AI-Driven Innovation in Fashion:
Enhancing the Design Process through Technology

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Abstract:

This study investigates the integration of artificial intelligence (AI) and digital tools in the workflows of professional fashion designers within mid-sized and large commercial companies. Through semi-structured interviews and reflexive thematic analysis, it identifies key opportunities for AI application, such as digital prototyping, material research, and creative ideation, as well as structural and cultural barriers to broader adoption. While design processes share common structures, the use of AI and digital tools varies significantly across different organizational contexts. Designers recognize AI's potential to streamline repetitive tasks, enhance creativity, and facilitate cross-functional collaboration. The findings offer practical insights to inform the development of AI-powered design tools that align with industry needs and support digital transformation in fashion design.

Keywords: artificial intelligence, fashion design, design process, fashion technology, digital transformation

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Tiivistelmä:
Tämä tutkimus tarkastelee tekoälyn roolia muotisuunnittelussa haastattelemalla kaupallisia suunnittelijoita eri markkinasegmenteistä. Aineisto on analysoitu refleksiivistä temaattista analyysitapaa hyödyntäen.

Tutkimus osoittaa, että vaikka muotoiluprosessin rakenne on yleisesti yhteneväinen, työkalujen ja tekoälyn käyttö vaihtelee yritys- ja yksilötasolla. Tekoälyä hyödynnetään erityisesti ideoinnin, tiedonhaun ja visualisoinnin vaiheissa, mutta sen laajempi käyttöönotto voi olla rajoittunutta organisatoristen ja teknisten esteiden vuoksi. Suunnittelijat näkevät tekoälyssä potentiaalia rutiinitehtävien tehostamisessa, luovan työskentelyn tukemisessa ja paremman tiedonhallinnan mahdollistamisessa.

Tutkimus tuo esiin konkreettisia kehityskohteita, joissa tekoäly voisi parantaa suunnitteluprosessin tehokkuutta ja luovuutta, ja se luo pohjan tekoälyä hyödyntävien suunnittelutyökalujen kehittämiselle.

Asiasanat: tekoäly, muotisuunnittelu, suunnitteluprosessi, muodin teknologia, digitaalinen muutos

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1. INTRODUCTION

Artificial Intelligence (AI) has rapidly emerged as a transformative force across industries, including fashion. The impact of AI on fashion design and advertising has become increasingly visible in recent years. The emergence of text-to-image and sketch-to-image applications has accelerated change within the field. What began with the circulation of futuristic fashion sketches on social media quickly evolved into AI-generated prints appearing on the runway, such as in Collina Strada's SS24 collection (Dazed, 2025), and is now evident in the normalization of AI-generated product imagery in e-commerce and advertising. These shifts illustrate how quickly AI is reshaping fashion's visual and creative language.

At the same time, the pace of change can feel overwhelming, especially in professional contexts where AI adoption is accelerating. As Choi et al. (2023) note, AI is one of the central forces reshaping contemporary society, alongside developments in big data, virtual reality, and other emerging technologies (Choi et al. 2023). Understanding its implications is no longer optional for designers and creative professionals, it is essential.

While AI is often portrayed as a revolutionary and intelligent system capable of solving problems across all domains, its limitations are frequently overlooked. As Crawford (2023) argues, AI is far from being either truly *artificial* or *intelligent*. Rather, it is a profoundly material technology that relies on an extensive infrastructure of data, labor, and natural resources. Despite popular perceptions, AI systems are fundamentally constrained in their ability to replicate human intelligence, particularly in areas requiring common sense reasoning, intuition, and embodied experience. (Crawford 2023.)

The primary aim of emerging technologies is generally to improve the efficiency of existing processes, making them easier, faster, more accurate, or more cost-effective. In addition, such technologies can enable entirely new capabilities, allowing us to accomplish tasks or create outcomes that were previously unattainable (Anantrasirichai & Bull 2021). This insight aligns with my own motivation to explore AI and its applications within the fashion industry. Over the past eight years, I have worked as an apparel designer in two fashion companies, with a focus on concept development for men's ready-to-wear as well as women's golf and RTW collections.

Professional experience. With over eight years of experience in design teams at global fashion companies, I have worked across both accessible luxury and mid-market levels in roles as a concept designer for menswear and a product designer for womenswear. Throughout my career, I have been involved in all stages of the design process, from developing concepts and designing collections to ensuring that the showroom sample collection accurately reflects the original vision and that the product is optimized for bulk production.

My role as a senior concept designer was with a large mid-European lifestyle clothing brand. The company offers a wide range of products including clothing, accessories, footwear, and leather goods. For four years I worked in the menswear department, where I was responsible for the collection concepts of the business, smart casual, and casual collections. In addition to this, the menswear concept design team I led collaborated extensively across departments including womenswear and men's athletic wear.

As a concept designer, I was responsible for developing global collection concepts. This involved creating seasonal design briefs and color cards, grounded in thorough trend and market research, to guide the design teams. I led the process from start to finish; ensuring a cohesive visual identity was maintained internally, from the initial concept phase through key milestone meetings, all the way to the final collection presentation and showroom set up.

My second professional role was as a Senior Product Designer at a Scandinavian lifestyle fashion company, with golf, ski, outdoor, racket sports, and ready-to-wear collections, where I worked for three years. I was initially responsible for the women's golf collection and later took over the women's ready-to-wear (RTW) line. Key markets for the golf collection included the U.S., Scandinavia, the U.K., Central Europe, and East Asia.

My role encompassed developing seasonal design concepts and building a well-rounded product assortment. The design process involved sketching, creating CADs, building detailed tech packs, selecting and developing fabrics and trims, preparing overview decks, and presenting collections at key milestone meetings. I collaborated cross-functionally with pattern makers, buyers, product developers, and sales teams throughout the entire product development cycle.

Throughout my career in fashion, I've often questioned the industry's traditionally conservative and manual approach to design work, as well as its slow adoption of new technologies compared to other creative industries. This has led me to explore how AI tools could help optimize time-consuming design and operational tasks, and potentially support the creative process itself. According to Dubey et al., designers need to remain vigilant about current and upcoming trends to understand changing consumer preferences and they need to design a multitude of apparel at a faster rate (Dubey et al. 2020).

Although AI has rapidly become a part of everyday life, particularly in tasks like information retrieval and text generation, it has not been widely adopted in commercial fashion design, based on my experience at the outset of this research in late 2023. Now, as I conclude this study in spring 2025 and continue engaging with designers across various companies and markets, it appears that widespread integration of AI tools within design teams is still limited. However, awareness of AI's potential is notably higher than when I began.

Academic and industry experts have similarly highlighted AI's potential in the fashion industry and recognize the importance of AI-based garment development technology (Choi et al. 2023). Specifically, AI-based garment development technology, incorporating the design process of human designers and fashion domain knowledge, can reduce the workload of fashion designers and product planners, thus increasing work efficiency (Dubey et al. 2020). Kause and McGrath suggest that the relationship between human specialists and AI will form a hybrid – combining artificial intelligence and human judgement for strategic foresight (Kause & McGrath, 2017).

To explore the current relationship between fashion design and artificial intelligence, this study will examine:

- What does the fashion design process entail?
- How do fashion companies use AI and digital tools in their design process?
- How can AI improve designers' work?

Design processes can vary significantly from one designer or company to another. In the context of both my professional background and this research, I consider it essential to map out these varying workflows in order to identify specific functions where AI could provide meaningful optimization for designers.

The aim of this study is to pinpoint opportunities in the design process and lay the groundwork for the development of an AI-powered design application. On a personal level, this research also serves as an opportunity to align my career with supporting design teams in navigating digital transformation and maintaining a competitive edge within the industry.

I have made use of advanced AI language models, including ChatGPT by OpenAI and Copilot by Microsoft, during the writing of this thesis. These tools supported the research process by assisting in the identification of relevant references and studies within the field. Furthermore, they were used to help rephrase text sections, contributing to improved clarity and coherence throughout the document. In addition, I used the AI-powered live transcription tool in Microsoft Teams and explored AI-assisted coding features available in the qualitative analysis software Atlas.ti. I have reviewed the document titled "Use *of Artificial Intelligence-Based Tools at the University of Lapland" (University of Lapland, 2023, version 3/2023).*

2. LITERATURE REVIEW

In this chapter, I review the key stages of the fashion design process and highlight where AI tools could help improve and support professional fashion designers. As AI technologies continue to develop, their potential to change fashion design, both creatively and practically, is gaining attention.

I reflect on how the role of the fashion designer and the design process are represented in existing literature, comparing these perspectives with insights from my own professional experience. While design processes often differ depending on the company, team structure, and individual designer, my experience working at two global fashion brands across different market levels has allowed me to identify recurring patterns and shared challenges. These observations are integrated throughout the text.

Through a review of academic literature and a comparison with both my own experiences and those of my peers in commercial fashion companies, it becomes evident that key challenges include the administrative workload and inefficiencies resulting from the use of multiple, disconnected design and product management systems. These challenges consume time that could otherwise be dedicated to creative work. Moreover, it is important to acknowledge that the repetitive design of similar collections can lead to a fixation of creativity (Crilly, 2015; Jansson & Smith, 1991).

To provide a foundation for these considerations of the design process and its challenges, this literature review begins by outlining the traditional fashion design process and its key phases. This is followed by a brief overview of fundamental artificial intelligence concepts relevant to fashion design practice. The review concludes by examining how AI-assisted design processes are currently represented in academic and industry research.

DESIGN PROCESS FOR APPAREL COLLECTION

Fashion market levels

The fashion industry is typically divided into different market levels, with Haute couture and ready-to-wear (RTW) being the primary categories. Haute couture represents the highest and most specialized level, characterized by pre-industrial fashion created in private ateliers, where handmade, bespoke garments are tailored to individual clients. According to Gwilt and Rissanen, the modern fashion design process can trace its roots back to the work of the first couturier, Charles Frederick Worth, in mid-19th century Paris. Worth established the first couture house in 1858, focusing on the creation of made-to-measure garments. Clients would make appointments to have their features and personal preferences assessed, and Worth would then design a gown he deemed suitable for them. His design process, which involved sketching and considering fabric, form, and body proportions through graphical representations, laid the foundation for the designer-driven approach to garment creation that we recognize today. (Gwilt & Rissanen 2011.)

Ready-to-wear, or *prêt-à-porter*, covers any collection that consists of garments produced in volume and in standardized sizes (Renfrew & Lynn 2022). By the middle of 19th century, two systems of fashion production had materialized: the bespoke work of the tailor and couturiers and the expansion of the ready-to-wear clothing industry, which developed especially in the US and UK. The start of RTW was especially producing uniforms and menswear daywear garments. In the 20th century, the impact of mechanization had a dramatic influence on the RTW increasing the productivity and profitability of manufacturing garments. (Gwilt & Rissanen 2011.) This study will primarily focus on the design process within RTW businesses; however, the design process of a runway collection will also be incorporated into the analysis.

The contemporary RTW market can be segmented into high-end fashion or luxury, middle-market and mass-market (Dissanayake et al. 2021). High-end RTW runs from established design houses to smaller independent labels and can be produced in limited quantities with high price points. Established design houses may have more RTW collections from high-end collections to diffusion lines, and the pricing, fabrics and finish are used to differentiate each level. (Renfrew & Lynn 2022). Often lifestyle merchandising elevates the brands status operating on a middle market level. The prices of the middle-market fall between the high-end and mass market (Dissanayake et al. 2021).

The concept of a lifestyle brand refers to an approach when a brand elevates a product, often mass-produced, by associating it with a particular lifestyle. By recontextualizing mass-market items within high-end settings, for example, Ralph Lauren reinvents pieces like traditional americana workwear, giving them a new identity. As a result, consumers come to associate the brand's products with exclusivity and status, further solidifying the brand's position in the high-end or luxury market. (Hancock 2022.)

Retailers drop RTW ranges at prescribed times as monthly collections which are called drops. Collections are staggered into early and high seasons. According to Renfrew and Lynn, this way customer is provided with a changing retail experience as subsequent stories are delivered over a number of weeks. Next to changing collections retailers might offer core lines where the design remains unchanged from season to season but only colours might be changed seasonally. (Renfrew & Lynn 2022.)

Design Process and the role of fashion designer

A generic fashion design process is multi-phased and involves a generic sequence of activities and phases that typically occur within all sectors of the fashion industry. These steps are well documented in various educational texts, such as Renfew & Lynn (2022), Sorger & Udale (2017), McKelvey & Munslow (2012), Jackson & Shaw (2006), Sinha (2002) and Gwilt & Rissanen (2011).

The design process includes phases such as sales review on past collections, research of new trends, selecting and testing fabrics and styles for the season, getting confirmation on the range, developing samples, and approving bulk developments. It depends on the size and market the company operates and the designer's personal work experience which phases the designer is involved. (Jackson & Shaw 2006.) McKelvey and Munslow divide the apparel design process into six stages: Analysis, Design brief, Research, Design development, Prototypes, and Solution (McKelvey and Munslow 2012). Although the activities and duties of the fashion designer differ across all the levels and sectors of the fashion industry a conventional fashion design process can be said to exist (Gwilt & Rissanen 2011). Sinha has outlined a general fashion design process as shown in Figure 1, which will be examined more closely in the following chapters. This process includes five phases.

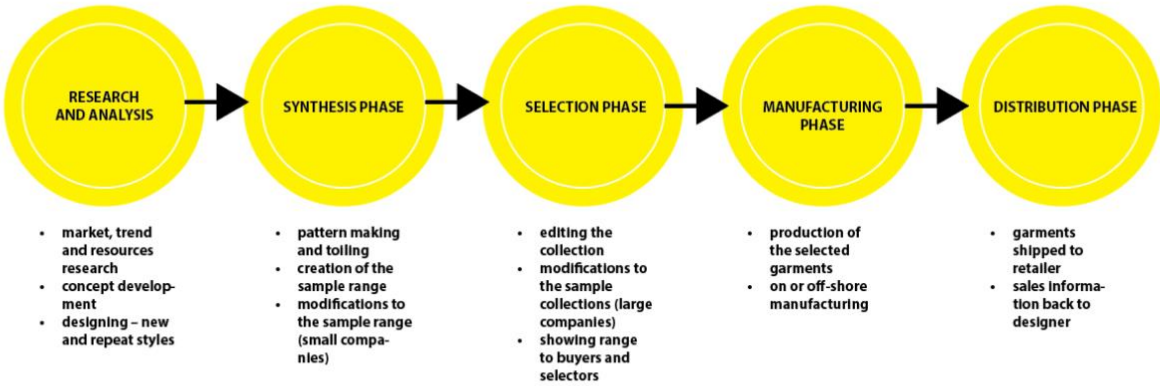

Figure 1. The five phases of fashion design and production. (Sinha 2002 in Gwilt & Rissanen 2011).

