FashionQ: An AI-Driven Creativity Support Tool for Facilitating Ideation in Fashion Design

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ABSTRACT

Recent research on creativity support tools (CST) adopts artificial intelligence (AI) that leverages big data and computational capabilities to facilitate creative work. Our work aims to articulate the role of AI in supporting creativity with a case study of an AI-based CST tool in fashion design based on theoretical groundings. We developed AI models by externalizing three cognitive operations (extending, constraining, and blending) that are associated with divergent and convergent thinking. We present FashionQ, an AI-based CST that has three interactive visualization tools (StyleQ, TrendQ, and MergeQ). Through interviews and a user study with 20 fashion design professionals (10 participants for the interviews and 10 for the user study), we demonstrate the effectiveness of FashionQ on facilitating divergent and convergent thinking and identify opportunities and challenges of incorporating AI in the ideation process. Our findings highlight the role and use of AI in each cognitive operation based on professionals' expertise and suggest future implications of AI-based CST development.

CCS CONCEPTS

• **Human-centered computing** → **Interactive systems and tools**; • **Computing methodologies** → **Artificial intelligence**.

KEYWORDS

creativity support tool, artificial intelligence utilization, fashion design, ideation process, cognitive operation

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1 INTRODUCTION

Creativity is the ability to generate and refine ideas. It involves coming up with new approaches to problems, original resolutions to conflicts, or fresh insights from datasets. Furthermore, creativity is the interaction among aptitude, process, and environment by which an individual or group produces a perceptible idea that is both novel and useful as defined within a social context [56]. Organizations consider creativity an important skill that helps identify potential opportunities and enables innovation. Creativity relates to design thinking, one of the core concepts that define human-computer interaction (HCI) and what HCI aims to support. A 2018 survey of creativity-related literature in ACM Digital Library indicates that HCI is almost exclusively responsible for creativity-oriented publications [25].

Displays of creativity or creative thinking vary depending on the individual, job, or environment. In the case of *fashion design*, in which artistic creativity plays a significant role in making design task outcomes successful, creativity is highly associated with the number of new ideas that design professionals can generate for a given design task [69]. Importantly, there also exists barriers to creativity. For example, during a design task, designers often encounter design fixation, which is an obstacle to the successful completion of a problem [37]. Here *divergent thinking* and *convergent thinking* comes into play [59, 60]. Divergent thinking develops new ideas by referring to various materials with the aim of expanding or transforming problems of existing ideas, and convergent thinking progressively delimits one's research space and supports finding a design solution that is both new and adapted to various constraints [9, 21, 53]. Research has suggested ways of supporting divergent and convergent thinking based on the following three cognitive operations: (1) *extending* the notion of concepts [77], (2) *constraining* concepts [7, 9], and (3) *blending* two or more concepts [22].

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 [19, 26, 27, 41, 55, 74]. Recently, a growing body of CST research has been adopting artificial intelligence (AI) and focusing on AI-based interface development

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to model large-scale datasets and provide analytic insights to users in many design domains, such as app interfaces [19, 71], graphics [47], and fashion [39, 74]. Our research shares the same goal as that of prior research in AI-based CST, and we extend previous efforts by (1) *identifying* and *applying* AI capabilities to facilitate cognitive operations that could overcome design fixations based on theoretical groundings in divergent and convergent thinking, (2) empirically *investigating* the role of AI through the development of an AI-based CST and a user study, and (3) *discussing* directions for the effective use of AI in creativity support. Our research takes the form of a case study of human-AI research.

In this paper, we present an AI-based CST, FashionQ. With the availability of AI in a fashion domain [1, 38, 42], the development of FashionQ was carried out in collaboration with fashion design professionals. Based on interviews with 10 fashion design professionals, we identified three phases of the fashion ideation process (i.e., recognizing a brand, understanding trends, and setting design directions) and externalized three cognitive operations representing the design phases using AI. Based on large-scale runway image data (302,772), we developed *AI models* with capabilities that include fashion attribute detection, style clustering, style forecasting, and style merging, all of which had *three analytical interfaces* (StyleQ, TrendQ, and MergeQ) integrated into FashionQ.

