - a. *A bit unclear at the nose area, the rest is very clear what it is.*
- 8. How complete do you think the design is? Are there any missing elements?
  - a. *Quite complete, just a bit blurry at the front, you need to fill it in a bit yourself. Also the branding is missing.*
- 9. How realistic do you think the design image is?
  - a. *Yes, it is very realistic.*
- 10. How aesthetically pleasing do you rate the design?
  - a. *You can definitely see it's a shoe design, not necessarily his taste. Beautiful shoe, but wouldn't wear it himself. But definitely more beautiful than the non-AI concept he created in 5 minutes, haha.*
- 11. How much does this output help you in the next steps of the design process, in terms of developing the concept?
  - a. *In terms of parts and patterns, it helps with how you distribute them. You can compare soles with what's available at factories, unless you develop your own. Distribution of the shoe, proportions, and surfaces.*

### **Additional questions**

- 1. What are your overall thoughts on the tool after using it? How do you feel about it?
  - a. *What did you like most?*
  - b. *What did you find challenging or less useful?*
  - c. *Liked that it was fast and saw the influence of reference, useful for inspiration. Challenging to change the sole, only used the prompt but should have done that in Photoshop first.*
- 2. Has this tool changed your outlook on what it means to be a designer?
  - a. *Did it have an influence on your perception of the role and skills you have and need in your job?*
  - b. *Think it's the future, but more as an aid, maybe much later it can take over roles, but for now, it's a tool that works very well. Immediately apply what you think.*
- 3. Do you feel ownership of the outputs that the AI generated?
  - a. *Do you feel connected or disconnected from the outputs?*
  - b. *Feels a bit disconnected, not really ownership. Not really your own idea, you're behind it but didn't really make it yourself.*
- 4. How do you envision using these tools in your work? Would you use it in your current workflow?
  - a. *If yes, in what phase of the design process do you think it will be most beneficial?*

- b. Would use it in the inspiration phase, first phase of design before developing and working it out.*
- 5. How much control do you feel you had over the designs produced by the AI tool?
  - a. Did you feel like you could guide or steer certain parts effectively?
  - b. Yes control with prompt, saw that it changed the design. Also saw that the influence of the FP style was more when the value was higher.*

## Notes

### Workflow 1 traditional iPad sketch

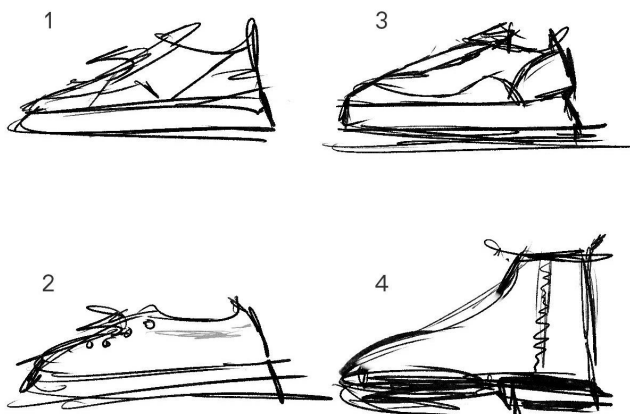
For the first sketch, he tried to make a Low Top, but with more straight lines to reflect the theme. He used underlays to sketch over the silhouettes.

For the second sketch, he tried to make a dress shoe, with materials that align with the moodboard is how he envisioned it. The big eyelets add to the theme as well as the moodboards. But he leaves the sole as is, because the chances that you make a completely new sole are very small, as it is a big investment.

Third sketch, a sneaker that has flowing lines, but yet is very static like the influences from architecture. Straight but slightly curved lines, to keep it clean.

The last sketch he envisioned it to be more trend driven, a Chelsea boot that aligns with the theme.

In 5 minutes, he made 4 rough sketches.



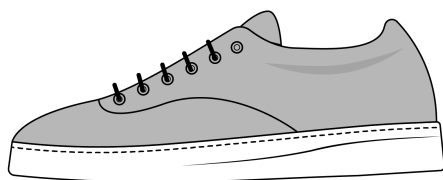
### Phase 2 translation to Illustrator

This was done very fast, 5 minutes is not really realistic as he normally spends about 30 minutes per design to create the CAD. The same applied to the sketching, as it was a very pressured environment. The sketch he chose (sketch 2) was not complete yet, he did not have an idea of what it was supposed to look like, so he just started doing something.

For development, you need a CAD, so this work always has to be done. This means that when generating designs with AI, you need to keep in mind that the image still needs to be translated to an Illustrator CAD. Keep in mind that you need to add the time that this takes to the AI process.

Normally, he also uses a lot of image references from other brands or styles to have an example of what the final shoe should look like. Next to that, the 5 minutes for creating a CAD was not really realistic, so the end result is not something that is really representative of his skills. So for the final evaluation, it is good to have 3 designs, also one that he had spent 30 minutes on to completely finalize. To compare the final AI generated design he made in 5 minutes to a CAD he made in 5 minutes, as well as a CAD he had a normal time for to complete. All made for the same theme.