Fashion designership

The definition of a fashion designer is dependent on their own experience, the company, the type of garments produced and the constraints upon the design. One could describe fashion designers' roles as market researchers and analysts of visual and qualitative data, an interpreter of meanings and a negotiator in an expansive decision-making process, experts in customer needs in changing social, cultural, economic, and political environments. (Sinha 2002.) The expert skills and knowledge on the business perspective that might be expected from a fashion designer to conduct a comprehensive fashion design process are (Sinha 2002):

- The ability to recognize new trends
- The ability to source relevant manufacturers of fabrics and trimmings
- The ability to analyze and interpret new trends

- A knowledge of market requirements for production
- Presentation skills for new ideas
- Time-management skills
- Team leadership qualities
- Communication skills; verbal and non-verbal (e.g., image making and sketching)
- Ability to contribute to sales revenue
- Self-confidence

According to Sinha the bigger the company size and market share is the less the designer is involved manually in the sample making and the more involved in gathering and analyzing market and trend information and applying these to update styles. (Sinha 2002.)

While Sinha (2002) outlines the wide-ranging skills and business acumen expected of fashion designers, it is equally important to understand how these capabilities are enacted within the design process itself. The act of designing is rarely linear; it is embedded in a dialogue between intention, materiality, and context. According to Schön, the designer makes things. Sometimes they make the final product; more often they make a representation, a plan, a program, or an image, of an artifact to be constructed by others. The designer works in particular situations, uses particular materials, and employs a distinctive medium and language and the making process is complex. The designer gains learnings and unintended changes in the process that shape the product. Designer works among multiple variables and the possibilities can be endless hence the product can shape up to be something different than what intended originally. In a good process of design, the conversation with the situation is reflective. (Schön 1983.)

When designing clothes for certain situations, feelings, or experiences, fashion designers use not just data and trend reports, but also their own personal and professional experience. (Särmäkari & Vänskä 2022). To understand fashion as a system, we need to examine its structural features, the types of workers it involves, and the roles they perform. Fashion consists of a network of institutions, organizations, groups, creators, events, and practices that collectively shape what we recognize as fashion, something distinct from dress or clothing. (Kawamura 2023.)

Dissanayake et al. have conducted a comprehensive study on the fashion design process at the mass market level, formulating a detailed process description based on an extensive literature review. In this study, they have also conducted interviews with design professionals about the design process. (Dissanayake et al. 2021.)

Figure 2. Compiled fashion design process. Dissanayake et al. 2021.

Figure 2. visualizes a chronological description of the fashion design process, which can be applied beyond the mass-market level to other market levels as well. The design process begins with a research phase, during which the designer explores trends aligned with overarching concepts and themes, while also identifying innovation in silhouettes and shapes. Based on this research, a collection concept, trend board, or sourcing pack is assembled. The next stage is the development of the collection design, encompassing activities such as sketching, selecting fabrics and trims, and determining garment construction techniques. This is followed by prototype development, allowing garment costs to be aligned with target pricing. The finalization phase involves defining the complete looks and making any necessary adjustments to the designs. The collection development process concludes with collection approval, at which point the designer’s role comes to an end. (Dissanayake et al. 2021.) The following chapters will examine the design process in greater detail, as outlined in Figure 2, drawing on insights from both my professional experience and relevant literature.

Trend research

The general design process and trend research vary based on each designer’s preferences. As designers advance professionally, their research approach often becomes more systematic. However, the process also depends on whether they are working on an established collection or creating an entirely new one. Seivewright describes research for fashion design as an investigation – the beginning of the journey. Learning something new and looking to the past by reading, visiting, and viewing. Research is above all recording information. (Seivewright 2012.) Creativity and seeking newness in research are viewed as central to the design process, reflecting consumers' growing demand for originality and uniqueness (Ming Law et al., 2004). Three types of research are visual inspiration, gathering tangible materials such as fabrics and trims and researching the market. This means identifying the target customer and their lifestyle and interests as well as competitors and the broader market. (Seivewright 2012.) Researching for a new season can consist of online research, shopping for competitor samples locally or travelling for inspiration for target markets to gain information about other fashion or cultural trends or the local environment and climate. Research can also consist of visiting fabric and fibre fairs to be informed about the latest developments in fabrications (Sorger & Udale 2017).

Research should inspire the designer to create something new every season as it stimulates the mind and opens new directions. Research should be broad and open at the beginning of the process to offer the designer the opportunity to explore a variety of creative possibilities before settling on a concept. (Seivewright 2012.) Researching can be a very personal journey as the designer has the freedom to discover information previously unknown and the findings might be something unexpected or the process may take unexpected turns. Sometimes the loose ends come together and create a new connection. The same characteristics of a process may apply even if the research is done as a team. However, in teams, one person usually has the creative vision and takes the lead. Research and creating a final understandable concept are the most important tools for showcasing the vision how a designer can differentiate oneself in the industry. (Seivewright 2012.)

The collection design process starts with the trend research phase, where the designer seeks newness and inspiration. Designers search for relevant sources of material inspiration on online platforms, design publications and other channels to refine and iterate upon their sketch ideas (Jiang et al. 2024). Early stages of design research can be done digitally looking into the latest runway collections. Inspiration can be found by visiting art and design shows, libraries, or fashion archives for collection themes or colours. Any kind of online research whether it is through social media, online fashion archives, magazines or online shops is a great resource for early inspiration.

On the mass market level trend research can be conducted very systematically. Shopping trips, catwalk analysis, trade shows and desk research, can include reading trend reports online, and browsing social media such as Instagram or TikTok (Dissanayake et al. 2021). Shopping trips enable designers to gain insights into the offerings of competitor brands. Although the collections displayed in stores are typically from previous seasons relative to the designer's current work, these excursions can still provide substantial inspiration and understanding regarding tactility, colour, and design details. Additionally, such trips can offer valuable perspectives from a customer viewpoint, as designers observe which items attract attention and which are overlooked in a shop environment.

Figure 3.Finding colour combinations from inspirational images from runway shows, trend forecast reports, art or design. Photos: Author 2021 and 2022.

Catwalk analysis seasonally can provide a good overview of trends in silhouette, colours and concepts (Dissanayake et al. 2021). Websites like Vogue.com and Tagwalk.com, among others, provide a wide selection of fashion shows, with their catwalk galleries updating almost in real-time during major fashion weeks. Trend forecasting services are also a way to access visual fashion information more easily online. A range of service providers on fashion forecasting offers catwalk galleries and ready curated text-based reports and analysis on fashion trends for specific markets e.g., men's and womenswear, activewear, colour and print reports. The forecasting companies such as WGSN, Trend Union, Peclers, Trendstop and Promostyl can offer very customized advice to specific fashion companies. (Jackson & Shaw 2006.) Runway images or an image of an artwork or design object can provide a great start and inspiration for creating seasonal colour cards.

Textile trade shows are the next step for research for fashion direction. Trade shows such as Premiere Vision in Paris, Performance Days in Munich and Pitti Immagine Filati in Florence are examples of European textile trade shows that are held 1–2 times per year. There designers can learn about the innovation in fabric, print and trims. (Jackson & Shaw 2006.) Trade shows offer designers a way to identify upcoming trends in materials, trims, and technologies (Dissanayake et al. 2021). Trade shows provide an excellent opportunity to discover new materials and manufacturing partners. They also serve as a great way to strengthen relationships with existing suppliers and explore their latest collections without the need to travel to the Far East.

Designers constantly do desk research, not just at the start of a season. This includes browsing social media like Instagram, TikTok, and Tumblr, and checking reports from trend forecasting agencies. It's helpful for designers to keep a list or library of inspiration sources for trends, shapes, colours, materials, trims, or mood images. Trend forecasting agencies continuously update their platforms with fresh content, including catwalk reports, design concepts, colour forecasts, and in-depth analyses of product category trends. However, in my experience, desk research is a vital part of a designer's work and must be conducted systematically. Finding the time for it can be challenging, especially when there are specific requirements to meet.

A professional designer needs to consider the commercial and market as well as economical manufacturing requirements while designing a garment or collection (McKelvey & Munslow 2012, 79). This can be something that the designer is basing their research on. The season starts with an analysis of the brand's internal data and sales review. This is provided by the merchandisers and buying departments who have detailed insight into target customers' shopping habits and access to sales data (Sorger & Udale 2017). During the research phase designer will receive or also partake in creating a range plan for the collection. This range of pieces may be inspired by a trend, theme, or design direction, reflecting cultural and social influences, and is usually produced for a season or particular occasion. (Renfrew & Lynn 2022). The collection range plan can be owned by the merchandising team or the product development team. Range plan is an overview of the entire collection and includes parameters such as the number of styles, colourways, design features and variations. The range plan can be seen as a collection skeleton to help the designer fill the essential needs.

Design concept development

A designer's work is concerned primarily with solving problems by developing and explaining ideas. You must be able to present your concept so others involved in the project understand it (Aspelund 2015.) In the context of fashion design, at the end of the process, the representation needs to show accurately how the designer interprets the theme and turns it into an actual product or collection. The designer's representation needs to use the correct domain language to make it understandable for everyone involved in the process, be it other designers, patternmakers, product developers, buyers or sales or anyone to who the design is shown along the process.

A collection is a range of garments, accessories or products brought together to tell a story (Renfrew & Lynn 2022). Once a designer has done their research, a collection concept and design brief must be created to maintain consistent storytelling and visualizing themes for the collection. This is especially important if multiple designers, product developers and pattern makers are going to be working on the collection in the development phase. Furthermore, a consistent collection concept is essential for the marketing, sales etc. teams to understand what is being developed and to base their planning on.

A ´design concept ´is the representation of a designer's abstract ideas of final entities, or garments in a case of apparel design (Lee & Jirousek 2015). A design concept brief typically includes colour cards, mood boards, a general theme description, storytelling elements, and definitions of sub-stories to offer a context for the collection. Based on my experience working as a concept designer, the brief is compiled into a book or digital file and distributed to product designers at the start of the collection development process. On the mid-market and luxury levels, the design brief is usually delivered between 2–1,5 years before the collection is delivered to the stores. Design briefs for sportswear can be delivered even more than two years before the delivery or drop.

Figure 4. An example of a collection concept brief and moodboards, showroom set-up and campaign image. Here demonstrating how the storytelling behind the initial concept is carried through each stage—from design development to showroom presentation and final product featured in marketing campaign visuals. Photos and images: Author 2020.

The design brief will convey a specific theme for the collection, supported by mood boards that illustrate the concept through curated colours, imagery, and visual references aligned with the intended product and desired aesthetic. The mood boards will serve as a foundation for the products to be designed, offering inspiration and, at times, guidance and conceptual direction for styles, fabrics, and trims for the designers.

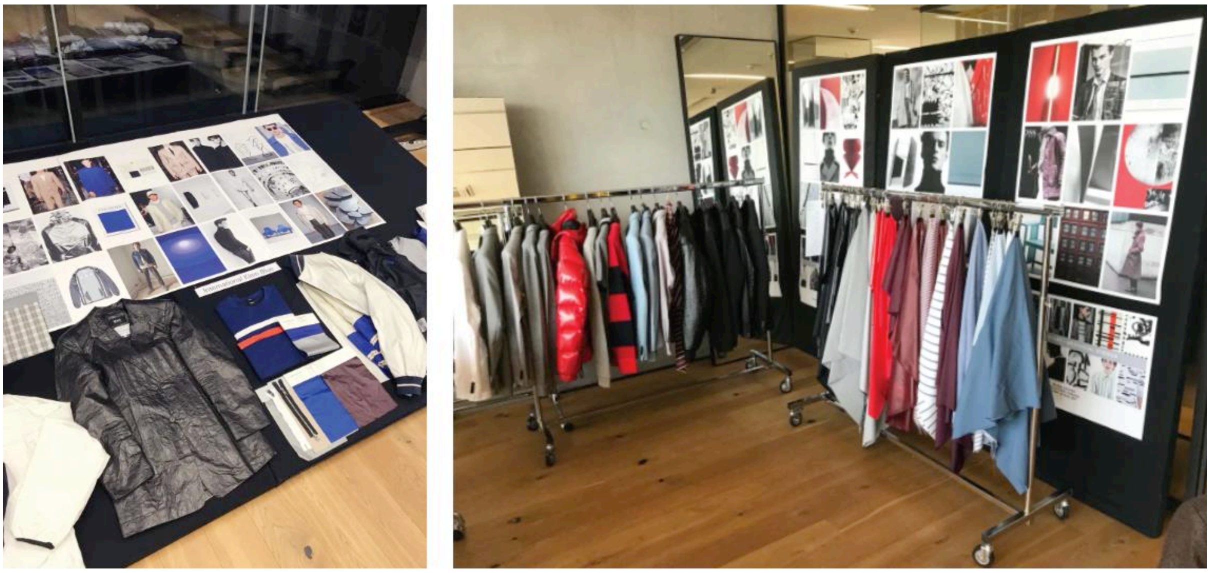

Figure 5. The collection concept is presented alongside tactile archive pieces, including fabric and trim ideas, to inspire product designers in the development of the upcoming collection. Photos: Author 2018.

Once the design brief is ready, it is usually presented to the entire company or at least to the teams closely involved. The concept presentation can be a large event with theme-specific installations and concept videos or a smaller presentation via online meeting. The goal of the presentation is to inspire everyone with a collection "big bang" and ensure a shared understanding of the visual aesthetic for the upcoming collection, fostering confidence in working with it. It's crucial to grasp the big picture, especially if you are focused on a specific segment of the collection, such as designing for a particular product category. However, a concept brief for a full season which consists of one to three deliveries is more typical in companies operating on luxury and mid-market levels to my experience and working with weekly or bi-weekly deliveries is more common at mass market level. According to an industry expert, designers might work without any collection concept on the mass market level; designers work more on the product to product or on a look level rather than creating collections around a story (Anonymous personal communication 12.2.2025).

Figure 6. An example of a concept design launch event featuring a theme-specific installation and an accompanying video presentation. Photos: Author, 2018.