We conducted a user study with 10 additional fashion design professionals who did not participate in the interview study for the evaluation of FashionQ. We examined the perceived effectiveness of FashionQ at each design step by means of a comparison analysis between the use and the nonuse of FashionQ. The results indicate that participants found FashionQ to be significantly more effective not only in each of the design steps but also in the overall evaluation of the design task outcomes. Participants responded that they were able to expand the concept of a specific style using the results of attribute-based style groups (StyleQ) and popular changes over the years (TrendQ) through visualizations; moreover, they noted their ability to access many design directions for potential use from the merged information of fashion styles and trends (MergeQ). We also observed limitations (e.g., accuracy issues, blackbox algorithms, limited explanations) to AI that the participants perceived during design tasking. In particular, the study results highlight the role and use of AI in each cognitive operation based on professionals' expertise. The participants were open and receptive of the results of AI when the results could be used as additional fashion information in the ideation process of recognizing a brand and understanding trends. However, the participants showed high and critical standards toward the AI results, when the results intervened in their area of expertise in the case of generating new ideas. In this regard, participants asked for more detailed and controllable functionalities to allow them to interact with AI, in hopes of making AI more customizable, explainable, and interpretable. These results indicate that the utilization of AI or its results should be considered along with user or domain characteristics and the application of human-AI methods, such as human-in-the-loop or crowdsourcing; furthermore, interface types for supporting such methods should be carefully considered in the ideation process.

The following are our research contributions:

- We articulated how AI can be used to help externalize three cognitive operations through the lenses of divergent and convergent thinking.
- We developed a AI-based CST, FashionQ, which leverages AI capabilities to support fashion design professionals' creativity and decision-making.
- We discussed challenges of AI use and possible directions and design implications for reliable AI use in creativity support.

Our research findings and contributions not only extend current CST research by applying AI informed by theoretical perspectives, but also provide insights that can be applied to other domains, such as product design, interior design, and interface design, which are highly dependent on image data of prior design work and case studies for inspiration.

2 RELATED WORK

2.1 Cognitive operations for supporting creativity

Finke et al. [23] identified that restructuring or reorganizing existing concepts provides the new understandings in tasks related with creativity. Engaging in both divergent and convergent thinking is the one of good solutions for people who undertake creative activities [21, 29, 59]. Divergent thinking refers to coming up with new ideas and unexpected solutions in a creative process [59, 60]. Contrary to divergent thinking, convergent thinking refers to the mode of human cognition that strives for the deductive generation of a single, concrete, accurate, and effective solution [29]. Eysenck [21] emphasizes that the support of both divergent and convergent thinking is essential for creativity support. Woodman et al. [80] mentioned that in order for a creative person to produce socially useful products, his/her divergent thinking must come with effective convergent thinking.

There are three main cognitive operations that support divergent and convergent thinking. The first operation is *extending* for divergent thinking. Ward et al. [78] stated that extending the concepts of instances in conceptual design is helpful for divergent thinking. Bonnardel [8] mentioned that extending the boundary of instances causes an expansion to a new conceptual design, which can entail creative design solutions. Similarly, Srinivasan and Chakrabarti [69] demonstrated that increasing the number of instances in a conceptual design has a significantly positive relationship with the novelty of design ideas.

The second operation is *constraining* for convergent thinking. Constraining means the construction of a "constrained cognitive environment," which delimits the space of research, on the basis of different kinds of constraints, in order to reach in-depth levels of understanding. Bonnardel [9] highlighted "management of constraints," delimiting designers' research space and evaluate ideas or solutions. These constraints can consist of *constructed* constraints, which depend on the designers' expertise, or *deduced* constraints, which depend on the current state of problem solving as well as on previously defined constraints [7]. Constraints provide the designer an opportunity to define, develop, and delimit his/her design space to make it auspicious for creative performance such as focusing on the direction of designing [53, 70].

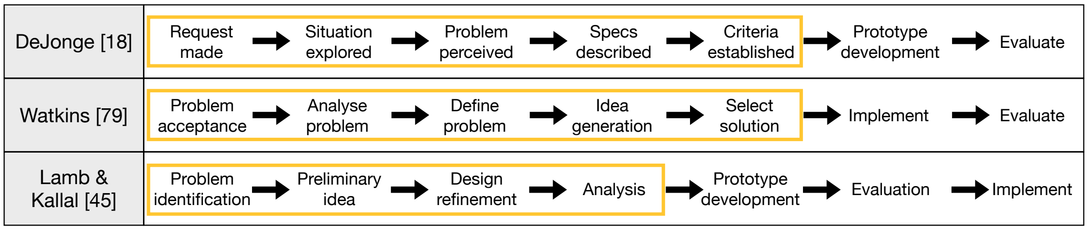

Figure 1: Summary of fashion design development processes (adapted from [44]). Yellow boxes indicate the ideation phases.

The third operation is *blending* for both divergent and convergent thinking. Fauconnier and Turner [22] highlighted that the blending of two or more instances in a conceptual design is indispensable for both divergent and convergent thinking. Louridas [50] argued that much design is bricolage, which refers to a construction or creation of a work from a diverse range of things that are available. Through blending, designers can have an opportunity to develop a brand new concept (convergence), and the concept becomes another instance that can broaden designers' insights (divergent) [53].

In this paper, we articulate how we employed these three cognitive operations for divergent and convergent thinking support in the context of fashion design. We present the development of AI models, externalizing three cognitive operations in a CST with AI capabilities for the purpose of supporting creative thinking.