In 5 minutes, he defined 1 CAD to a more complete concept. But again, 5 minutes was not really realistic. If he had 30 minutes, the outcome would have been much better.



### **Phase 3 AI workflow 1**

First he looked a bit at the theme moodboards, to come up with a prompt that he wanted the shoe design to look like. He changed it to a dress shoe, as that was what he was trying to achieve with the sketch as well. FP influence was low, so he increased that value. Wanted other materials as well, so changed the prompt again. Final concept he chose was a dress shoe upper on a sneaker sole, an interesting creative play from the AI, where he used the prompt: “neutral dress shoe, side view, clean, classic materials, basic lines”.



#### **Phase 4 AI workflow 2**

He used that image as the input for the second phase of AI. What he envisioned was to have the mix between the sneaker and dress shoe upper, but with a dress shoe sole. So he changed the prompt. However, the sole did not really change, only slight variations of the linework. That is why he used an even higher denoise value, to also change the silhouette of the image, instead of just making variations. He went outside of the range, to be even more creative.

He wanted to change and adjust the sole, but it did not work. However with a higher denoise value than the indicated range, the silhouette also got changed to make more creative variations of a dress shoe, rather than slight variations, which was the intended goal.

Wanted a dress shoe, but since the input had a sneaker sole, the goals got changed because he could not change the sole. However it was good to see that it made creative variations on the input design. And the final design is a very interesting play on a dress shoe-like sneaker. However, he still wanted to see what effect it would have if the sole was a more formal one, since he used the prompt: "colorful dress shoe, side view, clean, innovative materials, basic lines, dress shoe sole". Dress shoe sole did not really generate well, since it had a sneaker sole in the input image. If he wanted to see that effect, he realized that he would have needed to change that in Photoshop first, but that was too late.



But he said 5 minutes was a short time, and also that he had to learn the tool better to see what it was capable of.

## Phase 2: Quantitative Assessment

For the second phase, the qualitative evaluation, a survey was distributed to a group that included people with experience in the footwear industry, as well as people with design experience. This selection was made to ensure that participants were familiar with the context, to obtain valid responses. In total, an amount of 37 respondents (N=37) answered the survey.

The goal was to gather quantitative results on the quality of the outcomes of the user test, comparing designs made with the traditional process with AI-generated ones. This assessment would determine whether the design requirements were met. A Likert scale is used to rate the performance metrics, providing a quick and relatively easy way to analyze data from the qualitative questions. Rating responses on a Likert scale of 1 to 7, with each response option labeled, has been proven to lower response bias and increase consistency in answers (Weijters et al., 2010).

### Method

The evaluation survey began with an introduction explaining the goal of the study and providing an overview of the project, without mentioning Filling Pieces. Participants were asked to provide data on their design experience, experience in the footwear industry, and familiarity with AI tools. This information would be used to contextualize their responses and ensure a relevant and informed evaluation.

The survey showed the design outputs from the user test, both traditional and AI-generated, side by side. This allowed participants to directly compare the different design methods, without naming which design was created using which method. Participants rated the designs on the selected metrics using an online survey to determine the quality of the design outputs.

After this rating section, it was named how the two designs were made. To gain a comprehensive understanding of the participants' perspectives on AI in design, additional questions were included. These questions provided room for general comments and suggestions for improvement. Participants were also asked if they could identify the brand the designs were made for, to see if they could recognize the Filling Pieces brand identity.



## Procedure:

- Introduction
  - I will explain the goal of the study and the project overview NOT MENTION FP
  - I will collect data on years of design experience and footwear
    - Design experience
    - Footwear industry experience
    - Familiarity AI tools
- Show design outputs from Phase 2, both traditional and AI-generated, show them side by side
  - Rate the designs on metrics through online survey, to determine quality of the design outputs
- Ask additional questions to get comprehensive understanding on perspective of AI, room for general comments and suggestions for improvement. Also ask if they guess what brand it is for, to see if they can tell it is made for FP.

## Questions survey

Age

Experience as a designer

Experience in footwear industry

Familiarity with generative AI tools

### Rate Outputs (1-7 Likert Scale)

Show the output images of phase 1, A being output from traditional, B from AI

1. How novel/original do you think the design is?
  - a. A
  - b. b
2. How complex do you think the design is?
  - a. A
  - b. b
3. How feasible do you think the design is to produce?
  - a. A
  - b. b
4. How clear do you think the design is? Can you easily see what each part represents?
  - a. A
  - b. b
5. How complete do you think the design is? Are there any missing elements?
  - a. A
  - b. b
6. How realistic do you think the design image is?
  - a. A

- b. b*
- 7. How aesthetically pleasing do you rate the design?
  - a. A*
  - b. B*

### **Additional Questions**

1. Which design do you prefer overall?
2. What do you think of AI-generated designs in general?
3. What aspects of the AI-generated designs did you find most appealing or unappealing?
4. Do you have any suggestions for improving AI-generated design outputs?
5. What would be a reason to use this tool?
6. What would be a reason to not use this AI tool?
7. What footwear brand do you think the design was made for?
8. Could we reach out to you via email for any further questions? If you're comfortable, please provide your email below. This is optional

## **Analysis**

Qualitative: Analyze feedback from user test and interview

Quantitative: Compare performance metrics between AI-assisted and non-AI-assisted designs

Combine findings into comprehensive results.