Dissanayake et al. are talking about creating a trend pack at the beginning of a design process to provide enough time for sourcing materials and the fabrics are used as key inspirations. The main reason to start the design development process with fabrics is to minimize the lead time of the entire process. This is especially important if talking about fast fashion development where more than one collection is delivered per season and collections are released on a weekly basis. To reduce lead times, materials are often ordered before designs are finalized, requiring designers to work within the constraints of pre-selected materials. This limits the creativity and flexibility of mass-market designers. (Dissanayake et al. 2021.) According to an industry expert mass market designers might visit fabric fairs and buy fabrics directly from there to create in-house prototypes or buy samples from a supplier and make adjustments to them (Anonymous personal communication 12.2.2025).

In the luxury and mid-market levels, collections often have up to three monthly deliveries. To meet lead time requirements, trend packs or sourcing briefs are needed. These briefs are sent out before the main collection concept brief, in some cases more than two years before the deliveries. Sourcing briefs are usually themed by product category or fabric type. This allows product developers, fabric teams, and suppliers to start sourcing materials before the final, more thematical, collection brief is sent out.

Characteristically to fashion something new needs to be created every season. However, many fashion businesses count on their core items and range of basics. The core collection can be the base and majority of the collection. Seasonality is offered by changing colours, prints or minor amendments to the core styles. Newness is included in the range including more directional designs, some of which will sell better than others. (Jackson & Shaw 2006.)

Collection design

Design development starts usually with fabric selection. This is to minimize the lead time of the entire process. On the mass-market level, there is generally less than two months to complete the design process. Potential fabric and trim ideas are chosen, and suppliers are asked to develop those ideas with needed price indications. New fabric ideas can be new structures, wash effects, finishing effects et cetera. Trims might also have especially long lead times especially if they need to be developed with special branding or new molds need to be opened. This is the information stated in the sourcing pack before the actual concept brief is released. (Dissanayake et al. 2021.) In my experience designers start to sketch new ideas for silhouettes, put together potential looks and create sub-stories as stated in the concept brief, some colour ideas might be tried out. In this stage designer usually creates more ideas than what is needed for the final collections.

Sketching allows designers to explore and refine how their ideas and concepts work. New generations of designers are embracing tools like 3D CAD software, digital co-creation platforms, coding, and rapid manufacturing to modernize the field and move away from traditional designer-centered approaches. (Särmäkari & Vänskä 2022). Sketching can be done by hand, or digitally e.g., in Illustrator or even as 3D sketching on avatar. In this stage, designers can ideate freely, and it is commonly considered as the fun part of the design process. Hand sketching or flat sketches might be done also after receiving the first proto on a mass market level. On mass market level meeting lead times might mean that first protos need to be launched even before sketches. In this case, a base for the style might be a bought sample from another luxury brand or a sample from a supplier where the designer makes small adjustments. In this case, sketches might be done only for purpose of internal communication about the style. (Anonymous personal communication 12.2.2025).

After the sketching phase is completed and reviewed, approved tech packs are created. These tech packs are comprehensive files that include 2D line sketches of the designs, along with text descriptions and detailed images. Reference images for silhouettes or specific details can also be added, and coloured sketches may be included as well. Once a tech pack is finalized, it is sent out to the supplier or uploaded to the Product Lifecycle Management (PLM) system. The responsibility for creating, uploading, and sending the tech pack to suppliers varies depending on the company. After the style is uploaded or handed over to the product developers, product developers and pattern makers can start developing patterns, measurement lists and bills of materials (BOMs) to send out to the factories.

The production of contemporary fashion clothing continues to rely on meeting market expectations within budget and manufacturing constraints. These factors have evolved to become the basis of the designers' brief. (Gwilt & Rissanen 2011.) Buyers and the company directors generally authorize the spending of budgets that pay the ranges. Buyers and merchandisers usually have a say over the numbers of units per style and colour options. In this setting the designer needs approval for the collection during the design process before sampling is started. (Jackson & Shaw 2006.) This is normally done by presenting the coloured sketches and fabric hangers to the team to approval to start the collection development. These meetings can be called sketch reviews or collection colour breakdowns. The name of the milestone meetings varies from one company to another.

Prototyping and fitting

Fittings are a vital part of the design process, even though a designer's responsibilities are usually seen as limited to the creative aspects—such as research, ideation, sketching, concept development, and product creation. (McKelvey & Munslow 2012.) After sketching and design development are started and approved, the designer or product developer requests a sample from the factory, normally overseas. The reason to outsource prototyping is to reduce costs and to get a competitive advantage from production overseas, however, this can significantly increase lead times (Dissanayake et al. 2021). Based on the prototype garment costing can be calculated. Sometimes for designers, it is possible to oversee prototype production at the manufacturing plant and make instant comments and changes. This helps designers to learn about the manufacturing process and possibilities. (Dissanayake et al. 2021.) When designs are initially created through flat sketches, fittings often provide designers with their first opportunity to see the product in three-dimensional. These sessions allow the evaluation of fabrics, fit, and details on the model.

Samples range from toiles or prototypes to salesman samples to finish in production samples where the bulk production is based. Normally designer's role in design development ends with approving the production sample in a final fitting. Prototyping may also be carried out in 3D, depending on the company's practices. For instance, physical first prototypes could be replaced with 3D prototyping, enabling designers and patternmakers to quickly test designs before creating toiles in-house or sending them to factories for physical production. Digital prototyping minimizes fabric wastage and saves money and time but it also offers fast and cost-saving possibilities for marketing and sales departments to show collections at the development phase when physical samples are not available (Chaudhary et al. 2020). In my experience, digitally developing initial prototypes can accelerate the process by weeks.

Once the prototypes are received, the collection will be assembled for a review, where designers, product developers, pattern makers, merchandisers, buyers, and other key stakeholders will see it for the first time. The collection will be reviewed by considering factors such as cost, quality, profitability, and manufacturing feasibility (Dissanayake et al. 2021). Due to timing delays, not all products may be included in the review. The collection will be presented in prototype form, supported by flat sketches. At this stage, the collection is evaluated as a whole, allowing for potential style cancellations, additions of new styles, or colour adjustments.

Approval

After the collection has been reviewed as prototypes and necessary revisions have been made, the full collection is sampled for sales purposes. The collection is presented once again to the relevant stakeholders to get final approval. The collection range is evaluated in terms of selling potential, overall profitability, and return on investment. The design elements are not evaluated at this point. (Dissanayake et al. 2021.) Typically, all styles are produced in their intended colours and fabrics for the final sample collection. However, to minimize sampling costs, according to my professional experience, most companies order only one colourway per style for showroom presentation. Depending on company practices, designers may propose a colour selection for the salesman sample collection (SMS), which is then approved in a milestone meeting before the fabric order deadline. Once the complete SMS collection is received, it undergoes a final fitting and review by the same stakeholders to ensure readiness for bulk production. This stage is usually the last point of involvement for designers in the process.

Figure 7 & Figure 8. A comprehensive SMS collection color proposal from a designer for a women's golf collection. The products are also organized by full delivery drops, look suggestions, and color stories, ensuring cohesive storytelling in showrooms where the collection will be showcased. Photo and image: Author, 2024.

Typical for mid- to luxury market levels, once the SMS collection is finalized, it will be showcased in the showroom(s), depending on whether the company operates in multiple global markets. Digital showrooms are also used in some cases. Following the sales period and based on order volumes, bulk production can begin. During this phase, campaign imagery is created. Ultimately, the collection will be available in stores and online, approximately two years after development begins.

ARTIFICIAL INTELLIGENCE AND FASHION DESIGN

According to Bertola and Teurnissen digitalization of fashion design and its experimenting with algorithms in design work can be described as the 'fourth industrial revolution' (Bertola & Teunissen, 2018). Digital technologies are becoming an integral part of today's fashion industry and changing the role of the designer. Today's designer needs actively explore, understand, and apply new technologies in their work (Sun & Zhao 2018).

Claims about the potential of AI, particularly generative AI, to boost productivity in fashion businesses (McKinsey & Co. 2023) give designers hope that it could help reduce at least some of the manual tasks still required in the design process. From co-designing to speeding content development processes, generative AI creates new space for creativity. It can input all forms of data e.g. raw text, images and video but also output fully written scripts to 3D designs and realistic virtual models. (McKinsey & Co. 2023.) This has made me realize how valuable it would be to support designers in optimizing their workflow and allowing them to dedicate more time to the creative aspects of their work.

Understanding the foundations of artificial intelligence

There are varying interpretations of AI across different audiences. For some, AI refers to artificial life forms capable of surpassing human intelligence, while for others, almost any form of data processing technology may be considered AI. However, "AI" should not be treated as a countable noun; it is a scientific discipline, much like mathematics or biology, comprising a collection of concepts, problems, and methods for solving them (University of Helsinki & Reaktor, 2024). According to Kühl et al. (2022), recent definitions of AI fully transfer the concept of human intelligence to machines, assigning them cognitive characteristics such as perceiving, reasoning, learning, interacting with the environment, problem-solving, decision-making, and even creativity. Similarly, Luce (2019) explains that the field of AI aims to understand how humans think and how this intelligence can be replicated in machines.

Building on these definitions, it is also important to understand how AI differs from traditional approaches to programming. In rule-based programming, which is often considered the 'traditional' method, data is given to the machine and explicit rules are coded to define how the data should be processed. The machine produces responses based on these predefined rules. Although rule-based programming has been used in applications such as simulating natural language, it has proven impractical for complex tasks, as writing the necessary volume of rules is nearly impossible. Furthermore, in this approach, the program does not learn from the data (Kananen & Puolitaival, 2019).

In contrast, AI-based programming relies on algorithms that learn patterns from data. The AI is provided with data and corresponding outputs (known answers), allowing it to learn the relationships between them. This process, commonly referred to as training, involves identifying recurring patterns within the data to establish rules. These learned rules form the basis for the AI's predictions or decisions. Unlike rule-based systems, AI models evolve through exposure to data, and their accuracy depends on the quality and quantity of that data (Kananen & Puolitaival, 2019).

AI can outperform humans in specific, narrowly defined tasks by completing them faster and with greater precision. For example, while a person might quickly recognize that a parking lot is full of cars, an AI system trained to recognize car brands could, at the same moment, identify not only the number of vehicles but also their specific brands and models. In such focused tasks, AI offers several advantages: it is faster, more accurate, capable of unlimited repetition, consistent over time, and potentially unbiased—provided the training data is free from bias. The strengths of AI are particularly evident in areas involving classification, repetitive tasks, and the rapid processing of large datasets. In contrast, human strengths remain in areas that require creativity, emotional intelligence, and the ability to navigate complex or ambiguous situations. (Kananen & Puolitaival 2019.)

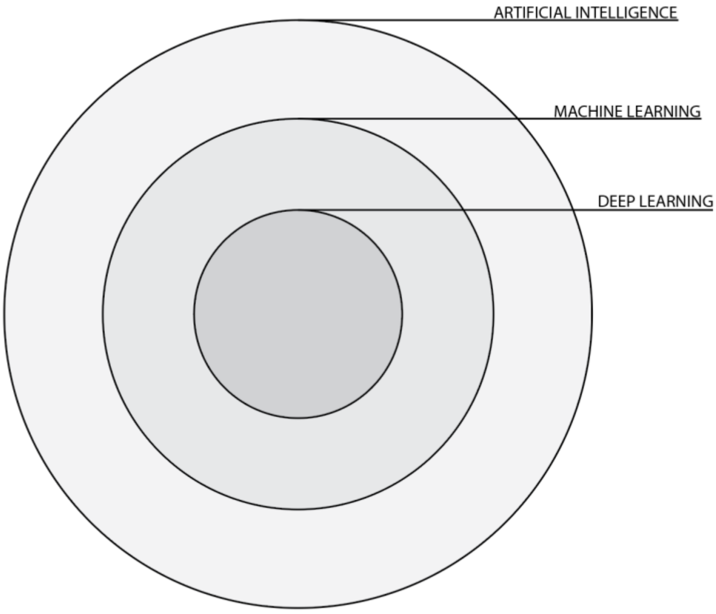

Figure 9. The relationship between AI, machine learning and deep learning according to Luce (Luce 2019).

According to Luce, up to 30% of activities in 60% of occupations across all industries can be automated. However, this requires time and reskilling the current workforce, but at this rate, AI will significantly impact the way we work. (Luce 2019.) Next, I will examine the concepts of AI, **machine learning (ML), deep learning** and **neural networks**, and explore how they relate to one another, as illustrated in Figure 9.

Machine learning

When discussing artificial intelligence (AI), it is important to clarify several related terms that are closely connected to the concept. Machine learning (ML) refers to systems that improve their performance in each task through experience and exposure to data. It is considered a subfield of AI (University of Helsinki & Reaktor 2024). As early as 1959, Arthur Samuel defined ML as “the ability to learn without being explicitly programmed.” In practice, machine learning involves using algorithms to detect patterns in data and often to predict values for unknown or future data points (Luce, 2019).

A foundational concept in the history of AI is the Turing test, introduced in the 1950s by Alan Turing, as a way to assess machine intelligence. The test evaluates whether a machine can perform human-like tasks to the extent that a human interrogator cannot distinguish between responses generated by a human and those by a machine (Kühl et al. 2022; Luce 2019).

According to Kühl et al. (2022), the growing popularity of AI has led to the term often being used interchangeably with machine learning. However, they emphasize that while related, the two are distinct. Machine learning is a major driver of AI today, and most modern AI applications rely heavily on ML techniques.

Closely related to these developments is data science, a broad field that encompasses machine learning, statistics, and aspects of computer science such as algorithms, data storage, and web application development. It is an applied discipline that also requires domain-specific knowledge, whether in business, science, or other areas, including an understanding of relevant goals, assumptions, and limitations. Many data science solutions incorporate elements of AI (University of Helsinki & Reaktor 2024).

Deep Learning and Neural Networks

Deep learning is a type of machine learning that uses artificial neural networks to learn from data. These neural networks are collections of mathematical units capable of learning by observing large volumes of input. For example, a neural network designed for image recognition can analyze and interpret visual data (Merilehto 2018). The term deep learning refers to the complexity of these models, specifically, the number of layers and parameters involved, which has been made feasible by the increasing computing power of modern systems. This advancement allows for models that not only perform better in terms of scale but also demonstrate qualitatively different capabilities compared to earlier approaches. (University of Helsinki & Reaktor 2024.)

Deep learning models are particularly effective when trained on large datasets, and one of their strengths lies in their ability to process raw, unstructured data without requiring extensive pre-processing (Merilehto 2018). The more data a deep neural network is exposed to, the better it can learn.