2.2 Creativity support tool (CST) research

Frich et al. [24] presented a tentative synthesis definition of a CST, namely a CST runs on one or more digital systems, encompasses creativity-focused features, and is employed to positively influence users of varying expertise in one or more distinct phases of the creative process. Shneiderman [65] proposed a framework to support the development of digital-interactive tools for creative problem-solving. To enhance creativity with a CST, HCI research emphasizes not only applying creative cognition for developing CST [17] but also understanding the creative process in the domain [24].

Davis et al. [17] used cognitive theories to explain how CSTs can address the needs in creative tasks. They employed theories of embodied cognition, situated cognition, and distributed cognition for creativity support. Embodied cognition supports to make users' ideas more concrete and interactive through interaction between users and embodiments [73]. Situated cognition describes a continuum of competency that shows how tools can support users for creative expression rather than consciously controlling tools [3, 66]. Distributed cognition describes how automating technical skills can support creative engagement, motivation, and reduce the barrier of entry [34]. Benedetti et al. [4] implemented a digital painting system, Painting with Bob, considering the concept that reflects novices' unique process of developing creative ideas.

In addition, CST research primarily focuses on three creative processes: ideation, implementation, and evaluation. CSTs for *ideation* provide cultural and conceptual diversity for collaborative brainstorming settings and additional ideas [61, 62, 75, 76], whereas CSTs for *implementation* perform collaborative digital sketching to improve artistic skills [16, 51, 63]. Furthermore, CSTs for *evaluation* provide feedback on users' work to provide opportunities to revise the work in a creative way [64, 67]. The central point here is that it is not necessary to include all three processes in the design of a CST; focusing on a single process is also of decisive importance [24].

In this work, we focused on the ideation process especially in a fashion design domain (Figure 1), considering three cognitive operations (extending, constraining, and belending). Laamanen and Seitamaa-Hakkarainen [43] explained that, during the ideation phase, designers use supporting practices (e.g., collecting, sketching, experimenting) and triggers (e.g., sources of inspiration, mental image, primary generator) for framing the design directions. Previous work [18, 45, 79] of fashion design development processes indicated that designers define problems and generate ideas prior to implementation (Figure 1). We adopted these insights and guidelines when conducting interviews with fashion design professionals, which allowed us to identify detailed processes and challenges in the ideation phases. We identify and discuss potential solutions based on three cognitive operations for creativity in each process.

2.3 Computer-based support for creativity in the design domain

Much research has investigated ways of using computer technologies to support creativity. Our literature review indicates two main approaches in CST research: crowdsourcing and AI.

A crowdsourcing-based CST helps users expand the boundaries of their thought by providing crowdsourced opinions. *Voyant* [81] is a CST that allows users to receive feedback on their design work from the selected "crowd." Based on multiple elements of design evaluation, such as first notice, impressions, goals, and guidelines, *Voyant* offers feedback with coordinated views. *Decipher* [83] provides designers with feedback through various computer-based functions, such as categorizing a crowdsourced feedback, identifying valuable feedback, and prioritizing which feedback to incorporate in a revision. Designers can recognize the strengths and weaknesses of various aspects of their design work and compare the feedback of different providers. However, crowdsourcing-based CST has some limitations. There may be an issue related to the lack of expertise of the crowd [41]. Conversely, a (novice or young) designer could experience design fixation because they overemphasize information provided by experts, which may inhibit divergent or convergent thinking [15, 52].

An AI-based CST helps users extend their ideas by applying various modeling and visualization techniques to analyze big data. *Rico* [19] supports designing a UI layout for mobile applications. It has functionalities to analyze the visual, textual, structural, and

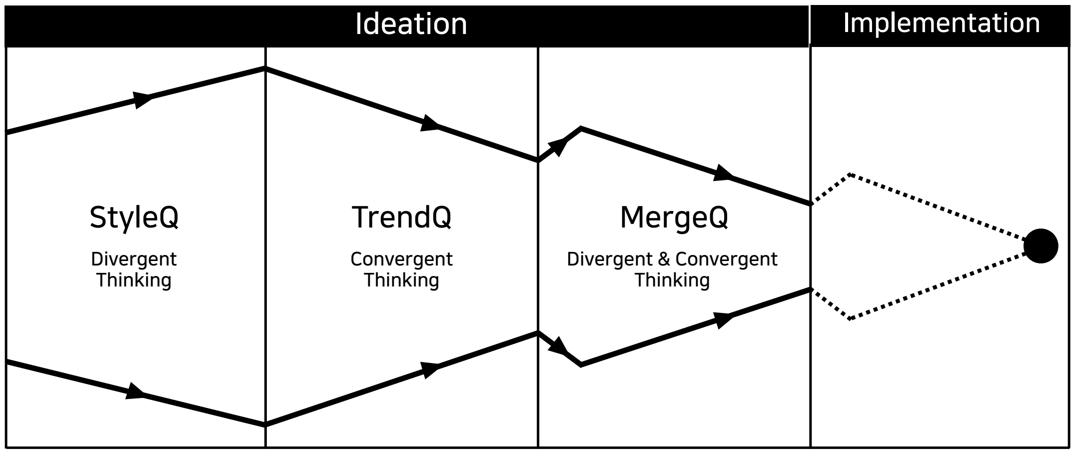

Figure 2: Schematic overview of our supporting design ideation phases based on divergent and convergent thinking (adapted from design funnels [11, 57]).

