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FashionCycle: AI-enabled Creativity Support Tool for facilitating iteration in fashion

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FashionCycle: AI-enabled Creativity Support Tool for facilitating iteration in fashion design

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ABSTRACT OF THE THESIS

FashionCycle: AI-enabled Creativity Support Tool for facilitating iteration in fashion design

by

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University of California, Los Angeles, 2024
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Recent studies on creativity support tools (CST) have increasingly harnessed artificial intelligence (AI) to enhance creative processes. This study explores the role of AI in supporting creative work through the lens of FashionCycle, an AI-driven CST developed for the fashion design sector. We conduct a formative study by interviewing 3 fashion design professionals to understand the design process and determine design goals for our system. This effort identifies two main design objectives aimed at enriching the design process, specifically the ideation and revision phases: firstly, to overcome design fixation by facilitating the efficient and flexible exploration of various design examples, and secondly, to provide an efficient method for modifying inspiration materials through interactive drawing. FashionCycle integrates three tools that combine interactive visualization with AI models: the Inspiration Generator, Sketchpad, and Prototyper, designed to meet our design goals. We showcase how Fashioncycle effectively integrates AI into fashion design professional existing workflows, and supports the various discrete tasks involved in the fashion design process. Our system underscores the role and utilization of AI in each cognitive operation and offers insights into the future implications of developing AI-based CST tools.

The thesis of Matthew Waliman is approved.

Yang Zhang

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2024

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CHAPTER 1

Introduction

Creativity is the ability to generate and refine ideas. It involves coming up with new approaches to problems, original resolutions to conflicts, and novel insights derived from datasets. Moreover, creativity represents the interplay of aptitude, process, and environment through which individuals or groups produce tangible ideas that are both original and valuable within a given social context [1]. Organizations recognize creativity as a crucial skill for identifying potential opportunities and fostering innovation. In the realm of human-computer interaction (HCI), creativity is closely intertwined with design thinking, a fundamental concept that HCI aims to support. An examination of creativity-related literature in the ACM Digital Library in 2018 reveals that HCI predominantly contributes to publications focusing on creativity [2].

The demonstration of creativity or creative thinking varies depending on the individual, job role, or environment. In the domain of fashion design, where artistic creativity significantly influences the success of design outcomes, creativity is strongly associated with the ability of design professionals to generate a substantial number of new ideas for a given design task [3]. It is important to note that barriers to creativity also exist. For instance, designers frequently encounter design fixation, which impedes the effective completion of a problem [4]. This is where divergent thinking and convergent thinking come into play [5, 6]. Divergent thinking facilitates the generation of new ideas by exploring various resources to expand or transform existing ideas, while convergent thinking progressively narrows down the research space and aids in finding a design solution that is both innovative and adaptable to various constraints [7, 8, 9]. Previous research has proposed approaches to support divergent and convergent thinking through three key cognitive operations: (1) expanding the concept framework [10], (2) constraining concepts [7, 11], and (3) blending two or more concepts [12].

One of the directions taken in creativity research in HCI is to elicit design elements or requirements of creativity support and/or to develop creativity support tools (CST) using computer techniques to facilitate creative thinking [13, 14, 15]. Recently, a growing body of CST research has been adopting artificial intelligence (AI) and focusing on AI-based interface development to model large-scale datasets and provide analytic insights to users in many design domains.

We present an AI-based CST, FashionCycle, that aims to support both divergent and convergent thinking in the design process of fashion sketches by supporting all three key cognitive operations. We accomplish this by employing three separate AI models that allow users to generate novel inspiration images, iterate on fashion sketches and blend multiple concepts to develop prototypes from their sketches. The development of FashionCycle was carried out in collaboration with fashion design professionals. Based on interviews with 3 fashion design professionals, we identified three phases of the fashion iteration process (i.e., Explore, Refine, and Prototype) and externalized three cognitive operations representing these design phases using AI: Inspiration Generation, Sketching, and Prototyping. This thesis first provides an overview of recent developments in creativity research and the role that AI has in supporting creative work. Then, the formative study and results will be described and key design goals stated. Then we present a description of the system and provide a walkthrough of a typical user flow.