Convolutional Neural Networks (CNNs)

A key subtype of neural networks is the Convolutional Neural Network (CNN). CNNs apply layered filters to input images or other high-dimensional data, enabling them to detect and classify visual features such as shapes, textures, or patterns (Goodfellow et al. 2016). This makes them particularly suitable for tasks like facial recognition, license plate reading, and object classification.

In fashion-related AI research, CNNs are widely used for classification tasks—such as categorizing garments by type or style. Kouslis et al. (2024) note that most studies in this field rely on CNNs for this purpose, with classification being a foundational capability in AI-supported fashion design systems.

Generative AI

Generative AI is a branch of artificial intelligence focused on producing new content, including images, text, audio, and video, rather than simply analyzing existing data. It is powered by foundation models, a category of deep learning models capable of handling multiple complex tasks simultaneously. Generative AI systems leverage training data to learn underlying patterns, enabling them to create new, original outputs that resemble the input data. The field of generative AI is evolving rapidly. Among the most well-known models are natural language generation systems, such as OpenAI's GPT series and Meta's LLaMA (University of Helsinki & Reaktor, 2024.) Text-to-image models like Midjourney (by Discord) are also prominent, as are other types of generative models such as Variational Autoencoders (VAE) and anomaly detection models (Demirdag, 2024).

Generative Adversarial Networks (GANs)

One of the most notable technologies within generative AI is the Generative Adversarial Network (GAN). GANs consist of two competing neural networks:

- A generator, which creates synthetic outputs, and
- A discriminator, which evaluates whether the output is real or generated.

This adversarial process pushes both networks to improve, resulting in highly realistic generated content (Merilehto, 2018). The generator continuously attempts to create outputs that can "fool" the discriminator, while the discriminator improves its ability to detect synthetic data. As Kananen & Puolitaival (2019) describe, it is as if “two AIs are interpreting each other”, one creating, the other judging.

GANs are among the most commonly used models for generation tasks in fashion-related AI. For instance, conditional GANs can generate fashion items from sketches, and when combined with CNN-style transfer algorithms, they can enhance the aesthetic quality of the output (Kouslis et al. 2024). Even though GANs are being integrated into the design process, traditional sketching and colouring methods still have limitations, including poor colour distribution and loss of detail (Jiang et al. 2024).

It is important not to limit the definition of generative AI to widely known public tools like ChatGPT or Midjourney. Many AI models are developed by large tech companies and research institutions such as OpenAI, Google, Meta, NVIDIA, and various universities. These organizations may choose to make their models open-source, offer them as commercial services, or develop customized solutions for other companies (Demirdag 2024).
The underlying principle of all generative AI models is the same: teaching an algorithm to generate outputs based on the patterns it learns from its training data. As these systems become more advanced, their impact on industries like fashion is expected to grow significantly. According to McKinsey & Co. (2023), generative AI could contribute $150–275 billion in added operating profit to the apparel, fashion, and luxury sectors within the next few years.

Text to image

Zhang and Liu (2024) explain the principles of text-to-image applications, highlighting significant advancements in AI-driven image synthesis. Technologies such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) have enabled the generation of high-quality images. (Zhang & Liu 2024; Jiang et al. 2024.) More recently, diffusion modelling-based text-to-image AI has gained popularity for rapidly producing high-resolution images in various styles from natural language prompts. This method is widely applied in fields like art, graphic design, illustration, and architecture. The diffusion modelling process involves three main steps: (1) using prompts (keywords or descriptions) to retrieve relevant images, (2) adding random noise to create variations, and (3) applying a denoising diffusion process to generate new images. Since repeated prompts produce unique outcomes due to random image selection, adjusting prompts to achieve desired results can be challenging. This has led to the development of prompt engineering, where input prompts are refined for more accurate results. Different fields, such as fashion and art, may require unique approaches for prompt refinement to achieve optimal outcomes. (Zhang & Liu 2024.)

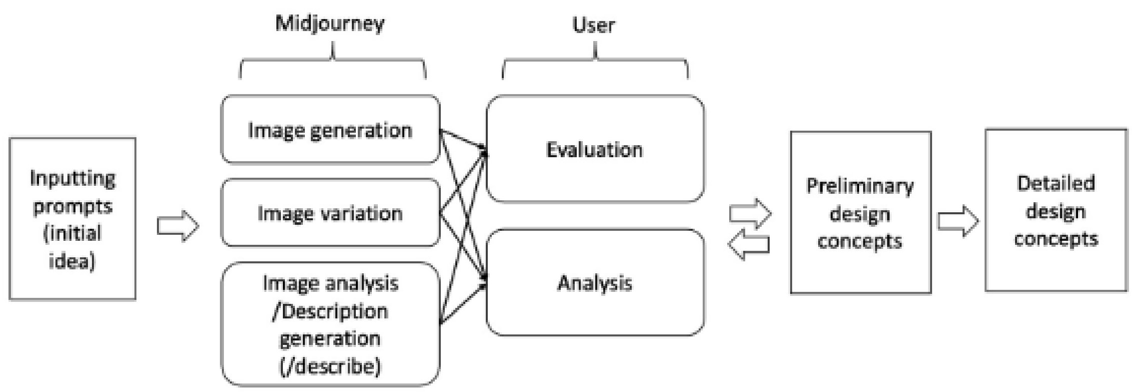

Figure 10. Concept generation workflow within Midjourney (Zhang & Liu 2024).

Midjourney is an example of a text-to-image generator based on the diffusion model and it is currently available in open beta and can be accessed through Discord. Midjourney quickly transforms basic ideas into detailed design concepts covering symbolic meaning, style, colour, fabric, silhouette, and craftsmanship. However, researchers must actively guide the process. (Zhang & Liu 2024.) Midjourney and similar image generators create visuals by calculating the probability that the verbal prompts they receive resemble the patterns found in the images they've been trained on (Drimmer 2025).

Big data and data collection

Data is said to be the most important to any task in machine learning. Without data, the machine would not have anything to train from. Data collection refers to the process of collecting data for analysis. Examples of data are information such as video, image, and text. Data mining refers to uncovering useful information in large amounts of data. (Luce 2019.)

Data exists over time, but what makes it special and big now is the rapid rate and different forms it's been produced in recent times. Big data is created digitally and collected automatically. The growth of available data in terms of quantity, diversity and access speed has been enormous. Big data can be characterized as the three key properties: *volume, velocity*, and *variety*. *Volume* refers to the size of the data, *velocity* refers to the data provisioning rate and the time within which it is necessary to act on them; *and variety* refers to the heterogeneity of data acquisition, data representation and semantic interpretation. (Laney 2001.) As technology continues to advance, the threshold for what is considered big data is likely to rise. This definition can differ across industries, depending on the typical size and type of datasets used in each sector. (Sedkaoui 2018.)

Fashion Data and AI-Assisted Forecasting

Technology is increasingly becoming a key driver in transforming the fashion supply chain. AI including machine learning, supports this shift by enhancing sales forecasting, optimizing supply chain efficiency, and improving personalized production. AI-based tools analyze large datasets to predict fashion trends and consumer demand, helping to reduce costs and minimize financial losses (Sun & Zhao 2018; Bienkowska 2024). With input from designers, generative AI can also be used to develop algorithm-based virtual models of products.

The fashion industry applies big data across various functions, including market identification, trend analysis, and gaining insights into consumer behaviour. Trend forecasting leaders such as WGSN and Edited use big data analytics to inform their reports, while mass-market retailers like Zara mine real-time sales statistics and social media data to quickly identify and respond to emerging trends (Silva et al. 2020; Brownlow et al. 2015). For such companies, big data often replaces traditional trend sources, such as runway shows, as the primary basis for design decisions.

However, the growing reliance on shared data sources for forecasting comes with challenges. A key concern is the potential loss of creativity, as data-driven processes may lead to homogenized trends across brands (Silva et al. 2020.) Despite this, big data remains valuable beyond trend prediction. For instance, it can be used for brand protection through pattern recognition technologies that help ensure quality control and reduce the dissemination of counterfeit goods.

Additionally, AI is improving the marketing landscape by enhancing data mining capabilities and enabling more targeted social media campaigns. The development of Real-Time Fashion Systems (RTFS) allows consumers to participate in co-designing, personalizing, and even planning production. In garment manufacturing, cloud factories and machine learning algorithms help brands efficiently fulfil orders and generate new designs. AI-driven 3D design tools also contribute by reducing development time, material use, and overall production costs. While some challenges remain, such as translating trend data into actionable product forecasts, AI continues to unlock new opportunities for innovation, efficiency, and consumer personalization in fashion. (Bienkowska, 2024.)

Computer vision

Computer vision refers to the use of algorithms and systems to process and interpret images and videos, automating tasks typically associated with human vision, and in some cases, extending beyond it. While computer vision is a distinct field, recent advancements have been largely driven by developments in artificial intelligence. Given the highly visual nature of the fashion industry, computer vision technologies are widely applied in areas such as visual research, smart mirrors, social shopping, trend forecasting, virtual reality, and augmented reality. (Luce 2019.) Computer vision operates by assigning weighted numerical values to the pixels within digitized images. During the classification process, a human identifies and labels the content depicted in the image (like the reCAPTCHA challenges to prove one is a human when logging in on Google). This is used on training data for a neural network, enabling it to issue a statistical estimation about whether the numerical value of a given image matches those of other images. (Drimmer 2025.)

Robotics

Robotics involves designing and programming robots to function in complex, real-world environments. In many ways, it represents the ultimate test for AI, as it requires integrating nearly all areas of artificial intelligence. In brief, a robot is a machine comprising sensors (which sense the environment) and actuators (which act on the environment) that can be programmed to perform sequences of actions. (University of Helsinki & Reaktor 2024).

In apparel manufacturing robotics is a unique area of study that requires domain expertise across fashion, mechanical engineering, and machine learning. Fashion has not yet caught up with robotics in manufacturing as e.g. automotive industry. This is due complexities of handling fabrics. (Luce 2019). Robotics can lower manufacturing costs by automating and optimizing routine tasks. When combined with various digital technologies in design and production, it enhances the efficiency of direct labor and local resource use, enabling more agile and adaptable sourcing strategies. Additionally, digital tools can help unify fragmented supply chains and close the knowledge gap between designers and manufacturers. (Sun & Zhao, 2018.)

Ethics and AI

Crawford (2021) challenges the perception of AI as an abstract, immaterial technology. They emphasize how AI systems are deeply entrenched in material processes that involve extensive extraction of natural resources, significant energy consumption and substantial human labor. They claim that AI is one of the largest planetary architectures ever built by our species, requiring vast amounts of energy, minerals, water, data, and labor. The technical infrastructure of AI is directly competing with humans for basic resources like water, energy, and land. The development and operation of AI technologies rely on mining rare earth minerals, consuming vast amounts of electricity and water, and utilizing low-paid labor for tasks like data labeling. These processes contribute to environmental degradation and raise concerns about sustainability. By highlighting these hidden costs, Crawford calls for a more transparent and equitable approach to AI development that accounts for its ecological and human toll. (Crawford 2021; Antonelli 2024.)

Human labor and AI. The article “The Exploited Labor Behind Artificial Intelligence” highlights how contemporary AI systems rely heavily on underpaid human labor, including data annotators and content moderators, often working under precarious conditions. While AI is often portrayed as autonomous and intelligent, its development depends on a global gig workforce earning low wages and facing harsh performance demands. This labor model, rooted in platforms like Amazon Mechanical Turk, exposes workers to exploitative environments and, in some cases, harmful content that affects their mental health. The authors argue that true ethical AI must include fair labor practices and support for transnational worker organizing. (Gebru et al. 2022.)

Designer’s copyright and authorship in the age of AI. Härkönen (2023) examines how the rise of advanced AI in fashion design affects copyright and authorship, particularly the role of human designers. As AI becomes a more cost-efficient design tool that is not subject to intellectual property rights, it poses a threat to already vulnerable human designers within the fashion value chain. The industry's tendency to overlook designers' moral rights, especially attribution, further weakens their position and blurs transparency around design origins. The increasing use of AI amplifies these issues for both consumers and competitors. They argue for greater recognition of designers' moral rights and propose extending a similar attribution framework to AI-generated designs to promote fairness and transparency in the creative industries. (Härkönen 2023.)

Creativity

It is essential to clarify the concepts of creativity and innovation while discussing the processes of a human designer and AI. Hallam and Ingold distinguish between creativity and innovation, noting that creativity involves the process leading to an innovative product, while innovation refers to the assessment of how a product can change or enhance an environment. (Hallam & Ingold 2007.)

Sawyer (2012) explores the intersection of creativity and decision-making through a sociological lens, identifying three key dynamics that influence creative decisions: the individual, the domain of creativity, and the field, which acts as a gatekeeping mechanism. From a sociological perspective, individuals are shaped by their cultural, temporal, and environmental contexts, but they also contribute to and influence these very contexts. This reciprocal relationship underscores how creativity is both a personal and socially embedded process. (Sawyer 2012.)

In the context of design, this dynamic is evident as designers draw on their own experiences, training, and personal perspectives, what might be described as their unique cultural idiosyncrasy, to address design problems. This individual lens is shaped by numerous factors up to the point of engaging in a specific design task. However, creative expression in design is not solely personal; it occurs within a domain of established practices, methods, and exemplars upheld by the discipline. These conventions, often learned through formal education (e.g., courses like *History of Design*), define what is considered valid or exemplary design work. As Sawyer notes, what becomes part of this domain must be recognized and validated by experts in the field, reinforcing the structured nature of creative disciplines. (Sawyer 2012.)

The ultimate achievement for AI according to some research is the machine's ability to create original works of art. For others, the creativity of a machine will never exceed human creativity. However, machines can provide excellent tools to the humans who are creating. (Luce 2019, 127). AI can be a great assistant to a designer and support their inspiration and creativity or serve as a creative assistant helping with mundane tasks, especially in the digital domain (Sbai et al. 2019).

Fixation is one of the most studied creativity blockers. This is a phenomenon by which the designer tends to stick to a limited space of familiar solutions instead of opening to new and unexpected paths (Crilly 2015, Jansson & Smith 1991). Generative design may constitute a different way of breaking creative blockings by letting the computer produce alternatives. This way the designer can explore a wider range of possibilities in product design faster which can create new aesthetic options. (Alcaide-Marzal et al. 2020.) Designers can choose from different AI-generated options which can refine the evolutionary system. It is important to note that generative algorithmic design should be contextual rather than random. (Särmäkari & Vänskä 2022.) In this way, the designer remains in control and owns the creative process. However, the study subject of Särmäkari & Vänskä, the finnish designer Matti Liimatainen questions the role of the designer and the myth of fashion in his process. The relevant question is what value human involvement adds to a garment. (Särmäkari & Vänskä 2022.)