interactive design properties of 72,000 popular designs (based on Google Play Store star ratings) with an autoencoder deep learning model [5]. *Rico* supports the setting of a design direction in various ways. Vaccaro et al. [74] analyzed text and image data related to fashion design on social networking services (SNS). They used latent dirichlet allocation (LDA) [6] 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 [12]. Based on similarity metrics of the recipe data from natural language processing and human annotation, it used hierarchical clustering to generate recipe clusters.

FashionQ is an AI-based CST that is designed to support divergent and convergent thinking in the ideation process through three interactive visualization interfaces – StyleQ, TrendQ, and MergeQ (Figure 2). It allows the insights obtained from analyzing a large-scale fashion image data (302,772) to be effectively used. With deep learning models designed for fashion attribute detection, style clustering, and popularity forecasting, FashionQ provides users with the results of AI-based data analyses with visualizations as well as the ability to interact with the results.

3 RESEARCH PROCEDURE

This study primarily comprises three stages: (1) Formative study: the design stage of AI-based CST for fashion ideation, (2) FashionQ: the development stage of AI and the CST interface, and (3) User study & discussion: the evaluation stage conducted through a user study. Figure 3 illustrates the overall research procedure.

In the first stage (Section 4), we interviewed 10 fashion design professionals to obtain an understanding of the fashion design ideation phases, the challenges of each phase, and solutions to the challenges. Based on the results of the interviews, we applied three cognitive operations (i.e., extending, constraining, blending) to support divergent and convergent thinking.

In the second stage (Section 5), we developed AI models that aimed to externalize three cognitive operations for divergent and convergent thinking. We built FashionQ, an AI-based CST for fashion ideation. FashionQ has three main interactive visualizations: StyleQ, TrendQ, and MergeQ. Each visualization was developed using a single or multiple AI models. These visualizations supported three cognitive operations for creativity (Section 2).

In the third stage (Sections 6 and 7), we evaluated the effectiveness of FashionQ in supporting divergent and convergent thinking, practical usability, and ideation for fashion design. This was achieved by giving the same set of the design tasks to two conditions — experimental (use of FashionQ) and control (nonuse of FashionQ but based on current work practice) — and comparing the results of user experience in completing each design task. Study results from the survey and interviews demonstrated that FashionQ effectively supported the ideation process. We discuss insights gleaned from the study, such as strengths, weaknesses, and solutions regarding AI application to creativity support, as well as design implications for the development of an AI-based CST.

4 FORMATIVE STUDY

We conducted interviews with 10 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.

4.1 Interviews with fashion design professionals

All 10 fashion design professionals (8 females and 2 males) majored in fashion design, and work in a fashion design company. Their work experience ranges from 3 to 15 years (mean=7.5, SD=3.1). The interviews were conducted in a lab seminar room on an university campus between October 1-15, 2019. Each interview took approximately 60 minutes. Two researchers (the first and second authors) conducted the interviews. The interviews were audio-recorded and transcribed for later analysis.