### **SURVEY**

Explain why I compare CAD with image, output of the phases. IN REPORT

Als je kijkt naar traditioneel process en AI oriented process, de output van de creatieve fase is anders, namelijk een CAD en een image. Dus deze outputs moeten worden vergeleken worden. Hypothesis ook dat de AI image nog niet clear en complete is, dat er nog een vertaalslag door de ontwerper gemaakt moet worden naar een CAD, om het duidelijk te maken voor communiceren naar de fabriek.

Hypothesis write that what I think the results will be

# APPENDIX E

## Bridging the Gap between AI and Footwear Design

The aim of this research is to evaluate the quality of AI-generated footwear designs. Your participation in this survey will provide valuable insights into your experiences and perceptions regarding the generated images. The survey is estimated to take approximately 5 minutes to complete. The anonymous data may be used for publication.

\* Indicates required question

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1. Do you give consent to participate in this study? \*

*Mark only one oval.*

Yes

2. What is your name? This is optional

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### General questions

3. What is your age? \*

*Mark only one oval.*

18-24

25-29

30-39

40-49

50+

4. How would you rate your experience as a designer? \*

*Mark only one oval.*

- No experience
- Student
- Novice (less than one year)
- Beginner (1-3 years)
- Intermediate (4-6 years)
- Advanced (7+ years)

5. How would you rate your experience in the footwear industry? \*

*Mark only one oval.*

- No experience
- Student
- Novice (less than one year)
- Beginner (1-3 years)
- Intermediate (4-6 years)
- Advanced (7+ years)

6. How familiar are you with generative AI tools for generating images? \*

*Mark only one oval.*

- Not familiar at all
- Slightly familiar (I've heard of them but never used them)
- Somewhat familiar (I've used them a few times)
- Moderately familiar (I use them occasionally)
- Very familiar (I use them regularly and am well-versed in their capabilities)
- Expert (I have in-depth knowledge and extensive experience using them in various projects)

### Purpose of the images

The images presented next in this survey represent the output of the creative phase in a footwear design process. These images will be used to create a tech pack, which is a document that contains all the necessary information about a product to manufacturers. It specifies the materials and details for each component of the shoe, ensuring that everything is clearly defined for the production process.

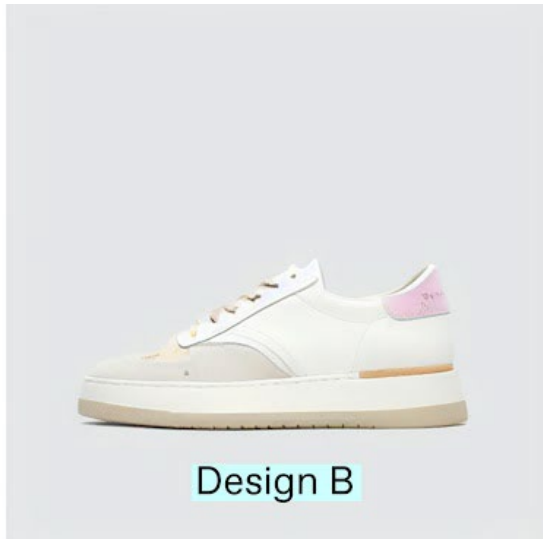
The quality of a design in terms of its development is determined by the following metrics, which you are asked to rate.

### Rate Outputs (novelty/originality)

Please indicate to what extent you (dis)agree with the following statements



Design A



Design B

7. How novel/original do you think design A is? \*

*Mark only one oval.*

- Very familiar
- Familiar
- Slightly familiar
- Neutral
- Slightly novel/original
- Novel/original
- Very novel/original

8. How novel/original do you think design B is? \*

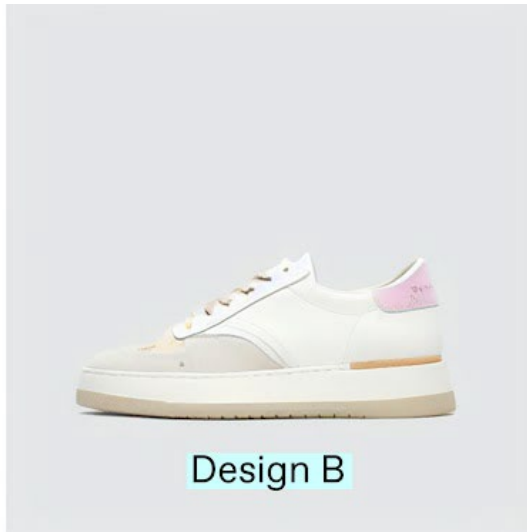
*Mark only one oval.*

- Very familiar
- Familiar
- Slightly familiar
- Neutral
- Slightly novel/original
- Novel/original
- Very novel/original