AI-powered software brings a sense of creativity to anyone who can write a prompt. On the simple level machines can only mimic the artworks it’s given and provide variations of it (Sbai et al. 2019). In that way prompting could be a new artistic medium. Systems like DALL-E 2, MidJourney, and Stable Diffusion enable users to generate complex, high-quality images from simple text prompts. Their popularity stems from a novel capability: the ability to create visual content without needing traditional skills in illustration, painting, or photography. These models lower the barrier to visual creativity, making image creation more accessible to non-artists and designers. However, in artistic contexts, a challenge arises, translating visual expression into words. Language may fall short in capturing the emotional or abstract qualities of certain artworks, such as those by Mark Rothko or Willem de Kooning (McCormack et al., 2023).

Digital transformation of fashion design

Designership and AI

Särmäkari & Vänskä have explored how AI and digital automation tools are reshaping the profession of fashion design. Their research focuses on the impact of ongoing digital transformation and algorithmic design processes on the role of the designer, emphasizing a comparison between human creative expertise and the capabilities of algorithmic systems. The designer's profession co-evolves alongside technological and societal changes. (Särmäkari & Vänskä, 2022.) On the contrary, Kawamura expresses her concern about the de-professionalization of designers. Even though the digitalization of fashion design aids designers in their work it also facilitates non-designers and even machines to design. (Kawamura 2023, 66).

Sun & Zhao (2018) have explored the changing role of designers in the emerge of new technologies. The designer profession has significantly evolved with the introduction of new technologies, particularly in the areas of digital tools and manufacturing processes. Designers are now required to balance technical and creative skills, integrating advanced tools like 3D software for design optimization and material knowledge. This shift has led to a more complex role, where designers must collaborate closely with makers and factory floors to understand manufacturing capabilities. Additionally, the need for engineers' knowledge, communication across fields, and familiarity with new post-processing methods have become essential. As a result, designers are expected to expand their expertise beyond traditional design, incorporating elements such as CAD skills, engineering principles, and consumer behaviour understanding to adapt to these technological advancements. (Sun & Zhao 2018.) This progress is expected to accelerate further with the advancement of AI-assisted design tools.

The advancement of AI may reduce the need for designers, while other stakeholders involved in the development process, particularly those working with physical products, will remain essential. According to Kato et al. (2019) image generation using deep learning has been explored for creating fashion designs, but research on converting these images into real clothing is limited. They proposed replacing the designer's sketch with generated images using generative adversarial networks (GANs), followed by human-made pattern-making and actual clothing production. GANs were trained with clothing images from the same brand to generate designs that maintain the brand's style. (Kato et al.2019.)

Lee (2022) proposes a human-AI collaborative design model that integrates generative adversarial networks (GANs) to foster innovation and creativity. This model suggests that GANs can complement human creativity by generating design ideas that enhance originality, allowing designers to explore new styles while maintaining high similarity to existing works. The collaboration between human designers and AI helps address complex system designs by combining human intuition with AI technology. As a result, designers can generate thousands of design variations, quickly reviewing them to find the best solutions for consumers. This collaboration improves design efficiency by enabling AI to handle routine tasks while designers focus on the more creative aspects of decision-making. (Lee 2022.)

AI-Powered design tools and workflow optimization in fashion

Algorithmic models often support fashion design by applying machine learning techniques, which use large datasets as input to create new design outputs (Luce 2019). The input can be professional or user-generated images from social media, platforms, editorials or runways, company websites and databases, and textual garment or style descriptions commissioned by fashion experts. The outputs, however, are whatever the algorithms generate based on the input and training, ranging from text-based prompts and rough sketches to photorealistic visualizations (Särmäkari & Vänskä 2022).

According to Särmäkari and Vänskä, neural networks are typically used for handling the imagery aspects of fashion design, while genetic algorithms are employed in product development tasks such as pattern optimization, generating complex 3D models, and searching for novel or random shapes. This redefines the designer's role, positioning them more as a conductor of processes rather than a sole creator. (Särmäkari & Vänskä 2022.)

Jiang et al. (2024) highlight that in the inspiration stage, designers seek quick access to references that inspire them. During the sketching phase, they prefer modifying existing templates instead of starting from scratch. In the colouring stage, designers aim to quickly preview and adjust colours. As a result, AI tools play a crucial role in minimizing the time and energy spent on non-creative tasks, thereby streamlining the design process. By automating these stages, AI allows designers to focus more on innovation and creativity, ultimately enhancing the overall efficiency of the design process. (Jiang et al. 2024.)

Building on this, Deng et al. (2024) stress the importance of flexible, shareable, and cross-device applications for design. Designers must manage a large volume of research images and rapidly conceptualize, sketch, and colour designs according to specific themes. They argue that there is an urgent need for a cross-device, AI-assisted fashion design framework that addresses these challenges while boosting both creative freedom and process efficiency. In response, they introduce a cross-device generative AI (GAI) framework for collaborative fashion design. Based on initial sketches, the system automatically generates and renders fashion images using integrated sketch generation and image synthesis modules. This streamlines the design process and accelerates style development, significantly improving efficiency. The platform also includes multiple functional modules that support different stages of the fashion design workflow.

In fashion specifically, data such as users' online purchases, liked garments and fashion images are used to train and evaluate AI models. By utilizing this data, these models can be trained to solve specific problems, assist in tasks, automate stages of the workflow, and provide insights across the design and production pipeline (Kouslis et al., 2024). Guo et al. (2023) further emphasize that AI systems, when combined with data on user preferences, body measurements, and style choices, can deliver highly personalized fashion recommendations. (Guo et al. 2023.)

While current literature addresses the transformative potential of artificial intelligence in fashion design, focusing on speculative models, independent creators, and technological capabilities, there is a notable gap in understanding how AI is integrated into the everyday workflows of commercial fashion designers. Most existing studies overlook the lived experiences of design teams working within larger or mid-size fashion companies, where organizational structures, role-specific tasks, and legacy systems heavily influence technological adoption. This study addresses that gap by offering an in-depth look at how professional designers currently engage with AI and digital tools, highlighting specific stages in the workflow where these technologies could offer meaningful support. Through interviews with designers across varied market levels, this research identifies both structural and cultural barriers to AI integration, while also uncovering moments of opportunity, such as digital prototyping, material research, and creative ideation, where AI could enhance efficiency and creativity. In doing so, it provides a grounded foundation for the development of AI-powered design applications that respond to the actual needs of industry professionals, while also contributing to the broader discussion on the evolving role of the designer in the age of digital transformation.

3. METHODOLOGY AND DATA

To explore how artificial intelligence is used in fashion design, I conducted semi-structured interviews with three practising designers. This method provided a balance between focused questions and open-ended discussion, allowing for in-depth insights into each participant's experience. The interview data was analyzed using Reflexive Thematic Analysis, a qualitative approach that supports identifying patterns and meanings across the data while acknowledging the active role of the researcher, also a practising designer, in the analytical process.

SEMI-STRUCTURED INTERVIEW

Data collection can be done by interviewing, observing, collecting, examining and feeling (Yin 2015, 138). Stakeholder interviews focus on information from specific roles or people who may have a vested interest in the particular inquiry (Hanington & Martin 2012.) For this study, I collected data by interviewing working designers about their design process and use of AI. The approach to choosing the interviewees was to gather insights on different market levels and company sizes.

In qualitative interviews, the relationship between the researcher and the participant is not strictly scripted. I used semi-structured interviews, as they create openings for narratives to unfold. Semi-structured interviews incorporate both open-ended and more theoretically driven questions, eliciting data grounded in the experience of the participant. Each question should be clearly connected to the purpose of the research. (Galletta 2013.)

The semi-structured interview follows a conversational mode, and, in this way, a qualitative interview requires intense listening (Yin 2015, 138). Usually, the questions need to be sufficiently open to enable the researcher to elicit data grounded in the experiences of the study participants. Openness also offers the researcher and participants room to explore the phenomenon under study, while retaining some relationship to the theoretical anchors in the literature. (Galletta 2013). The researcher tries to understand a participant's world (Yin 2015, 142).

REFLEXIVE THEMATIC ANALYSIS

Reflexive thematic analysis (RTA) is a research method for identifying, analyzing, and interpreting themes within qualitative data. RTA emphasizes the researcher's active role in creating rather than discovering themes. It differs from other analytic methods that seek to describe patterns across qualitative data – such as discourse analysis or grounded theory. (Braun & Clarke 2006.) In thematic analysis researcher looks for themes, structures the data into those themes and then talks about how the data fits into or interacts with the themes. (Gournelos 2019).

Within the context of design research, this methodology helps researchers understand user's needs, behaviors, emotions and experiences to inform better decisions for design or design process development. In reflexive thematic analysis, the researcher's subjectivity is viewed as a resource, allowing me, as a designer-researcher, to actively shape the analysis rather than remain a neutral observer. RTA can be a realist method of reporting participants' experiences, meanings, and their reality (Braun & Clarke 2006). Assumptions and positionings are always part of qualitative research. In reflexive practice, it is vital to understand and unpack these. It is good practice to reflect on and identify what you're assuming, and then interrogate whether those assumptions hold for any particular project. (Braun & Clarke 2019.)

For this study, I have chosen the theoretical approach of identifying codes and themes in my data as my research questions were quite clear from the start of this research. In this way, my thematic analysis is driven by my theoretical and analytic interest in AI in the fashion design process. (Braun & Clarke 2006; 2019) My research questions:

- What does the fashion design process entail?

- How do fashion companies use AI in their design process?
- How can AI improve designers' work?

have affected the coding of the interview data rather than stemming from it. The level of identifying the themes can be semantic (explicit) or latent (interpretative) level. With a semantic approach the themes are identified within the surface meaning of the data and an analyst is not looking at anything beyond what a participant has said. In contrast, a thematic analysis at the latent level goes beyond the semantic content of the data and starts to examine the underlying assumptions or ideologies. (Braun & Clarke 2006.)

Themes are analytic outputs developed through and from the creative labor of researchers' coding. They do not passively emerge from data or coding nor are they in the data waiting to be identified by the researcher. Themes are interpretative stories about the data, produced at the intersection of the researchers' theoretical assumptions, their analytic resources and skills and the data themselves. Reflexive thematic analysis is properly conducted when the researcher engages reflectively and thoughtfully with both the data and the analytic process. (Braun & Clarke 2019.)

The process of thematic analysis starts with familiarizing oneself with the collected data which is followed by generating the initial codes for it. Coding might require revisiting and recoding. By coding data, it can be divided into potential themes, gathering all data relevant to each potential theme. Then reviewing themes is essential as the next steps defining and naming themes set the overall story the analysis tells. The analysis concludes in producing the report that selects vivid, compelling extract examples, a final analysis of selected extracts relating the analysis to the research questions and literature, producing a scholarly report of the analysis. (Braun & Clarke 2006.)

PARTICIPANTS

This study involved three participants, all of whom are professional fashion designers currently employed at globally operating fashion companies. The participants were selected through purposive sampling to ensure relevant expertise in fashion design practices and their perspectives on the integration of AI within their work processes. The sample included designers from companies of varying scales, ranging from large multinational corporations to a mid-size brand, in order to capture a diversity of experiences and insights. The limitation to European and North American companies was based on the availability of professional connections, as well as considerations informed by my personal experiences and career objectives within the industry. The participants had between 5 and 20 years of professional experience in the fashion industry and represented a variety of apparel design roles, including womenswear and menswear and performance and activewear—referred to as sportswear in this analysis for the sake of simplicity—as well as runway and special projects collections.

PARTICIPANT	ROLE	COMPANY SIZE	COMPANY BASED	YEARS OF DESIGN EXPERIENCE
P1	Senior designer	Large global brand	Europe	8 +
P2	Senior design manager	Large global brand	North America / Europe	20 +
P3	Designer	Medium-sized brand	Europe	5 +

Figure 11. Interview participants.

Understanding that the design tasks of a designer can vary depending on the company's market and size, I made a deliberate decision to involve designers, both working in larger and smaller companies in the study. Furthermore, an important factor influencing my choice of participants was ensuring that the designers either had a demonstrated interest in AI-powered design or were employed at companies that, in my assessment, had the potential means or interest to adopt AI-driven design processes.

4. ANALYSIS

My interview questionnaire was structured around six thematic areas aimed at gaining a comprehensive understanding of the participants' professional context and perspectives on AI in design. These included: understanding the designer's current **design process** and the **structure of their team and company**; exploring their **goals and expectations**, particularly through free association about ideal scenarios without limitations; identifying **challenges and concerns regarding AI** they face in their workflows; discussing the role of **data and technology** in their day-to-day work; and examining aspects of **collaboration and the potential implementation** of new tools, such as AI, within their existing processes. The initial questionnaire was thematically structured into 20 questions following the identification of the research questions and the completion of the literature review.

The interviews were conducted remotely via Microsoft Teams, as participants were based across Europe and North America. This platform also enabled the use of a live transcription tool, facilitating the transcription process. The transcriptions were subsequently uploaded into Atlas.ti, a qualitative data analysis software. Although Atlas.ti offers an AI-powered coding feature, I chose to code the data manually in order to engage more deeply with the material and ensure an additional thorough reading. Given that I had approached formulating the interview questions and subsequent data analysis from a deductive perspective, the coding process was relatively straightforward, allowing for the initial drafting of a thematic structure.

After coding three interviews with fifteen codes, I defined three distinct themes for my data:

Theme 1: Design process
Theme 2: Digital design tools and the use of AI
Theme 3: Data practices and opportunities for AI integration

For the final analysis, I chose to simplify the initial theme structure by organizing the data into three broader themes instead of six.

THEME 1: DESIGN PROCESS

As previously mentioned, the participants hold different design roles across various companies, resulting in variations in their design processes. I considered it important to gain an understanding of these processes, as this would enable me, as a researcher, to better evaluate their positioning about the use of AI. The design roles vary from Senior design manager and Senior designer to Designer (Figure 11.).

The development process for a runway collection and VIP dressing can differ notably from that of a standard ready-to-wear (RTW) or sportswear collection, particularly in terms of structure, collaboration, stakeholders, and timelines. According to Participant 1 (P1), the process begins with comprehensive trend research, followed by the creation of a design briefing. Unlike RTW briefings, which often consider broader commercial strategies, the runway collection briefing is developed internally by the design team in close collaboration with the company's creative director.