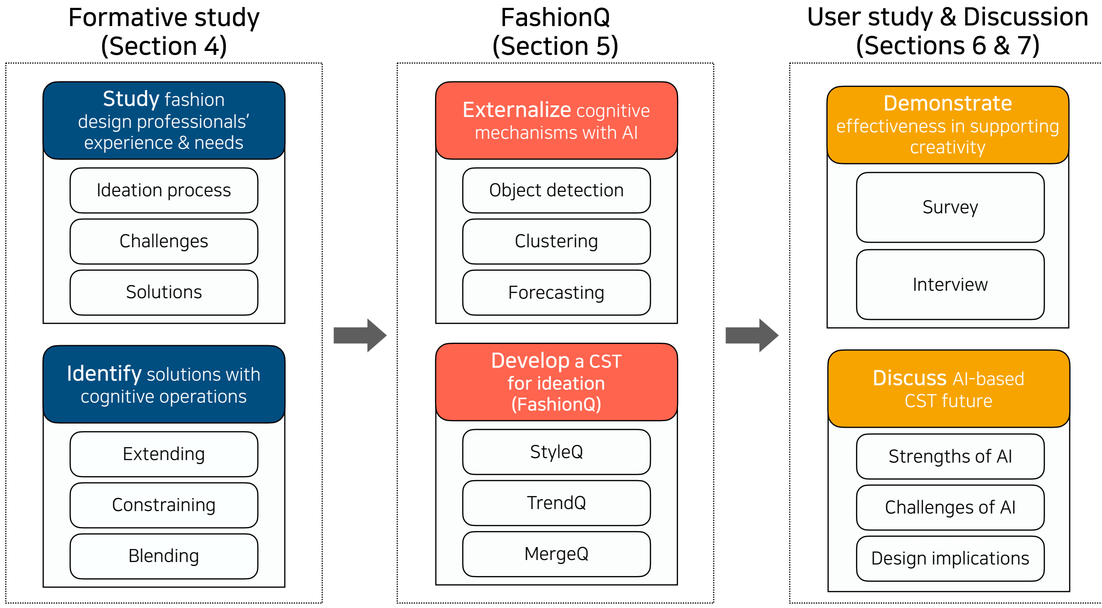

Figure 3: Overview of the study procedure.

During the interview, we asked about (1) their current practices of fashion design ideation, (2) barriers and challenges that interfere with their creative tasks, and (3) potential solutions and coping strategies to address these challenges.

After the interviews were completed, we applied thematic analysis and iterative open coding [14] to analyze the interview transcripts. Two researchers coded and analyzed the transcripts for emerging themes, and the findings were discussed among the co-authors iteratively until consensus is reached.

4.2 Results

Below, we summarize the fashion design ideation process and current challenges and possible solutions emerged from the interviews. When reporting interview quotes, we use P_f^X to denote participant number X in the formative study.

4.2.1 Fashion design ideation process. Our findings identified three phases of the fashion design ideation process:

- *Recognizing one's brand*: designers individually analyze the style of the past fashion designs of their brand to recognize their brand style.
- *Understanding trends*: designers identify fashion trends by analyzing the fashion designs that appear at popular major fashion shows through websites and trend reports from a fashion trend analysis company.
- *Setting design directions*: designers establish the direction of design development based on their understandings of their brand style and trends.

In the *recognizing one's brand* phase, designers try to identify the brand identity based on their understanding of the brand's past design results. Generally, the fashion style that has been used consistently for a long time is understood as the identity of the brand. Designers identify design attributes (e.g., type of clothes, colors, detailed attributes) that are continuously used or that have high production or sales volumes. Based on this understanding of past design results, designers finally grasp their brand identity. Note that at this stage, designers work individually, rather than together.

In the *understanding trends* phase, designers try to analyze major fashion shows (e.g., "fashion weeks"), which is the most efficient and accurate method to identify current fashion style trends [68]. A fashion week is a fashion industry event lasting approximately one week, during which fashion designers, brands, or houses showcase their latest collections in runway fashion shows to buyers and the media. These events influence trends for the current and upcoming seasons. The most prominent fashion weeks are held in the fashion capitals of the world: New York, London, Milan, and Paris. These so-called "Big Four" receive the majority of press coverage. Designers individually analyze the styles at fashion weeks on websites that provide fashion image data, such as U.S. Vogue[1] where designers can explore the entire range of major fashion weeks from 1993 to now. In addition, designers can exploit the trend reports published by trend analysis companies, such as WGSN,[2] which allow them to access fashion design professionals' trend analyses of the styles at major fashion weeks. In this way, designers share opinions with other co-workers at meetings in order to define fashion style trends for their company.

In the *setting design directions* phase, designers establish design directions by mixing the style of their brand and with those in trend reports. In other words, ideation means combining their style with the characteristics of trends in order to redesign their style to be more fashionable, attractive, and valuable at sale. Usually, at this phase, designers need to consider the combinations of

[1] https://www.vogue.com/fashion-shows
[2] https://www.wgsn.com/en/products/fashion

representative fashion attributes (e.g., types of clothes, dominant colors, detailed attributes) of their style and trend styles by roughly sketching clothes. For example, if the representative cloth type of their style is an ankle-length maxi-skirt and the representative detail of trend styles is beads, a designer might set the direction to include designing a maxi-skirt adorned with beads. Designers try to make as many combinations as possible to extend variations of designs and then establish a direction among the combinations, which normally takes a significant amount of time and effort.

4.2.2 Challenges and possible solutions. We also identified fashion design professionals' thoughts on the challenges that interfere with their ideation during each phase, as well as possible solutions to address these challenges.