Rate Outputs (complexity)



Please rate the design outputs based on a scale from 1-5:



9. How complex do you think design A is? \*

*Mark only one oval.*

- Very simple
- Simple
- Slightly simple
- Neutral
- Slightly complex
- Complex
- Very complex

10. How complex do you think design B is?

*Mark only one oval.*

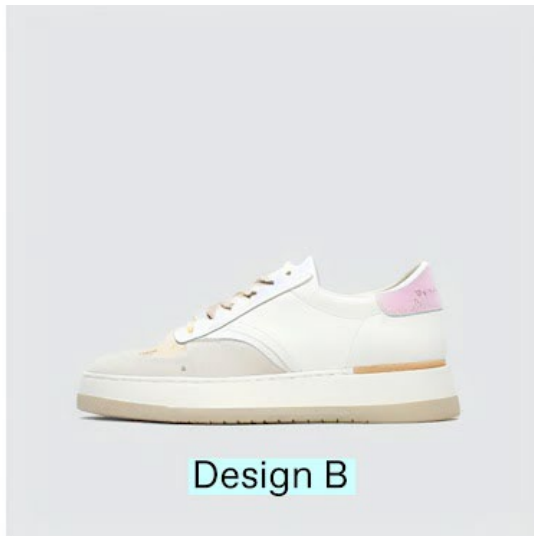
- Very simple
- Simple
- Slightly simple
- Neutral
- Slightly complex
- Complex
- Very complex

Rate Outputs (feasibility)

Please rate the design outputs based on a scale from 1-5:



Design A



Design B

11. How feasible do you think design A is to produce by a factory? \*

*Mark only one oval.*

- Very infeasible
- Infeasible
- Slightly infeasible
- Neutral
- Slightly feasible
- Feasible
- Very feasible

12. How feasible do you think design B is to produce by a factory? \*

*Mark only one oval.*

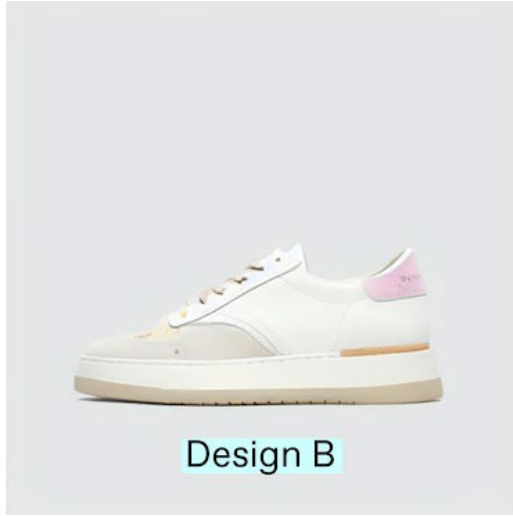
- Very infeasible
- Infeasible
- Slightly infeasible
- Neutral
- Slightly feasible
- Feasible
- Very feasible

Rate Outputs (clarity)

Please rate the design outputs based on a scale from 1-5:



Design A



Design B

13. How clear do you think design A is? Can you easily see what each part represents? \*

Mark only one oval.

- Very unclear
- Unclear
- Slightly unclear
- Neutral
- Slightly clear
- Clear
- Very clear

14. How clear do you think design B is? Can you easily see what each part represents? \*

*Mark only one oval.*

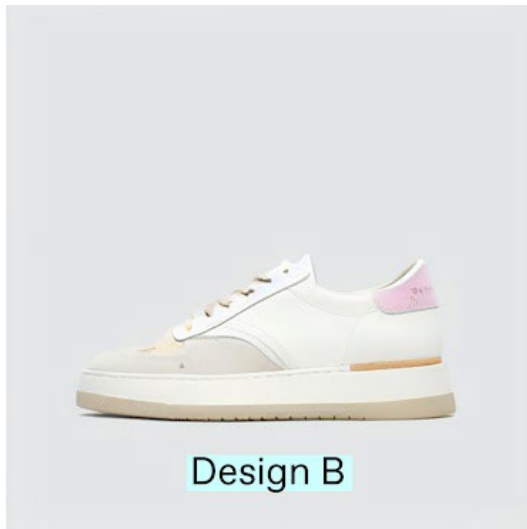
- Very unclear
- Unclear
- Slightly unclear
- Neutral
- Slightly clear
- Clear
- Very clear

Rate Outputs (completeness)

Please rate the design outputs based on a scale from 1-5:



Design A



Design B

15. How complete do you think design A is? Are there any missing elements? \*

*Mark only one oval.*

- Very incomplete
- Incomplete
- Slightly incomplete
- Neutral
- Slightly complete
- Complete
- Very complete

16. How complete do you think design B is? Are there any missing elements? \*

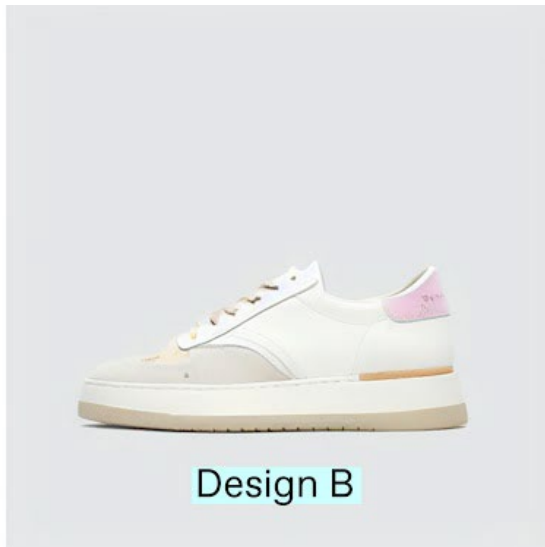
*Mark only one oval.*

- Very incomplete
- Incomplete
- Slightly incomplete
- Neutral
- Slightly complete
- Complete
- Very complete

Rate Outputs (realism)



Please rate the design outputs based on a scale from 1-5:



17. How realistic do you think image A is? \*

*Mark only one oval.*

- Very unrealistic
- Unrealistic
- Slightly unrealistic
- Neutral
- Slightly realistic
- Realistic
- Very realistic

18. How realistic do you think image B is? \*

*Mark only one oval.*

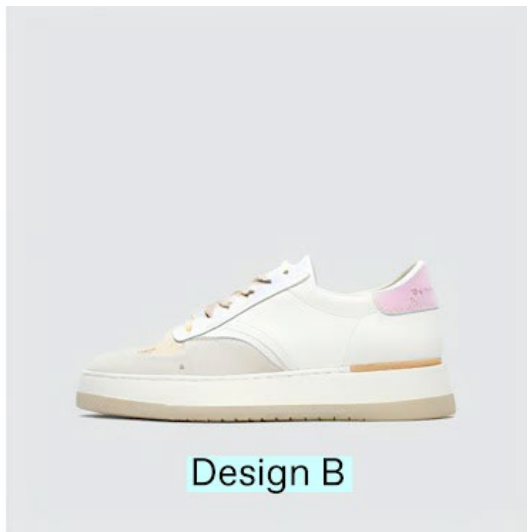
- Very unrealistic
- Unrealistic
- Slightly unrealistic
- Neutral
- Slightly realistic
- Realistic
- Very realistic

Rate Outputs (aesthetics)

Please rate the design outputs based on a scale from 1-5:



Design A



Design B

19. How would you rate the overall aesthetics of design A? \*

*Mark only one oval.*

- Very unattractive
- Unattractive
- Slightly unattractive
- Neutral
- Slightly attractive
- Attractive
- Very attractive

20. How would you rate the overall aesthetics of design B? \*

*Mark only one oval.*

- Very unattractive
- Unattractive
- Slightly unattractive
- Neutral
- Slightly attractive
- Attractive
- Very attractive

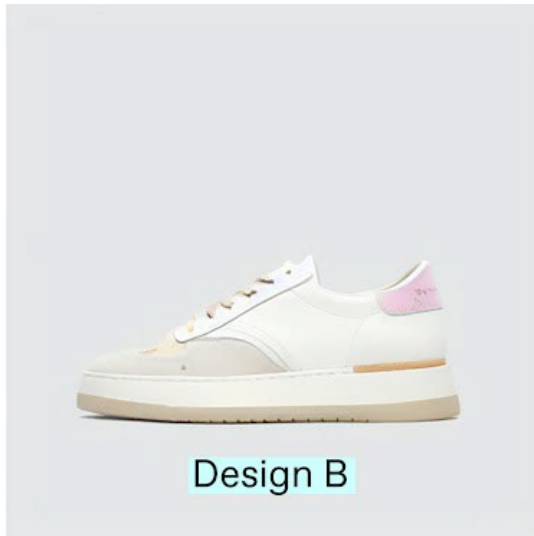
Rate Outputs (alignment)

The inspiration for the design brief was United by Design - Modern Architecture

Please rate the design outputs based on a scale from 1-5:



Design A



Design B

21. How well does design A align with the inspiration of the theme (Modern Architecture)? \*

Mark only one oval.