CHAPTER 2

Background

2.1 Creativity support tool (CST) research

Frich et al. [16] proposed a definition of a CST as a tool that runs on one or more digital systems, encompasses one or more creativity-focused features, and is employed to positively influence users of varying expertise in one or more distinct phases of the creative process. While broad, Frich et al. suggest that rather than try to develop a "one size fits all" solution, it may be more useful to develop more specific, contextualized definitions for subsets of CSTs. Shneiderman [17] introduced a model to facilitate the creation of digital-interactive tools for creative problem-solving. In the realm of enhancing creativity through CSTs, HCI research focuses on both leveraging creative cognition in the development of CSTs [18] and grasping the nuances of creative processes within specific domains [16]. Davis et al [18] applied cognitive theories to delineate how CSTs meet the demands of creative endeavors. They drew upon principles of embodied cognition, situated cognition, and distributed cognition as foundations for aiding creativity. Embodied cognition aids in transforming user concepts into tangible, interactive forms through user interactions with physical representations [19]. Situated cognition outlines a spectrum of skills, illustrating how tools can aid users in expressing creativity without the need to overtly manipulate the tools [20]. Distributed cognition highlights how the automation of technical skills can enhance creative involvement, motivation, and lower the threshold for beginners. Additionally, CST research tends to concentrate on three pivotal creative stages: ideation, implementation, and evaluation. For ideation, CSTs offer a platform for collaborative brainstorming that brings a wide range of cultural and conceptual perspectives, alongside a plethora of ideas. For implementation, they facilitate collaborative digital drawing to refine artistic abilities . For evaluation, CSTs deliver critiques on user projects, opening avenues for creative revision of the work. It is crucial to note that incorporating all three stages into a CST design is not mandatory; focusing exclusively on a single stage can also be significantly beneficial [16].

2.2 AI Based CST's in the design domain

An AI-based CST helps users extend their ideas by applying various modeling and visualization techniques to analyze big data to support divergent and convergent thinking. Jeon et al. [21] presented FashionQ, an AI-based interface to support fashion designers in the ideation of fashion designs. FashionQ supports designers' divergent and conversant thinking with AI models. Liu et al. [22] integrated DALL-E [23], GPT-3 [24], and CLIP [25] within CAD software in 3DALL-E, a plugin that allows users to construct text and image prompts based on what they are modeling for supporting divergent and convergent thinking. Rico [13] supports designing a UI layout for mobile applications. It has functionalities to analyze the visual, textual, structural, and interactive design properties of 72,000 popular designs (based on Google Play Store star ratings) with an autoencoder deep learning model [26]. Rico supports the setting of a design direction in various ways. Vaccaro et al. [27] analyzed text and image data related to fashion design on social networking services (SNS). They used latent dirichlet allocation (LDA) [28] for clustering fashion style topics (25 groups). Based on the results, they built a CST that provided fashion design professionals with design ideas that take TPO (time, place, and occasion) into consideration. RecipeScape is an interactive system for browsing and analyzing the hundreds of recipes of a single dish available online [29]. Based on similarity metrics of the recipe data from natural language processing and human annotation, it used hierarchical clustering to generate recipe clusters.

2.3 Enhanced Human Control in AI-Driven Image Generation

Recently, there has been a push in the field of machine learning to provide humans with greater control over AI models. One notable advancement in this direction is Pix2Pix [30], which operates on the principles of conditional generative adversarial networks (cGANs), allowing for the generation of photorealistic images from input-output pairs. Pix2Pix has demonstrated versatility across various applications, including image colorization, style transfer, and the conversion of sketches into realistic images. Building on this foundation, InstructPix2Pix [31] introduces a method to edit images using written instructions, allowing users a high degree of control over both the style and semantics of an image. Most recently, Controlnet [32] has emerged as an architecture designed to enhance fine grained control over diffusion-based generative models, such as Stable Diffusion [33]. Controlnet introduces conditional controls to generative models in the form of depth maps, edges, segmentation or pose etc, allowing users both control over the content, style and also composition of the output image.

CHAPTER 3

Formative Study

We conducted interviews with 3 fashion design professionals to understand the ideation process for fashion design, the challenges that interfere with ideation, and solutions to address these challenges using AI-based cognitive operations.

3.1 Interviews with fashion design professionals

All 3 fashion design professionals majored in fashion design and work in a fashion design company. Their work experience ranges from 2 to 10 years (mean=5.6, SD=3.3). The interviews were conducted in a lab seminar room on a university campus between May 1-10, 2023. Each interview took approximately 60 minutes. The interviews were transcribed for later analysis.

During the interview, we focused on three main research questions: **Q1) What is your process for ideation in fashion design? Q2) What barriers and challenges interfere with creative tasks? Q3) What is the potential of AI to support your creativity in the ideation?** Below, we summarize the fashion design ideation process, current challenges, and possible solutions that emerged from the interviews.