First, in the *recognizing one's brand* phase, designers have difficulty defining fashion styles in the absence of quantitative standards. Since designers tend to define the style of their brands by themselves (relying on experience or intuition), they might recognize a particular style differently. One designer with 15 years of experience noted, *"The difference of recognizing styles could be resolved by having a meeting. However, the gray area still exists"* (P_f^5), which means 5th participant from the formative study). Another designer with eight years of experience remarked, *"If we could define a style with some quantitative standard, it would have been very useful for me to extend the boundary to understand a style"* (P_f^9). Designers feel difficulties that come from the limitation of defining a style with ambiguous standards. This reveals the potential usefulness of a quantitative metric as a design guide to defining and understanding design styles and boundaries.

In the *understanding trends* phase, designers also face challenges in the absence of quantitative standards. Designers use trend reports regularly published by third-party fashion companies to understand style trends. However, since these trend reports focus on identifying trends with a single season, it is difficult for designers to obtain a holistic and comprehensive overview of style trends over multiple seasons. Understanding longitudinal style trends is useful for gaining insights in overall style trends. One designer with four years of experience observed, *"In the trend meeting, designers tend to infer style trends based on their experience and intuition rather than quantitative data. For example, they might say that I have seen a recent trend of minimalist styles on the street and on social media"* (P_f^2). Lack of explicit criteria in collecting and analyzing style trends hinders the ability for fashion designers to quickly and accurately gain the fashion trends and set design directions, which also means narrowing down the boundary of selecting trends. Conversely, to facilitate creative thinking, designers strongly wanted to have quantitative and multi-year, large-scale trend information which helps figure out quantitative popularity of each trend.

In the *setting design directions* phase, we observed two challenges. The first is that a task for idea combination is highly time-consuming. Making fashionable combinations between two styles requires expertise. The lack of expertise interrupts with designer's ability to differentiate common and popular style trends versus unique design elements that could highlight the designer's brand and are worthy of being introduced in design combination prototypes. The designer with seven years of experience noted, *"By trying various combinations, designers try to find valuable and fashionable combinations. Less experienced designers will likely spend a large amount of time making combinations much more than experts"* (P_f^8). The second challenge is having too many designs to consider. According to Guardian,[3] there are more than 300 fashion shows a season in New York Fashion Week, one of the four major fashion weeks. Given that designers need to analyze designs of multiple fashion shows spanning across the multiple seasons, the amount of designs is simply out of any individual's control. Designers can only reasonably analyze trends in a limited range (e.g., fashion shows, season, cloth types), resulting in an information overload problem. Having limited time constraints to cover a wide amount of information poses a significant challenge for designers, and one designer with 15 years of experience expressed the following: *"It was inefficient to spend a great deal of time on this design task, but a bigger problem is that I could not find more diverse design sources in a limited time"* (P_f^1). These limitations of personal ability may be a fundamental factor preventing creative thinking. Designers wanted to efficiently combine valuable and fashionable designs (i.e., convergent thinking) while considering various design materials to the greatest extent possible (i.e., divergent thinking) within a relatively short period of time.

In summary, the fashion design professionals responded that the key challenges preventing creative thinking are ambiguous and volatile qualitative criteria in defining a style and limitations to large-scale data access and analysis. To address such challenges, the professionals suggested (and fervently requested) a tool for analyzing a large number of designs across multiple fashion shows and time periods and identifying style trends quantitatively, while also suggesting data-driven style combinations.

4.3 System design goals

Based on the interview results, we derived three major goals for the design of an AI-based CST (Table 1): **Goal 1** provides attribute information on design and style clustering based on the attributes for divergent thinking; **Goal 2** provides visualizations for the popularity analysis of a particular style over the season for convergent thinking; and **Goal 3** combines designs based on attributes of users' styles with a trend style and provides additional fashion show data for ideation for both convergent and divergent thinking.

5 FASHIONQ

Based on three design goals, FashionQ supports creativity through divergent and convergent thinking in ideation processes (Figure 4). FashionQ provides three main visualizations: StyleQ, TrendQ and MergeQ (Figure 5). With FashionQ, fashion design professionals can recognize their style quickly and analytically in a quantitative way, identify fashion trends across the seasons, and broaden the extent of ideation with a combination of styles.

[3]https://www.theguardian.com/fashion/fashion-blog/2011/sep/16/new-york-fashion-week-numbers

Table 1: Ideation goals of Fashion Design (Formative Study)

Ideation phase	Requirements	Goals	Interactive Visualizations	Cognitive operations
Recognizing one's brand	Style classification	**Provide attribute information on design and style clustering based on the attributes.** This helps extend the boundaries of understanding styles (divergent thinking).	StyleQ	Extending
Understanding trends	Style comparison	**Provide visualizations for the popularity analysis of particular styles over the season.** This helps narrow down the boundary of trend styles needed in ideation (convergent thinking).	TrendQ	Constraining
Setting design directions	Style combination	**Combine designs based on attributes of users' style with a trend style and additional fashion show data for ideation.** This helps merge into the design directions (convergent thinking) and extend boundaries to facilitate new directions in design development (divergent thinking).	MergeQ	Blending