- Very misaligned
- Misaligned
- Slightly misaligned
- Neutral
- Slightly aligned
- Aligned
- Very aligned

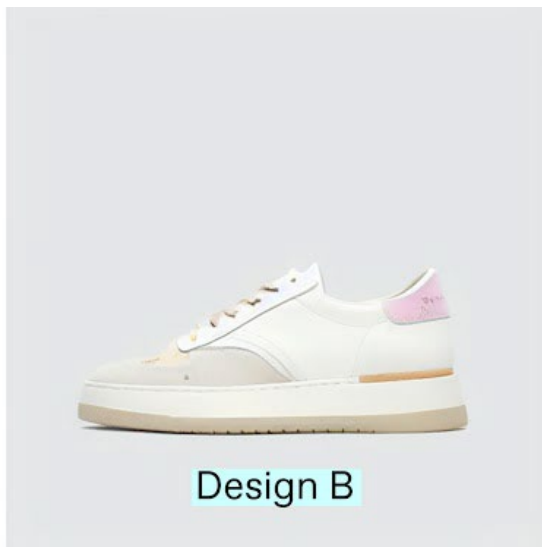
22. How well does design B align with the inspiration of the theme (Modern Architecture)? \*

Mark only one oval.

- Very misaligned
- Misaligned
- Slightly misaligned
- Neutral
- Slightly aligned
- Aligned
- Very aligned

Additional questions

Design A is created manually,  
Design B is generated by Artificial Intelligence (AI)



23. Which design do you prefer overall? \*

Mark only one oval.

- Design A
- Design B

24. What do you think of AI-generated designs in general? \*

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25. What aspects of the AI-generated designs did you find most appealing or unappealing? \*

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26. Do you have any suggestions for improving AI-generated design outputs? \*

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27. What would be a reason to use a tool that produces images like design B? \*

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28. What would be a reason to **not** use this AI tool?

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---

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---

---

29. What footwear brand do you think the design was made for? \*

---

30. Could we reach out to you via email for any further questions? If you're comfortable, please provide your email below. This is optional

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Thank you!  
- Joram

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Google Forms

# APPENDIX F



## IDE Master Graduation Project

### Project team, procedural checks and Personal Project Brief

In this document the agreements made between student and supervisory team about the student's IDE Master Graduation Project are set out. This document may also include involvement of an external client, however does not cover any legal matters student and client (might) agree upon. Next to that, this document facilitates the required procedural checks:

- Student defines the team, what the student is going to do/deliver and how that will come about
- Chair of the supervisory team signs, to formally approve the project's setup / Project brief
- SSC E&SA (Shared Service Centre, Education & Student Affairs) report on the student's registration and study progress
- IDE's Board of Examiners confirms the proposed supervisory team on their eligibility, and whether the student is allowed to start the Graduation Project

#### STUDENT DATA & MASTER PROGRAMME

Complete all fields and indicate which master(s) you are in

Family name	<input type="text" value="Steen"/>	IDE master(s)	IPD <input checked="" type="checkbox"/>	Dfi <input type="checkbox"/>	SPD <input type="checkbox"/>
Initials	<input type="text" value="J.C."/>	2 <sup>nd</sup> non-IDE master	<input type="text"/>		
Given name	<input type="text" value="Joram"/>	Individual programme (date of approval)	<input type="text"/>		
Student number	<input type="text" value="4860454"/>	Medisign	<input type="checkbox"/>		
		HPM	<input type="checkbox"/>		

#### SUPERVISORY TEAM

Fill in the required information of supervisory team members. If applicable, company mentor is added as 2<sup>nd</sup> mentor

Chair	<input type="text" value="Toon Huysmans"/>	dept./section	<input type="text" value="HCD/AED"/>	<p>! Ensure a heterogeneous team. In case you wish to include team members from the same section, explain why.</p> <p>! Chair should request the IDE Board of Examiners for approval when a non-IDE mentor is proposed. Include CV and motivation letter.</p> <p>! 2<sup>nd</sup> mentor only applies when a client is involved.</p>
mentor	<input type="text" value="Tianhao He"/>	dept./section	<input type="text" value="SDE/IOT"/>	
2 <sup>nd</sup> mentor	<input type="text" value="Denis da Silva"/>			
client:	<input type="text" value="Filling Pieces Fashion B.V."/>			
city:	<input type="text" value="Amsterdam"/>	country:	<input type="text" value="Netherlands"/>	
optional comments	<input type="text"/>			

#### APPROVAL OF CHAIR on PROJECT PROPOSAL / PROJECT BRIEF -> to be filled in by the Chair of the supervisory team

Sign for approval (Chair)

Name	<input type="text"/>	Date	<input type="text"/>	Signature	<input type="text"/>
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### CHECK ON STUDY PROGRESS

To be filled in by SSC E&SA (Shared Service Centre, Education & Student Affairs), after approval of the project brief by the chair. The study progress will be checked for a 2<sup>nd</sup> time just before the green light meeting.