An early and ongoing collaboration with the runway stylist is a key feature of this process. Initial meetings focus on defining the overall silhouette of the collection, which enables the design team to engage in a more focused and in-depth exploration of forms, cuts, and design details. In parallel, extensive material research is conducted, covering fabrics, techniques, and knitwear possibilities.

Once the initial research phase is completed, the team moves into prototyping. Prototypes are developed and subsequently reviewed in meetings with the stylist and the creative director, during which design adjustments are made. This cyclical process of refinement continues up until the collection is finalized. Final decisions regarding the selection and styling of looks are made approximately three days before the runway show, in collaboration between the design team, the stylist, and the creative director.

Importantly, unlike RTW and sportswear collections, runway collections are not intended in this case for mass production following the show. They serve primarily as conceptual showcases for the brand’s creative direction and marketing purposes. The entire development timeline for a runway collection spans approximately five months and typically culminates in two runway presentations per year.

In the development of a runway collection, the most time-intensive phase is the creation of technical packs. In contrast, the research and design phase tend to require comparatively less time. Due to the absence of a dedicated technical developer for all product categories within the team, designers are responsible for direct communication with suppliers. This direct engagement increases the time required during the technical development phase.

The development process for sportswear collections according to Participant 2 (P2) begins with a seasonal kickoff meeting, which typically occurs up to two months before the merchandising brief is officially received. During the kickoff, a preliminary brief is shared, wherein the concept team introduces materials of interest and may present initial concept pieces to all design teams. At this stage, the colour palette and overall storytelling direction for the season are also communicated.

Following the kickoff, designers receive the end-of-market report and begin their research phase. Throughout this period, marketplace merchandising teams provide feedback to the central merchandising and design teams, offering insights from both a market and trend perspective. Based on this input, the central merchandising team constructs a range plan grounded in revenue goals and commercial viability. Simultaneously, a trend research brief is distributed to designers, initiating the sketching phase alongside fabric selection.

Approximately one week after receiving the merchandising plan, an internal review with the design director takes place, followed by another cross-functional review involving directors and other departments. This structure imposes a continuous weekly deadline cycle throughout the development period. Pre-costing meetings then occur, during which designers present black-and-white sketches, interior sketches, and rough design details. Final trim selections, including specific codes and technical information, must also be completed at this stage. This information is compiled into a one-page technical pack, which is handed over to the development team and subsequently sent to sourcing teams to begin pre-costing.

If a product fails to meet the target Free on board (FOB) cost at this stage, the full technical pack will not be finalized, and the product development process for that item will be paused. Weekly reviews continue for products that meet the FOB target, allowing for ongoing adjustments to designs and technical specifications based on feedback. Designers have approximately three weeks allocated for the creative sketching phase. After this period, patternmaking and product development continue; however, no digital prototyping is conducted. Early elimination of designs that do not meet FOB requirements helps streamline the process and minimizes cancellations at later stages due to unachievable margin targets. While some 3D designs are produced, they serve solely for presentation purposes and are not used for actual pattern development.

The pre-costing phase takes a lot of time, especially when finalizing designs and finding the correct codes for trims. Identifying and managing these codes is challenging, mainly because there is no strong Product Lifecycle Management (PLM) system in place. Most of the work related to trims is done manually. For example, designers often need to "shop" for trims in the showroom, which slows down the process. During pre-costing meetings, every trim must be listed along with its specific code, which makes accurate trim management very important for both design and cost planning.

Another issue is the lack of standardization in the design process. There are no clear rules for things like logo placement, or pocket sizes, until recently, so designers have had to decide these details individually. It also takes extra time to find the right fit for garments because the company does not have a garment block library. Instead, designers use reference garments from past seasons, but these are not standardized.

The company of Participant B has not fully embraced technology, and different parts of the collection development process use separate systems that are not connected. For example, one system is used for black-and-white technical drawings, another for coloured sketches, and a third e.g., for merchandising line plans. Another one is used for teamwork and collaboration. In total, designers use about five different tools, but since they don't link together, information must be repeated or managed manually. Designers rely on these systems daily, which adds to their workload.

In Participant 3's (P3) company the development process for a sportswear collection typically spans approximately two years prior to product drops in shops. Designers generally have around two months dedicated to the initial sketching and design phase, followed by approximately one month allocated for creating technical packs. This is succeeded by the prototyping stage, during which the goal is to develop at least two physical or digital prototypes. Salesman sample (SMS) development follows, culminating in a sales conference.

Over the past two years, notable changes have occurred in the design process. Previously, sketches were created in 2D and subsequently translated into 3D. Currently, the workflow has shifted toward using 3D sketching as the primary design method from the outset for all designers in sportswear. Additionally, the integration of AI-based design tools, such as ChatGPT and Newarc, at the concept briefing stage has further influenced and reshaped the development process.

3D sketching and product design require a significant amount of time, especially when the design process starts directly in 3D. While many would consider the tech pack phase to be the most time-consuming, participant 3 noted that investing more effort in the 3D sketching phase makes the tech pack phase faster and easier. This is because much of the necessary information is already defined and visualized in the 3D models. As a result, fewer adjustments are needed later. The participant also felt that they wished they had more time available for the initial sketching phase and adjusting the prototypes.

THEME 2: DIGITAL DESIGN TOOLS AND USE OF AI

Use of 2D and 3D design tools

Participant 1 (P1) explained that 2D sketching is initially done in Adobe Illustrator. The design process then transitions to 3D sketching by the designer after the patternmaker has created the base style. At this stage, the designer adds details such as trims, colourways, including contrast colour options, and may even simulate sewing the digital garment, depending on project timelines.

To create 3D fabrics, the team uses Adobe Substance 3D Sampler, which allows designers to generate realistic fabric textures from images or custom graphics. These textures are transformed into normal maps that can be imported into 3D software such as CLO 3D. The trims department also uses Adobe Sampler to create 3D versions of trims, which are then added directly to the digital garment.

P2, in contrast, relies more heavily on traditional digital tools. Their team works almost exclusively in Adobe Illustrator for both sketching and tech pack development. Hand sketching and Photoshop are not part of the workflow. All designs are created in black and white, with colour applied later based on direction from the central hub. As a result, designers have little room to explore colour concepts early in the design process.

P3 presented a more exploratory use of digital tools. CLO 3D is the primary software used for garment design, allowing for full visualization early in the process. In addition, AI tools are actively integrated into the early sketching stage. For instance, ChatGPT is used to gather information on fabrics and fibres, while Newarc is employed to quickly generate visual design ideas. Although P3 acknowledged that the AI outputs are not always refined, they noted that these tools help accelerate ideation and spark creative direction early in the process.

Digital prototyping

The use of digital prototyping varied significantly across participants, reflecting different levels of technological integration and organizational openness to new tools.

For P1, 3D prototyping typically replaces the need for early physical prototypes. This speeds up the process, as potential design issues can be identified and addressed earlier, rather than waiting for physical samples that take weeks to produce. Digital prototypes allow designers to evaluate aspects such as garment shape, volume, and the positioning of pockets and graphics. In the case of runway collections or VIP dressing, the first physical prototype is often production-ready, or in some cases, styles move directly from digital prototype to production. According to P1, this significantly reduces development costs and is made possible through the integration of 3D and AI tools. P3 follows a similar approach to working with 3D designs; however, the use of 3D tools during the sketching phase often results in the creation of an initial digital prototype even before the style is passed on to patternmaking or product development.

CLO-SET is used to manage 3D-designed styles in P1's company. This software supports automated colouring based on seasonal colour cards and can be connected to a PLM system. This automation is especially useful for repeat styles, which only require updates to colourways.

In contrast, P2 does not currently use AI or 3D tools in their personal design workflow. The team has access to Browzwear, a digital apparel design and development software comparable to CLO 3D. When 3D sketches are created, they are used solely for presentation and concept development, without generating digital patterns or true 3D prototypes. However, P2 has experience working with digital 3D prototypes in previous companies. Furthermore, the use of other external 3D or AI tools is restricted in the current company. For instance, access to ChatGPT is blocked on company equipment due to security concerns.

P2 also noted that while there is potential value in using 3D and AI technologies for visualization and concept development, particularly in special projects, these tools are not yet embedded in the company's workflow or culture. The limited adoption is attributed to an organizational culture that has been slow to embrace new technologies, further hindering the integration of digital prototyping into everyday design processes.

Software ecosystem

For P1, the design process often begins with photographing physical vintage or archive garments. P1 then experiments with these references using AI tools to test various features. While many results are generated, only a few are typically useful, making the process time-consuming but potentially inspiring. Positive results occur when AI generates unexpected ideas, such as novel pocket placements or garment shapes. These AI outputs are refined further in Photoshop. Newarc is also used to convert 2D sketches into 3D or photorealistic images, serving as a fast way to visualize ideas before handing them to the patternmaker. P1's company is also developing an internal AI image generation tool, customized to align with its brand identity. P1 is involved in this development, providing input on usability and design logic, such as garment types and wearing occasions. They also curate image datasets used to train the model, which is built using a Generative Adversarial Network (GAN). The tool includes functions like text-to-image and image-to-image generation.

Even though P2 does not use AI currently in their own workflow, they noted that the company has developed an internal AI-powered application designed to convert 2D sketches into 3D visualizations, similar to the functionality of tools like Newarc. This tool allows for attributes such as fabrication, colour, and background to be prompted, creating visuals primarily intended for presentation purposes. Despite this development, the application has not yet been fully implemented across the design team. So far, only one designer, who has shown a particular interest in 3D design, has experimented with the tool.

P3 also relies on a combination of software tools to streamline both creative exploration and technical design. They use Newarc for quickly mocking up visual concepts, which are then developed further in CLO 3D. Additionally, ChatGPT plays a central role in their daily workflow, particularly in the context of sportswear design, where fabric innovation and material knowledge are essential. P3 uses the language model to research technical yarns, fibre innovations, and generate new design ideas, often tailored to specific sports or performance needs. The tool is also used to explore competitive innovations, allowing the designer to stay informed about trends and emerging technologies. While P3 finds this functionality highly valuable, they emphasize the need to approach AI-generated information critically, often prompting the model to justify or explain its outputs.

Together, these examples reflect a growing reliance on AI-supported tools across the design process, from initial concept development to digital garment visualization and design research. While AI streamlines tasks and accelerates ideation, participants also highlighted the importance of human oversight, particularly in evaluating the quality and relevance of AI-generated content.

AI and creative exploration

AI tools are becoming increasingly embedded in the creative exploration phase of fashion design across all participating companies.

P1 takes photos during fittings, which are then modified using AI to create reference images. They use AI tools to design and style outfits for VIP guests attending runway shows. Since public images of the guests are readily available online, AI tools can be used to mock them up in planned outfits. Tools like Procreate, with AI extensions, assist in this process.

P3's team has also begun exploring AI applications for creative visualization. Discussions within the team have centered around the potential of an AI-powered tool capable of generating realistic photo shoots, such as look books or e-commerce imagery, as well as converting product photos into 2D technical sketches for use in tech packs. Although P3 has not yet worked directly with such a tool, its use is under active consideration within the design team.

P3 further noted that their company is taking steps toward developing customized AI applications, tailored to support internal design processes. Unlike some companies where AI tools are heavily restricted, P3's organization allows AI usage within the boundaries of internal compliance guidelines, reflecting a cautious but proactive approach to technological integration.

Role of AI in the design process

According to P1, AI does not always speed up the design process but can offer surprising and creative outcomes. For example, they've used tools such as Stable Diffusion, Newarc, Leonardo, and OpenArt, and expressed interest in trying Doji, particularly for future VIP dressing applications.

Ideally, P1 envisions AI being used to create fashion looks directly from inspiration images, such as generating a complete outfit based on the aesthetics, textures, and colours of the reference image. In their view, AI could also be useful for locating images of archived fashion pieces or generating design references from past decades. Practical use cases could include drafting emails to specific vendors or automating file conversions, for example, transforming an AI-generated image into a vector file with Pantone colours and automatically saving it in the appropriate system or whiteboard application, enabling smoother collaboration between teams.

Despite the promise, P1 recognizes the limitations of current AI models. They note that AI-generated images are ultimately variations of existing data, often lacking originality. Still, they find value in the "mistakes" AI makes, which can unexpectedly spark new ideas. P1 sees AI as a creative partner, similar to a colleague for bouncing around ideas, but not as a replacement for human designers, particularly because AI cannot replicate the collaborative, interpretive nature of human interaction.

P2 expressed optimism about AI's potential to address several challenges within the current design workflow, particularly the inefficiencies caused using multiple, disconnected systems. They noted that if AI could streamline processes and reduce administrative workload, it would allow designers to focus more on creative tasks. This, in turn, could free up time for the team to explore and adopt AI-powered applications, including the company's internal AI design tool.

P2 also highlighted the potential benefits of using language model applications, such as ChatGPT, for practical tasks like analyzing design processes or developing project plans. In addition, they envisioned AI playing a role in more technical aspects of the workflow, such as supporting complex tech pack creation. As the company is working toward greater product standardization, P2 suggested that AI could help build and manage a design system. For example, a partially automated tech pack tool could include pre-defined, standardized elements, such as fit blocks or hood constructions, which designers would simply need to review and approve. This would reduce repetitive work and enhance overall efficiency in the design process.

P3 mentions that in an ideal scenario, AI could enable designers to spend more time refining the final physical product, whether through optimizing fit, fabric, or detailing, ultimately improving product quality. They noted that, under current conditions, designers often lack sufficient time to engage deeply with physical prototypes and make meaningful changes. They believe AI has the potential to shift this dynamic by streamlining earlier phases of the process, allowing the team to focus more on creating products that are fit for purpose and truly valuable to the customer.

P3 also highlighted the role of language models, such as ChatGPT, in enhancing the design process. These tools can support conceptual development, aid in research, and help streamline workflows before the physical product design even begins. From their perspective, AI can democratize design by leveling the playing field, and offering support to designers with varying skill sets and backgrounds. This includes assistance with tasks such as trend forecasting, fabric research, sourcing, and technical development, areas that can often be time-consuming or resource-dependent.

Looking to the future, P3 recognizes the possibility that AI could automate larger portions of the design process and potentially reduce the number of roles required within the industry. However, they also believe AI holds great promise for independent or early-career designers. Tools powered by AI can already generate mood boards, develop social media strategies, create tech packs without prior experience, and identify suitable manufacturing partners, making it increasingly feasible for individuals to launch fashion brands with limited resources. In this way, AI not only streamlines technical tasks but also facilitates creativity and entrepreneurial access, allowing anyone with a vision to take on roles traditionally reserved for trained professionals. P3 believes this shift could also have a significant impact on the future of design education, potentially reshaping what skills are considered essential in the fashion industry.