3.2 Results

The initial phase in design involves gathering inspiration, where designers collect a wide array of potential designs from various sources, such as significant fashion shows like New York Fashion Week and trend-forward brands like ZARA. This exploration aids in uncovering unexpected designs, significantly influencing their creative direction. However, this process presents two primary challenges: the significant time investment required, especially for novices, and the risk of design fixation, where a designer's creativity becomes constrained by existing ideas, potentially leading to issues of originality and even design plagiarism. Overcoming design fixation demands access to an expansive and easily navigable pool of design resources throughout the ideation phase.

The second step is the revision phase. Designers develop their unique designs from the collected materials. They often use pens or iPads to try various designs, combining different design elements, omitting specific aspects, or repeating certain elements to discover new design directions. However, this task also tends to be time-consuming, limiting the opportunity for new trials. To try new designs, the designer must erase the current work and start the drawing process from scratch. This limitation restricts the creativity that comes from diverse attempts. To address this issue, it is necessary to provide opportunities during the ideation process that allow designers to make new modifications quickly and easily using their methods.

3.3 Design goals

The insights we derived from the formative interviews directly informed the design of an AI-based CST system - FashionCycle. We introduce our two design goals as below.

1. Support efficient and flexible exploration of multiple design examples to encourage exploration in ways that expand the design direction.

2. Provide a powerful and direct means to modify the inspiration materials through the use of drawing interaction

CHAPTER 4

System Description

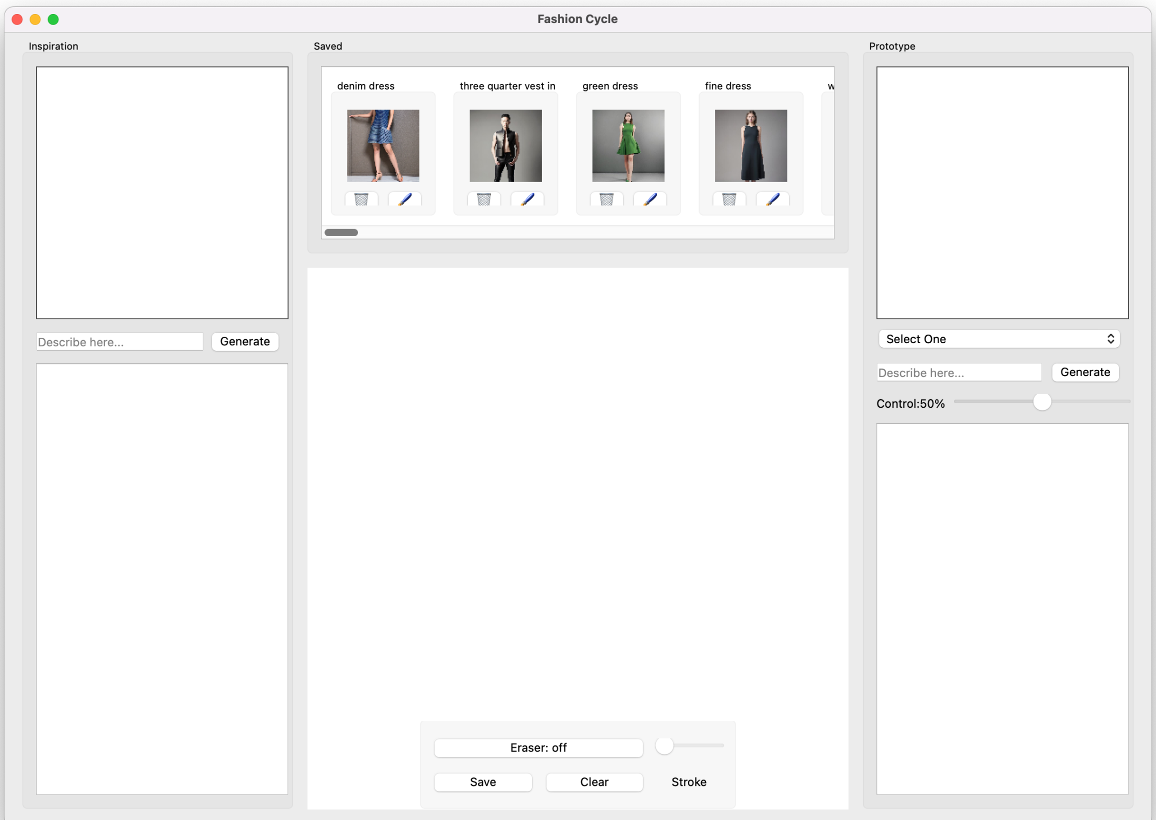

Figure 4.1: **View of FashionCycle upon opening.** FashionCycle is comprised of three main panels. The center panel is comprised of the canvas and saved image library: the main area for revision and browsing saved designs. The Inspiration panel allows designers to generate inspiration images using a descriptive prompt. The Prototype panel takes a sketch as input and renders the sketch in a certain style using a descriptive prompt.