Master electives no. of EC accumulated in total  EC

Of which, taking conditional requirements into account, can be part of the exam programme  EC

<input type="checkbox"/>	YES	all 1 <sup>st</sup> year master courses passed
<input type="checkbox"/>	NO	missing 1 <sup>st</sup> year courses

Comments:

Sign for approval (SSC E&SA)

Name

Date

Signature

DATE NAME

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### APPROVAL OF BOARD OF EXAMINERS IDE on SUPERVISORY TEAM -> to be checked and filled in by IDE's Board of Examiners

Does the composition of the Supervisory Team comply with regulations?

YES	<input type="checkbox"/>	Supervisory Team approved
NO	<input type="checkbox"/>	Supervisory Team not approved

Comments:

Based on study progress, students is ...

<input type="checkbox"/>	ALLOWED to start the graduation project
<input type="checkbox"/>	NOT allowed to start the graduation project

Comments:

Sign for approval (BoEx)

Name

Date

Signature

DATE NAME

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## Personal Project Brief – IDE Master Graduation Project

Name student **Joram Steen**

Student number **4,860,454**

### PROJECT TITLE, INTRODUCTION, PROBLEM DEFINITION and ASSIGNMENT

Complete all fields, keep information clear, specific and concise

**Project title** **Accelerating Footwear Innovation through 3D Development and Generative Artificial Intelligence Assisted Design**

*Please state the title of your graduation project (above). Keep the title compact and simple. Do not use abbreviations. The remainder of this document allows you to define and clarify your graduation project.*

#### Introduction

*Describe the context of your project here; What is the domain in which your project takes place? Who are the main stakeholders and what interests are at stake? Describe the opportunities (and limitations) in this domain to better serve the stakeholder interests. (max 250 words)*

My graduation project aims to bring a fresh and innovative approach to the development and design processes of the footwear industry. The current development process involves sending tech packs, including 2D technical drawings with specifications, to the factory that in its turn produces samples of the shoe that are shipped back to the headquarters. This conventional development process is not ideal, since the production and shipment of the samples take time and cost money. Typically, each new style involves 3-4 sampling rounds with various colorways, with only a select few reaching the final production round to later be sold.

The current design process involves creating analog and digital 2D drawings and subsequently technical vector drawings in Adobe Illustrator. This manual process is time-consuming. To enhance creativity and efficiency, visual generative AI tools can be used to quickly generate designs, for this project specifically focusing on creating new version of the existing FP Cruiser style (image 1). These 2D generations can then be converted to a 3D output using AI. This 3D visualisation can help clients envision what the end product looks like without the need for excessive physical samples.

Next to that, the development process can be digitalised with the use of 3D tools such as Emersya (image 2), which is a user-friendly 3D platform that facilitates real-time visual development of products. By importing 3D mesh models and assigning materials to different components of the shoe to make a real-time render, this approach accelerates the development phase, eliminating the need to wait for physical prototypes in the first stage of the process. This method also potentially reduces costs, assuming that unfavorable designs can be identified early in the process, to minimize the amount of shoes to be sampled physically.

Research questions: How can the integration of 3D and AI tools optimize the overall footwear design an development process for Filling Pieces? What are the key challenges when transitioning from a traditional workflow to 3D-AI approach, and how can a 3D-AI framework effectively address these challenges? How is the footwear development cycle impacted by the 3D-AI framework and how can it be benchmarked against the traditional process? How does the quality of designs generated by the AI framework compare to those created through the traditional human design process? What are the indices to measure the performance of the framework versus human processes?

→ space available for images / figures on next page

introduction (continued): space for images



image / figure 1



image / figure 2



## Personal Project Brief – IDE Master Graduation Project

### Problem Definition

*What problem do you want to solve in the context described in the introduction, and within the available time frame of 100 working days? (= Master Graduation Project of 30 EC). What opportunities do you see to create added value for the described stakeholders? Substantiate your choice. (max 200 words)*

The main issue is the cost and time intensity of conventional footwear development processes. The design process, involving iterative manual sketching, is time-consuming. Generative AI can speed up the idea generation, resulting in faster ready-to-use designs, and can additionally lead to unexpected and innovative designs. The physical development process, dependent on manual labor outsourced to Portugal, is inefficient and expensive. Multiple sampling rounds cause delays, and only a fraction reaches final production. Cancelling ideas before physical sampling avoids unnecessary expenses and delays. It is also beneficial for the factory to not stop the production line for sample creation, but to keep the production running for regular larger scale production. The sampling process is costly for both Filling Pieces and the factory, so reducing this results in better margins for both parties. All these processes contribute to a long time-to-market (~1 to 1.5 years), which can be also be a problem in a trend-sensitive market like footwear. Larger brands lead in innovative technology adoption due to greater resources and risk-taking ability. While 3D design initially takes more time, the long-term efficiency makes it a worthwhile risk. New innovations like AI may seem complex when rooted in conventional processes, but as acceptance and proof grow, risk lowers, allowing brands like Filling Pieces to explore their use more confidently. Improving design efficiency, reducing sampling rounds, and ultimately cutting time-to-market benefits Filling Pieces.