Challenges and concerns

While participants acknowledged the potential of AI to support and enhance design workflows, they also raised several important concerns, ranging from creative and cultural issues to environmental and ethical considerations.

P1 expressed concerns about over-automation in design workflows, particularly in areas like tech pack generation. They believe that creative exploration and the opportunity to learn from trial and error could be lost if AI handles too many steps. Maintaining human control over every stage of the design process is essential, in their view. They also voiced environmental concerns about the energy consumption associated with running AI systems. P3 echoed similar concerns about the use of AI. They questioned whether tools like ChatGPT should be employed for minor, everyday tasks given the high energy cost, and expressed disappointment that sustainability is not more widely discussed in relation to AI.

P2 identified the primary challenge in adopting AI as the broader corporation's reluctance to fully embrace it. Another concern raised by p2 was the potential for AI-generated designs to be impractical or too costly to produce. However, P2 emphasized that this would likely become a significant issue only if the physical aspects of product development were entirely deprioritized and designs were created solely through AI, without considering real-world constraints.

P3 also cautioned against over-reliance on language models, warning that unquestioned acceptance of AI-generated information could lead to errors or misinformation. They raised data security concerns as well, particularly around the use of company-specific information in open AI models. Furthermore, P3 noted that if AI were to fully automate processes like tech pack creation, it could erode a designer's sense of connection and ownership over the product. In their view, meaningful interaction with the design, especially the physical product, is essential to delivering purposeful and user-focused outcomes. Together, these reflections suggest that while AI offers clear efficiencies, it must be implemented thoughtfully, with careful attention to creative autonomy, environmental impact, data ethics, and the preservation of human-centered design values.

Resistance to AI adoption

All participants acknowledged a degree of resistance to AI adoption within their respective teams, though the reasons behind it varied. P1 noted that while a small group of designers is actively experimenting with AI tools, the majority remain sceptical or uninterested. This mirrors the earlier introduction of 3D design tools, where acceptance took time due to the need for training and a willingness to work with aesthetics that may initially appear incomplete or unfamiliar.

Similarly, P2 observed that low motivation to adopt the company's internal AI application is largely due to practical constraints rather than outright resistance. Designers already manage multiple systems on a daily basis and learning yet another tool is seen as too time-consuming. According to P2, the AI tool has also not been widely integrated into workflows across other company hubs, which further discourages its use. However, P2 emphasized that their team is generally open to new technologies, and resistance tends to arise only when there is insufficient time or support to integrate new tools effectively into existing routines.

P3 anticipates potential resistance to AI within their own team as well as the fashion industry more broadly. They noted that some designers may be reluctant to accept that AI-generated work could match, or even surpass, human-created designs. This hesitation often stems from a belief in the superiority of human creativity. However, P3 makes a clear distinction between using AI as a creative assistant and viewing it as a replacement for designers. In their view, AI should be seen as a tool that supports and enhances the creative process, rather than a threat to the designer's role. Furthermore, now they think the 3D design and AI are separate things but eventually, they will merge. Also, the same will happen with 2D designs and AI-created images. The design process will be a lot more efficient and faster and take fewer people.

THEME 3: DATA PRACTICES AND OPPORTUNITIES OF AI INTEGRATION

P1 primarily collects visual data, including image files of vintage garments and past fashion show looks. Before sourcing physical archive pieces, initial research is conducted online. However, locating certain archival items can be challenging, particularly when the garments predate the internet. In such cases, conventional image searches (e.g., Google) are often insufficient, and more in-depth searching is required. Additionally, poor image quality can limit the usability of found references. P1 sees significant potential for AI to support archival research.

P1 does not use PLM for managing design assets; instead, all data, such as images and links, is stored on a shared Miro whiteboard. Styles stored in PLM can be linked to Miro to maintain organization. For 3D assets, CLO-SET is used, allowing designers to share data directly with suppliers. This system also provides automated processes for tasks like repeat-style colouring. P1 also notes that multiple cross-departmental teams within their company are currently working on digitalizing the design process, indicating a broader institutional commitment to innovation.

P2 described a more fragmented system for storing design data, which is spread across several platforms. Unlike P1's company, P2's organization does not have a dedicated in-house technical team to support the design team in managing digital assets. Trend data is gathered through external sources such as WGSN, store visits, and fabric fairs. P2's team also produces their own visual research by photographing materials and inspirations while travelling, which are shared internally and across different design hubs. However, this process, typically done through shared folders or presentation decks, is time-consuming and often deprioritized due to workload. Nonetheless, P2 values this exchange of visual data, particularly because not all teams have the opportunity to travel for inspiration.

When it comes to material innovation, any new fabrics or technologies must go through a centralized innovation team at the company's main hub, as such developments are usually tied to a marketing narrative. New materials are limited each season and must be tested, assigned codes, and sourced from approved suppliers before being made available to design teams. As a result, P2’s team engages minimally in material research. Despite the company owning multiple sportswear brands, supplier lists are siloed, with no shared or centralized system for access.

P2 sees potential in an AI-driven tool that could learn the brand’s aesthetic and product DNA to assist the design team. A centralized platform for past designs, trend forecasts, and consumer insights could support faster, more informed concept development, especially for capsule or seasonal collections. This would reduce reliance on time-consuming online searches and streamline inspiration gathering.

P3 gathers trend inspiration largely from social media platforms and expresses a desire to use internal consumer behaviour data, which is currently not made available to designers. PLM is used to manage design assets. There is limited integration of AI in the design process at this stage. Although an internal IT specialist has explored AI-powered design applications with the team, these tools have not yet been formally implemented.

5. RESULTS

This chapter presents the findings of the reflexive thematic analysis conducted on semi-structured interviews with three professional fashion designers. The analysis resulted in three main themes that reflect the complexities of the contemporary fashion design process and the growing role of AI and digital technologies. These themes are: **Design Process**, **Digital Design Tools and the Use of AI**, and **Data Practices and Opportunities for AI Integration**. While the design roles, company cultures, and levels of technological integration vary, shared patterns were evident, particularly in how designers experience time pressures, navigate digital tools and different systems, and envision the role of AI in supporting their work.

Design process. This theme highlights the diversity of design workflows across different fashion companies and market levels. While the overall structure of the design process appears largely consistent, there are clear strategic and operational differences, particularly between runway and sportswear collections. These differences are shaped by the collection's purpose, the involved stakeholders, and the degree of creative freedom. Across all participants, common challenges emerged, including time constraints, limited technological support, and a lack of standardized processes. The theme also illustrates how designers adapt their workflows in response to organizational demands, available tools, and production requirements.

All participants provided detailed accounts of their design processes and discussed specific challenges. Many elements aligned with both my own professional experience and insights from the literature. However, the involvement of stakeholders varied depending on the type of collection. For runway collections, the concept is developed internally by the design team and the creative director, offering greater creative freedom and space for in-depth research. Designer working on runway collections saw the potential for AI to support more advanced visual and material research.

In contrast, sportswear designers operate under more structured commercial constraints, often guided by merchandising input and sport-specific fabrication needs. In these contexts, AI could assist by summarizing customer feedback or merchandising requirements and by conducting advanced research into innovative fibres and materials. Additionally, participants noted the need for standardized elements, such as logo placement and fit blocks, which AI could help automate, especially during the resource-heavy tech pack phase. A recurring concern across all interviews was the fragmentation of digital tools. Participants emphasized the need for AI integration to bridge disconnected systems and reduce the growing burden of manual tasks.

Digital design tools and the use of AI. This theme captures participants' experiences with both digital and AI-assisted tools throughout the fashion design process—from 2D sketching and 3D visualisation to AI-supported concept ideation. It highlights the varying degrees to which emerging technologies have been integrated into their workflows, shaped by factors such as company infrastructure, personal interest, and organisational culture. The findings reveal how AI and digital tools are being used to streamline routine tasks, accelerate ideation, and support rapid prototyping, while also pointing to systemic barriers that continue to limit broader adoption.

To structure the insights clearly, this theme is divided into seven sub-sections:

Use of 2D and 3D Design Tools

Digital Prototyping

Software Ecosystem

AI and Creative Exploration

Role of AI in the Design Process

Challenges and Concerns

Resistance to AI Adoption

Two of the three designers interviewed have already integrated AI tools into their design workflows, and two also actively use 3D design tools. Notably, 3D users expressed a clear preference for 3D sketching over traditional 2D tools, citing its ability to better visualise garment shape, volume, and detail, sometimes even replacing the need for physical prototyping altogether. From my own experience, I can confirm that 3D sketching provides valuable clarity, especially when collaborating with product developers and suppliers. However, for complex garments such as outerwear with multiple construction layers and trims, 3D modelling can be time-intensive.

AI tools explored by participants include ChatGPT, Newarc, and internal company-developed applications. These are mainly used for early visualisation, archival research, and material investigations. Designers use AI-generated images for internal presentations and mock-ups, particularly for VIP looks or conceptual stages where fast visual output is required. 3D and AI visualisation were described as particularly valuable in facilitating communication between designers, pattern makers, and product developers, as they enabled a shared understanding of the product early in the design process. In these scenarios, AI offers an advantage over hand sketching or 3D rendering, which can be more time-consuming or visually unfamiliar to stakeholders who are not used to the aesthetics of 3D avatars. One company is also considering AI integration in lookbook and e-commerce image generation.

All three designers described AI as a helpful assistant for creativity and research. Language models reduce the time needed for information gathering and even assist with writing tasks such as composing emails. Image-generation tools are valued for their potential to spark unexpected ideas. However, these tools aren't always reliable time-savers, prompting them effectively can be difficult, and outputs may be inconsistent. Ideally, participants envision AI reducing administrative workload and supporting design system linking, freeing up time to improve the final physical product. AI could also help automate technical tasks like tech pack creation and support less-experienced designers, potentially making design more accessible.

Despite these benefits, designers expressed concern about the risk of over-automation. Losing creative control and reducing the designer's hands-on connection with the product were cited as key risks. Environmental concerns were also frequently raised, especially the energy and water consumption associated with using AI tools. Issues around data security and the erosion of designer-product ownership were discussed as well.
Currently, the AI tools available to designers are largely off-the-shelf applications, though two of the three participants work in companies developing internal AI tools. One designer is directly involved in developing a GAN-based internal image-generation tool, though it

remains in the testing phase. Another participant mentioned that their company's internal AI tool has only been tested by one team member and has not yet been widely adopted. Across all interviews, there was a clear need expressed for a unified AI-powered system that could integrate multiple design and product databases to reduce repetitive, manual input.

Importantly, AI adoption is not yet consistent across design teams. Usage still largely depends on individual designer interests. Some team members remain sceptical, questioning whether AI can match the capabilities of a human designer, a sentiment that mirrors earlier resistance to adopting 3D design tools. However, younger designers with 3D design training have already begun to influence team attitudes toward new technologies. A similar shift could occur with AI as tools become more accessible and AI literacy becomes part of design education. Still, the lack of time to learn and experiment with new tools remains a practical barrier to AI adoption in many design environments.

Data Practices and Opportunities for AI Integration

This final theme focuses on how design data, whether visual, technical, or trend-related, is collected, stored, and accessed within fashion companies. It highlights the common challenges designers face with fragmented systems, limited access to consumer insights, and a lack of centralized infrastructure to support material or trend research. Additionally, it explores how participants envision AI assisting in streamlining data use for inspiration, concept development, and broader design workflows in a way that is more systematic and aligned with brand identity.

All participants reported gathering significant amounts of visual material from various sources including the internet, social media, trend forecasts, and their own photography. These images are typically stored in folders, pasted directly onto whiteboards, or saved within working files. Visual data is then used to build mood boards, reference materials for presentations and tech packs, or simply as inspiration during the early design stages before a sketch or prototype is created. However, managing and sharing this visual research across different platforms is time-consuming. One designer also noted that relevant imagery is sometimes only available in pre-internet print publications, making digital access and retrieval even more difficult.

Design assets such as sketches, colourways and tech packs are managed across systems like PLM platforms, CLO-SET, and shared whiteboards. Whether these systems are connected varies by company, which directly affects how easily data can be transferred or reused. All designers agreed that having these systems better linked would simplify asset management and save time in daily work.

Participants also shared ideas for how AI could assist in these areas. Suggestions included AI-enabled tools to locate rare vintage garments or images from archival materials, the creation of centralized platforms combining past design assets, trend intelligence, and consumer data, and faster access to internal insights. Designers noted that gaining access to internal consumer behaviour data, currently restricted in most cases, would be especially helpful during product design. I strongly agree with these relatively simple but impactful suggestions. As I stated at the outset of this thesis, it was the continued reliance on manual tasks, disconnected systems, and traditional design methods that motivated me to explore the role of AI in fashion design.

6. CONCLUSION

This study explored the relationship between fashion design and artificial intelligence through interviews with professional designers working in different market levels, collections, and product categories. The results show that while the core structure of the design process remains relatively consistent, workflows and tool usage vary widely depending on the company, collection type, and individual designer. AI and 3D tools are used selectively, primarily in early ideation, research, and visualisation phases, yet their full integration into daily workflows is limited by organizational, technical, and cultural barriers.

Designers see significant potential in AI to streamline repetitive tasks, enhance creative exploration, and improve cross-functional collaboration, particularly through better data management and system integration. These findings respond directly to the research questions by offering a detailed account of current design practices, existing uses of AI, and areas where AI could improve efficiency and creativity. The insights lay a foundation for developing AI-powered applications or holistic fashion design systems and support the broader goal of helping design teams navigate digital transformation in a fast-evolving industry.

7. REFERENCES

Anantrasirichai, N., & Bull, D. (2021). Artificial intelligence in the creative industries: A review. *Artificial Intelligence Review,* 55, 589–656. https://doi.org/10.1007/s10462-021-10039-7

Antonelli, P. (2024). Kate Crawford Metabolic Images in Aperture No. 257 Winter 2024.

Aspelund, K. (2015). *The design process*. New York, NY: Fairchild Books.

Bertola, P., & Teunissen, J. (2018). Fashion 4.0. innovating fashion industry through digital transformation. Research Journal of Textile and Apparel, 22(4), 352–369.