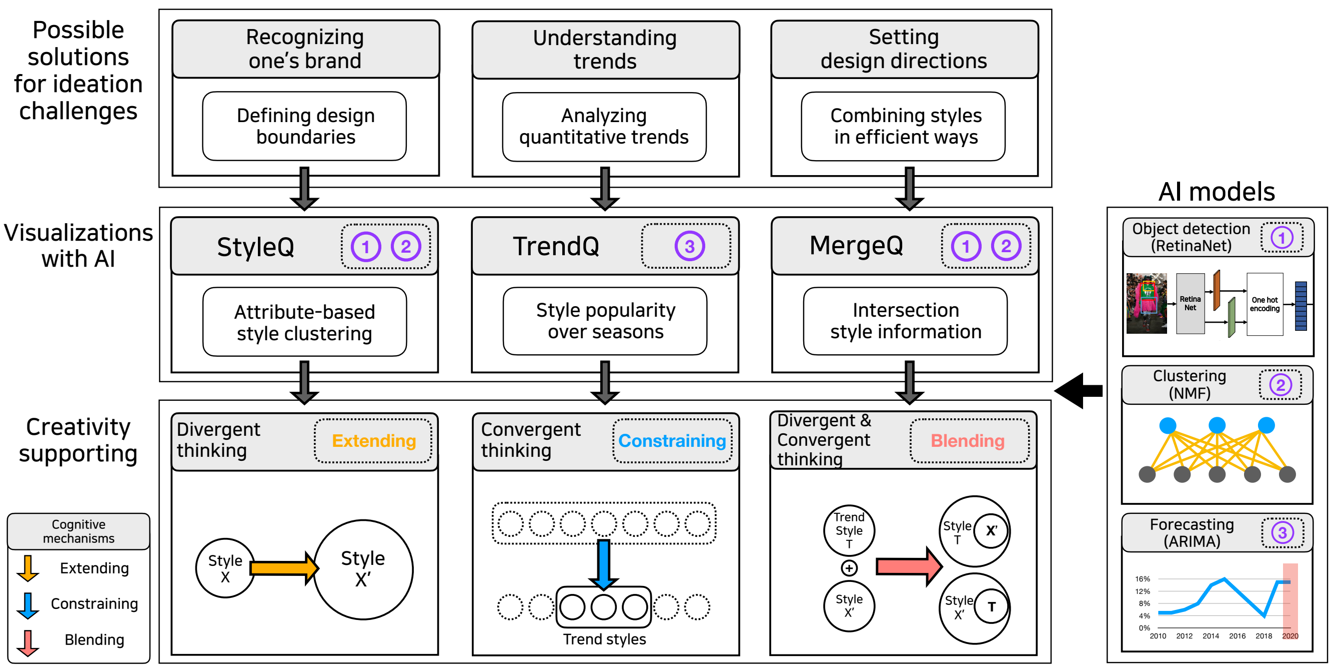

Figure 4: Supporting creativity through divergent and convergent thinking support. FashionQ was designed to support three cognitive operations – extending, constraining, and blending – by providing StyleQ, TrendQ, and MergeQ, with the support of AI.

5.1 StyleQ: Attribute-based quantitative style recommendation (Goal 1)

StyleQ provides clustered styles based on quantitative fashion attributes to extend the boundary of concept of a particular by recognizing differences in the criteria of individual designers (extending). This is expected to increase divergent thinking possibilities by allowing designers to think about that they have not considered before during the early design process.

For more accurate attribute identification, StyleQ allows a user to choose appropriate attributes among the detected ones. Only user-selected attributes among the attributes found by the object detection model will be retained. The user can take a closer look at the attribute used as a criterion for quantitative style clustering. StyleQ then calculates the similarity between the attributes (A) and the representative attributes (B) of each of the 25 clustered styles by using Jaccard similarity [35]. These 25 styles were derived from 327,772 fashion show images with attribute information (this will be explained in the following section).

StyleQ deals with the similarity search results by presenting the top three styles with 15 representative fashion images for each