### Assignment

*This is the most important part of the project brief because it will give a clear direction of what you are heading for. Formulate an assignment to yourself regarding what you expect to deliver as result at the end of your project. (1 sentence) As you graduate as an industrial design engineer, your assignment will start with a verb (Design/Investigate/Validate/Create), and you may use the green text format:*

*Design and execute a comprehensive 3D-AI oriented design and development framework to optimize and enhance the creative processes for Filling Pieces by reducing time-to-market and lowering costs in context of the dynamic and trend sensitive footwear industry.*

*Then explain your project approach to carrying out your graduation project and what research and design methods you plan to use to generate your design solution (max 150 words)*

**Familiarise & analyze:** conducting research on the current processes of FP, exploring literature on existing solutions, analyzing the context to solidify the project scope and interviewing experts and stakeholders to set requirements for the framework.  
**Ideate, create & iterate:** Designing the framework iteratively and applying it on a redesign project, training it on-the-go with a trial-and-error approach, using multiple databases of FP pictures including various styles, other brands, sketches, and AI-generated images, to stay within the brand identity.  
**Validate & evaluate:** compare and benchmark the quality and performance against KPIs and requirements to assess it objectively, evaluate readiness for production and manufacturing, considering the extent of human involvement required, validating the framework and concept with human designers, customers and the team to assess readiness for use.  
**Finalize:** document the process in a report and present the result as a final presentation for the team to facilitate discussion.



### Project planning and key moments

To make visible how you plan to spend your time, you must make a planning for the full project. You are advised to use a Gantt chart format to show the different phases of your project, deliverables you have in mind, meetings and in-between deadlines. Keep in mind that all activities should fit within the given run time of 100 working days. Your planning should include a **kick-off meeting, mid-term evaluation meeting, green light meeting and graduation ceremony**. Please indicate periods of part-time activities and/or periods of not spending time on your graduation project, if any (for instance because of holidays or parallel course activities).

Make sure to attach the full plan to this project brief. The four key moment dates must be filled in below

Kick off meeting	14 Feb 2024
Mid-term evaluation	8 Apr 2024
Green light meeting	10 Jun 2024
Graduation ceremony	26 Jul 2024

*In exceptional cases (part of) the Graduation Project may need to be scheduled part-time. Indicate here if such applies to your project*

Part of project scheduled part-time	<input type="checkbox"/>
For how many project weeks	<input type="text"/>
Number of project days per week	<input type="text"/>

Comments:

### Motivation and personal ambitions

Explain why you wish to start this project, what competencies you want to prove or develop (e.g. competencies acquired in your MSc programme, electives, extra-curricular activities or other).

Optionally, describe whether you have some personal learning ambitions which you explicitly want to address in this project, on top of the learning objectives of the Graduation Project itself. You might think of e.g. acquiring in depth knowledge on a specific subject, broadening your competencies or experimenting with a specific tool or methodology. Personal learning ambitions are limited to a maximum number of five.

(200 words max)

I have a passion for footwear, and combining this passion with design aligns perfectly with my career aspirations. An earlier internship validated my dream to pursue a career in the footwear industry. Therefore I am eager to graduate as an industrial design engineer with a footwear focused graduation internship project.

My interest in innovative design methods and tools drives my decision to apply these concepts to a project. Despite having showcased my 3D skills in personal and study-related projects, I want to demonstrate my proficiency for a footwear company as a client.

Additionally, I wish to expand my knowledge about footwear design and development processes. This project provides a platform for me to more deeply explore the intricacies of the industry, broadening my understanding and contributing to my professional growth. Also, I am excited about the experimentation with AI tools in the design process, aiming to incorporate state-of-the-art design tools to enhance the creative aspects of footwear design.

In essence, this graduation project will not just be a conclusion of my academic journey; it's also an opportunity to merge my passion for footwear with my design ambition, and a stepping stone towards realizing my dream career in the dynamic world of footwear design.

Week	0	1	2	3	4	5	6	7	8	9	10	11
Date	12-Feb	19-Feb	26-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr	8-Apr	15-Apr	22-Apr	29-Apr
Days off	Friday	Friday		Friday		Fri	Good Friday	Mon + Fri		Fri		Fri
Cumulative working days	2	6	11	15	20	24	28	31	36	40	45	49
Phase	Kick-off	Familiarize		Analyze		Ideate		Create			Evaluate	Iterate
Meetings (with Denis every week)	Kick-off 14-f	Denis	Tianhao	Denis	Tianhao	Denis	Tianhao	All	Midterm	Tianhao	Toon	Denis
Planning												
Research												
FP approach												
Technologies												
Context analysis												
Interviews												
AI experts												
Footwear experts												
User												
Consumer												
Peer review												
Setting requirements												
Designing the framework												
Designing the concept												
Validating the concept												
Validating the framework												
Benchmarking the framework												
Future recommendations												
Documenting in report												
Finalising report												
Presentation												
Report deadline												
Showcase deadline												
Graduation ceremony												