Bieńkowska, J. (2024). The effects of artificial intelligence on the fashion industry—Opportunities and challenges for sustainable transformation. *Sustainable Development*. https://doi.org/10.1002/sd.3312

Braun, V. & Clarke, V. (2006) Using thematic analysis in psychology, Qualitative Research in Psychology, 3:2, 77-101, DOI: 10.1191/1478088706qp063oa

Braun, V. & Clarke, V. (2019) Reflecting on reflexive thematic analysis, Qualitative Research in Sport, Exercise and Health, 11:4, 589-597, DOI: 10.1080/2159676X.2019.1628806

Brownlow, J., Zaki, M., Neely, A., & Urmetzer, F. (2015). Data and Analytics - Data-Driven Business Models: A Blueprint for Innovation. *Cambridge Service Alliance*. https://cambridgeservicealliance.eng.cam.ac.uk/system/files/documents/2015MarchPaperTheDDBMInnovationBlueprint.pdf

Chaudhary S, Kumar P, Johri P. (2020) Maximizing performance of apparel manufacturing industry through CAD adoption. International Journal of Engineering Business Management. 12. doi:10.1177/1847979020975528

Choi, W., Jang, S., Kim, H.Y., Lee, Y., Lee, S.G., Lee, H. & Park S. (2023) Developing an AI-based automated fashion design system: reflecting the work process of fashion designers. Fashion and Textiles. https://doi.org/10.1186/s40691-023-00360-w

McCormack, J., Cruz Gambardella, C., Rajcic, N., Krol, S. J., Llano, M. T., & Yang, M. (2023). Is writing prompts really making art? In C. Johnson & N. García-Pedrajas (Eds.), *Artificial Intelligence in Music, Sound, Art and Design* (pp. 196–211). Springer. https://doi.org/10.1007/978-3-031-29956-8_13

Crawford, K. (2021). The atlas of ai: Power, politics, and the planetary costs of artificial intelligence. Yale University Press.

Crilly, N. (2015). Fixation and creativity in concept development: The attitudes and practices of expert designers. Design Studies, 38, 54–91.

https://doi.org/10.1016/J.DESTUD.2015.01.002

Dazed (2025). To Collina Strada's Hillary Taymour, AI is just a tool. https://www.dazeddigital.com/fashion/article/66241/1/to-collina-strada-s-hillary-taymour-ai-is-just-a-tool Read: 23.4.2025

Demirdag, P. S. (2024). *What is generative AI* [Video]. LinkedIn Learning. https://www.linkedin.com/learning/what-is-generative-ai

Deng, H., Jiang, J., Yu, Z., Ouyang, J., & Wu, D. (2024). CrossGAI: A cross-device generative AI framework for collaborative fashion design. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 8*(1), Article 3. https://doi.org/10.1145/3643542

Dissanayake, D.G.K., Druckman, A., Munasinghe, P.D. (2021). An Investigation of the mass-market fashion design process. Research journal of textile and Apparel. Vol. 26 No. 4, 2022, pp. 323–342. DOI 10.1108/RJTA-08-2020-0089

Drimmer, Sonja. (2025). Machine Yearning in Artforum international. April 2025.

Dubey, A., Bhardwaj, N., Abhinav, K., Kuriakose, S. M., Jain, S., & Arora, V. (2020). AI assisted apparel design. *arXiv preprint* arXiv:2007.04950. https://doi.org/10.48550/arXiv.2007.04950

Galletta, A. (2013) *Mastering the semi-structured interview and beyond: From research design to analysis and publication*. New York University Press.

Gebru, T., Miceli, M. & Williams, A. (2022) The exploited labor behind artificial intelligence in Noema 13.10.2022. https://www.noemamag.com/the-exploited-labor-behind-artificial-intelligence/ Read: 4.5.2025.

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.

Gournelos, T. (2019). *Doing academic research : A practical guide to research methods and analysis*. Taylor & Francis Group.

Gray, C., & Malins, J. (2007). *Visualizing research : A guide to the research process in art and design*. Taylor & Francis Group.

Guo, Z., Zhu, Z., Li, Y., Cao, S., Chen, H., & Wang, G. (2023). AI assisted fashion design: A review. *IEEE Access, 11*, 88403–88415. https://doi.org/10.1109/ACCESS.2023.3306235

Gwilt, A., & Rissanen, T. (Eds.). (2011). *Shaping sustainable fashion : Changing the way we make and use clothes*. Taylor & Francis Group.

Hancock, J.H., II (2022). Fashion Brand Stories. London: Bloomsbury Visual Arts. DOI: 10.5040/9781350135581.ch-3

Hanington, B., & Martin, B. (2012). *Universal methods of design : 100 ways to research complex problems, develop innovative ideas, and design effective solutions*. Quarto Publishing Group USA.

Hallam, E., & Ingold, T. (2007). Creativity and cultural improvisation: An introduction. In E. Hallam & T. Ingold (Eds.), *Creativity and Cultural Improvisation* (pp. 1–24). Oxford: Berg.

Härkönen, H. (2023). *The impact of artificial intelligence on the fashion sector: A moral rights' perspective*. In E. Rosati & I. Calboli (Eds.), *The handbook of fashion law* (Chapter 36, forthcoming). Oxford University Press. https://ssrn.com/abstract=4573087

Jackson, T. & Shaw, D. (2006). The Fashion Handbook. New York. Routledge.

Jansson, D. G., & Smith, S. M. (1991). Design fixation. Design Studies, 12(1),

3–11.

Jiang, J., Wu, D., Deng, H., Long, Y., Tang, W., Li, X., Liu, C., Jin, Z., Zhang, W., & Qi, T. (2024). HAIGEN: Towards human-AI collaboration for facilitating creativity and style generation in fashion design. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 8*(3), Article 107. https://doi.org/10.1145/3678518

Kananen, H., & Puolitaival, H. (2019). Tekoäly: Bisneksen uudet työkalut. Alma Talent.

Kato, N., Osone, H., Oomori, K., Ooi, C. W., & Ochiai, Y. (2019). GANs-based clothes design: Pattern maker is all you need to design clothing. In *Augmented Human International Conference 2019 (AH2019)*, March 11–12, 2019, Reims, France (pp. 1–7). ACM. https://doi.org/10.1145/3311823.3311863

Kause, P & Salonen-McGrath, H. (2017) Hybridiennakointi – Ihmisen ja tekoälyn yhteistyö strategisessa ennakoinnissa. Futura 3/2017, s. 43–51.

Kawamura, Y. (2023). Fashion-ology: Fashion Studies in the Postmodern Digital Era. London: Bloomsbury Visual Arts. http://dx.doi.org/10.5040/9781350331907.ch-003

Kawamura, Y. (2011) Doing research in fashion and dress. An introduction to qualitative methods. New York. Berg.

McKelvey, K., & Munslow, J. (2012). *Fashion design : Process, innovation and practice*. John Wiley & Sons, Incorporated.

McKinsey & Co. (2023). Generative AI: Unlocking the future of fashion. 8.3.2023 https://www.mckinsey.com/industries/retail/our-insights/generative-ai-unlocking-the-future-of-fashion Read: 14.4.2025

Kouslis, E., Papachristou, E., Stavropoulos, T. G., Chalikias, A. P., Chatzilari, E., Nikolopoulos, S., & Kompatsiaris, I. (2024). *AI in fashion: A literature review*. Electronic Commerce Research. https://doi.org/10.1007/s10660-024-09872-z

Kühl, N., Schemmer, M., Goutier, M. *et al.* Artificial intelligence and machine learning. *Electron Markets* 32, 2235–2244 (2022). https://doi.org/10.1007/s12525-022-00598-0

Laney, D. (2001)**.** 3D Data Management: Controlling Data Volume, Velocity, and Variety. META Group Research Note, 6.

Lee, J. S., & Jirousek, C. (2015). The development of design ideas in the early apparel design process: a pilot study. *International Journal of Fashion Design, Technology and Education*, *8*(2), 151–161. https://doi.org/10.1080/17543266.2015.1026411

Lee, Y. K. (2022). How complex systems get engaged in fashion design creation: Using artificial intelligence. *Thinking Skills and Creativity, 46*, 101137. https://doi.org/10.1016/j.tsc.2022.101137

Luce, Leanne. (2019). *Artificial Intelligence for Fashion : How AI Is Revolutionizing the Fashion Industry*. Apress.

Merilehto, A. (2018). Tekoäly: Matkaopas johtajalle. Alma Talent.

Ming Law, K., Zhang, Z. M., & Leung, C. S. (2004). Fashion change and fashion consumption: The chaotic perspective. Journal of Fashion Marketing and Management: An International Journal, 8(4), 362–374.

Renfrew, E. , & Lynn, T. (2022). Developing a Fashion Collection London: Bloomsbury Visual Arts. http://dx.doi.org/10.5040/9781350132573.ch-001

Sawyer, R. K. (2012). *Explaining creativity : The science of human innovation*. Oxford University Press, Incorporated.

Sbai, O., Elhoseiny, M., Bordes, A., LeCun, Y., & Couprie, C. (2019). DeSIGN: Design inspiration from generative networks. In L. Leal-Taixé & S. Roth (Eds.), *Computer Vision – ECCV 2018 Workshops* (pp. 37–44). Springer. https://doi.org/10.1007/978-3-030-11015-4_5

Schön, D. A. (1983). *The reflective practitioner: How professionals think in action*. New York: Basic Books.

Sedkaoui, S. (2018). *Data analytics and big data*. John Wiley & Sons, Incorporated.

Seivewright, Simon (2012). Research and Design. New York. Bloomsbury Publishing Plc.

Silva, E. S., Hassani, H., & Madsen, D. Ø. (2020). Big Data in fashion: transforming the retail sector. *Journal of Business Strategy, 41*(4), 21-27.

Sinha, P. (2002). *Creativity in fashion*. Journal of Textile and Apparel, Technology and Management, 2(4), 1–16.

Sorger, Richard & Udale, Jenny (2017). *The Fundamentals of Fashion Design.* Bloomsbury Publishing Plc.

Stecker, P., (1996), The Fashion Design Manual, Macmillan Education, Australia.

Sun L. & Zhao L. (2018): Technology disruptions: exploring the changing roles of designers, makers, and users in the fashion industry, International Journal of Fashion Design, Technology and Education, DOI: 10.1080/17543266.2018.1448462

University of Helsinki & Reaktor. (2024). *Elements of AI*. Read: 1.10.2024 in https://www.elementsofai.com

University of Lapland (2023). Use of Artificial Intelligence-Based Tools at the University of Lapland" 3/2023

Yin, R. K. (2015). *Qualitative research from start to finish*. Guilford Publications.

Zhang, Y., & Liu, C. (2024). Unlocking the potential of artificial intelligence in fashion design and e-commerce applications: The case of Midjourney. *Journal of Theoretical and Applied Electronic Commerce Research, 19*, 654–670. https://doi.org/10.3390/jtaer19010035

APPENDICES

1. Appendix A: Interview questionnaire

Master's thesis Interview questions – 19.3.2025

This is an open question interview and I want to learn about your thoughts about the use of AI in your design process and your general thoughts about the topic.

Interview questions

Understanding your design process and information about the company and team you work in

1. Could you describe the company you work for (size and market) and what is your current role?

2. How big is your team and what are its main responsibilities?

3. Could you describe your current design process and evaluate how long it is in your company?

Understanding Your Current Process

4. What aspects of your design process are currently most time-intensive or resource-heavy?

5. What kind of digital tools do you use in your design process?

6. Do you currently use any AI tools in your design process? If so, which ones, what do you use them for and how effective are they?

7. How do you gather and analyse trends and consumer preferences today and what role does it play in your decision-making for design and production?

8. Does your company have a design related AI-strategy? If so, are you using or is there a plan to develop a customized AI app for design purposes? How does it help your work?

Goals and Expectations (free association – if anything would be possible)

9. What specific outcomes or improvements do you hope AI can bring to your design process?

10. Do you see the primary benefit of AI as helping to facilitate creativity or improving efficiency, or both?

11. Do you see AI as a tool for assisting designers, or do you envision it automating parts of the design process entirely?

Challenges and Concerns

12. What challenges or barriers do you anticipate in integrating AI into your workflow?

13. Are there any concerns about AI-driven designs?

14. Do you foresee resistance to adopting AI tools from your design team, and how would you address it?

Data and Technology

15. What kind of data (e.g., consumer behavior, past designs, trend forecasts) do you currently collect that could be useful for AI integration in your design process?

16. Do you have a centralized system or platform for managing your design assets and data?

Collaboration and Implementation

16. How do you envision the collaboration between designers and AI tools in your workflow?

17. Would you prefer off-the-shelf AI solutions, or are you interested in developing custom tools tailored to your needs?

18. Do you have an in-house technical team, or would you rely on external experts for implementation and support?

19. In an ideal situation, how could AI help your design process workflow? Please describe your ideas.

20. Do you receive AI software provider marketing, or have you been approached by any direcly recently? Have you seen anything that interests you?

Thank you for your participation!

2. Appendix B: Interview transcript example

And yeah, so I think and with the new Ark platform, we're doing that more and more at the beginning of the sketching.
Phase. Yeah. Is that, does that work? Does that describe?

5:52
That describes, yeah, and I have more questions about the digital process. So you can talk more deep into that.

5:55
OK, amazing.
OK.

6:01
So it comes here basically. So just understanding your current process. So first question is.
What aspects of your design process what you described earlier are currently most time intensive and or resource heavy.

6:24
Aspects of you that.
Hmm sure, I think.
I feel like for me the most.
Time intensive, the most focus that I need is when I'm actually doing the designs and the research, and they're doing the 3DS.
That is actually, I would say the most intensive because that's when I'm creating the products. And then obviously I think a lot of people would probably say the tech pack phase is the most intensive, but I think.
If you put more work into the products from the beginning, the 3D, then it makes the tech pack come a lot quicker and easier because you have all of the information from that and everything's finalised at that point. So it's just a case of.
Putting it into production.
So I would say that, yeah, I feel like that that is the beginning sketching phase is the bit that I wish that I had the most time for.
And yeah, and then resource heavy, yeah, I would say that bit is the is the beginning bit basically.

3. Appendix C: Data coding and thematical structure in Atlas.ti

Code Manager

Name		Groups	Quotations
AI in an ideal world		2. Digital design too	39
AI tool for designer		2. Digital design too	50
AI tools design process		2. Digital design too	58
AI tools design process internal app		2. Digital design too	36
centralized data storage system		3. Data collection	12
challenges and concerns about AI		2. Digital design too	22
data collection		3. Data collection	20
design process description		1. Design process	15
digital design tools		2. Digital design too	39
resistance towards AI among designers		2. Digital design too	13
tech team		3. Data collection	14
AI marketing			6
company description			16
team description			12
design process	1	1. Design process	6