FashionCycle is composed of 3 tools that work together to facilitate fashion designers' sketching process: Inspiration Generator, Sketchpad and Prototyper. Each tool has its own visual interface and makes use of a different model.

4.1 Inspiration Generator

Figure 4.2: **Three inspiration images generated using the Inspiration Generator tool.** Prompts used: "three quarter vest in leather", "floral evening dress with large silk flowers", and "chevron patterned red denim pants, rocker style".

Located on the left panel, the Inspiration Generator creates images that a designer can use for ideation and to further iterate upon in the rest of the system. It utilizes Stable Diffusion [33], to generate original images from text prompts that a user provides. The interface is composed of a text box where the user enters prompts, a viewing window where the generated image is displayed, as well as a list of previous images that the user has generated that the user can browse through. These images can then be saved to a user's saved set of images and used in the rest of the system.

4.2 Sketchpad

The Sketchpad is the primary mode of interaction within FashionCycle and its main purpose is to refine the structure of the design the user is currently working on. It consists of a large canvas where the user can either load images from their saved images or draw original designs using a simple set of drawing tools. As sketches are the primary medium that designers use when designing a garment, we take care to emphasize the Sketchpad as a method to generate sketches rather than a generic image editor. As such, when loading inspiration images, we convert them to sketches using an image-to-image model [34] that converts photos to line drawings. Thus, the user is able to quickly and efficiently edit the structure and contours of the garment, rather than focus on details such as texture or fabric used to create the final product.

4.3 Protoyper

Figure 4.3: **Three different prototypes created from the same input sketch.**

The Prototyper is located on the right panel and its function is to convert sketches into fully fleshed out concepts by adding texture, fabric and styling to the sketches. It utilizes Controlnet [32] to apply the styling described in a text prompt to a sketch to fully realize the design idea as a photorealistic prototype. Controlnet takes in a prompt and an image (in our case sketches), and generates a new image from the text that remains faithful to contoours in the sketch. The model uses the text as guidance to generate images in the style that the text dictates. Users are also able to change the amount that the model adheres to the text guidance, allowing for a certain amount of randomness in the generation process.

CHAPTER 5

System Walkthrough

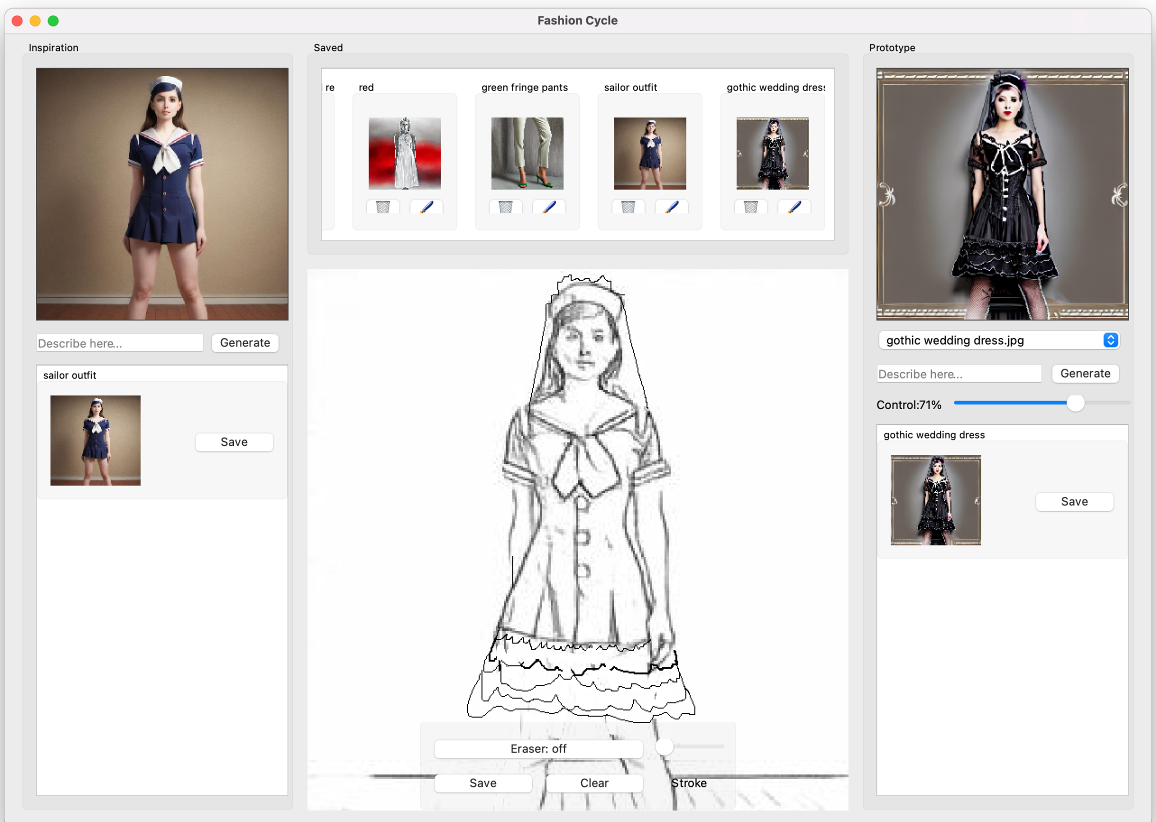

Figure 5.1: **Example of possible user interaction with FashionCycle.**

We describe users' interaction with FashionCycle and its key features using a demonstrative example of a user designing a gothic wedding dress. Upon first opening the FashionCycle app, the main interface is a large canvas, an interface that designers are familiar with and comfortable working in. Using a simple set of drawing tools, the user can sketch an initial design idea in the canvas area. However, if they are unsatisfied with their design or are seeking a different creative direction, they can turn to the Inspiration panel on the left. In this panel, they are able to generate images by describing what they would like to see and view and save these images. Here, the user generates a nautical themed sailor dress as an initial starting point. Once they are satisfied with the images they have generated, they can then save their favorites to a gallery located at the top of the main interface. This gallery links all the tools within FashionCycle and allows users to save images or sketches from anywhere in the app. As a next step, the user might take an image that they generated from the Inspiration panel and iterate upon it, as designers often do during the design process. When transferring the image from the saved gallery to the sketchpad, a sketch version of the image is loaded, allowing users to easily modify ideas using the sketch as the base unit. In the sketchpad, the user decides to augment the dress by adding layers to the bottom hem, and decides to add a veil. Once they are satisfied with the structure of the design they load the sketch into the right panel to generate a full rendered prototype using their sketch. The user selects the sketch they'd like to use, then adds some description of how they'd like to render their design. In the text prompt, they can add any style, aesthetic, mood or fabric they'd like to see incorporated into their design. Selecting the generate button shows them a rendered version of their sketch using the prompt as guidance for the style of the image. From here, the user can save their rendered design, and if desired, continue iterating by modifying the sketch in the sketch pad and continuing to seek inspiration or generate more prototypes in different styles.

CHAPTER 6

Conclusion

We present an examination of the role of creativity in the domain of HCI through the lens of fashion design. Our examination of the connection between creativity and technological innovations reveals how AI can play a crucial role in advancing and enriching creative workflows within the fashion industry. We introduce FashionCycle to underscore the significance of supporting both divergent and convergent thinking in creative endeavors. The formative study, conducted through interviews with fashion design professionals, not only highlighted the current challenges faced during the ideation process but also paved the way for the development of FashionCycle. This tool, designed to foster exploration, refinement, and prototyping phases in fashion design, represents a step forward in integrating AI with creative processes.

Through the development and implementation of FashionCycle, we have demonstrated how AI can serve as a support system in the creative workflow. By facilitating the generation of novel inspiration, streamlining the sketching process, and enabling the blending of multiple concepts into coherent prototypes, FashionCycle offers a unique platform that addresses the key cognitive operations involved in creative work. We hope that this work not only contributes to the field of HCI by providing valuable insights into the integration of AI in creative practices but also offers practical implications for the fashion design industry.

Looking forward, the implications of this research extend beyond the realm of fashion design, suggesting a broader potential for AI-based CSTs to revolutionize various creative industries. As AI technologies continue to evolve, so too will the ways in which we can support and enhance human creativity. The journey of integrating AI into creative processes is only in its beginning stages, and continued exploration and development of such technologies will unveil new opportunities for creative expression. We hope that this thesis not only contributes to the existing body of knowledge on creativity and AI in HCI but sets the stage for future research and development in the field.

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