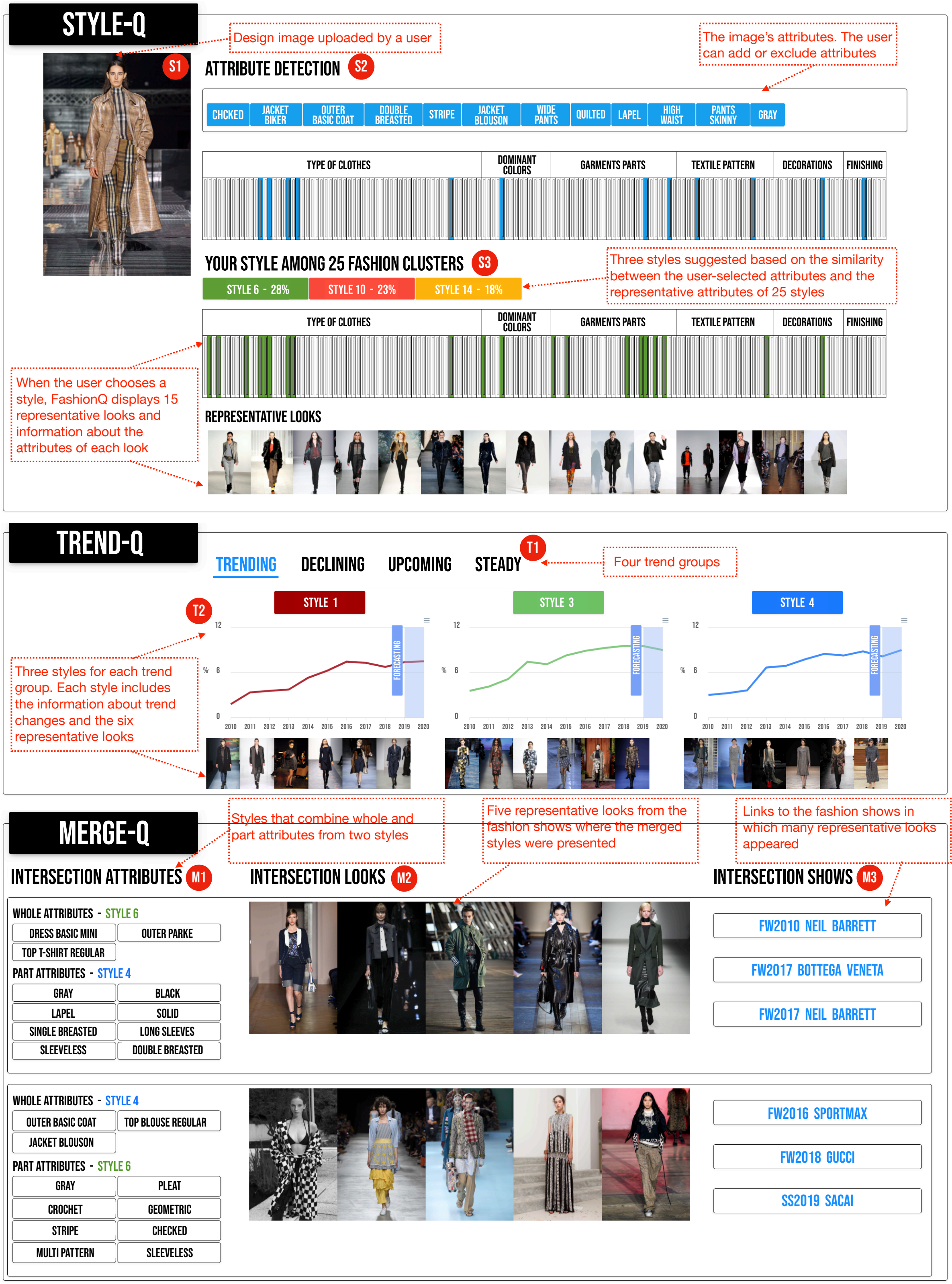

Figure 5: FashionQ system with three main interactive visualization interfaces – StyleQ, TrendQ, and MergeQ.

style to help the user understand the style characteristics and relationships with other styles.

In summary, StyleQ has the order of usage as fellows.

- *Image upload* allows the user to upload his/her own design image (Figure 5-S1).
- *Attribute detection* allows the user to check the image's attributes and add or exclude them (Figure 5-S2).
- *Style recommendation* provides the user with three styles (Figure 5-S3) which were based on the Jaccard similarity between the user-selected attributes and the representative attributes of 25 styles. When the user chooses a style, FashionQ displays 15 representative looks and information about the attributes of each look.

In the following subsections, we will explain the algorithms used for StyleQ implementation.[4]

5.1.1 Attribute detection modeling. We defined 146 fashion attributes used in fashion design in the interviews conducted with 10 fashion design professionals. The attributes are composed of the type of clothes (60 attributes), dominant colors (14), garments parts (27), textile patterns (21), decorations (15), and textile finishing (9). We collected a total of 25,470 fashion images from the Fashion14 dataset (12,190) [72] and by web crawling Google Images (13,280). We worked on labeling with three fashion design students for a month, and the labeling results were double-checked by a fashion design professional. After the labeling work, we developed a model which detected 146 defined fashion attributes in the fashion images, using RetinaNet [48] which shows the best performance in object detection tasks. Our model yielded good performance (Precision=0.47, Recall=0.47, and F1-score=0.45) over the baseline performance (Precision=0.32, Recall=0.46, and F1-score=0.36) of Faster RCNN [58] which is widely used for object detection tasks in a computer vision domain.

5.1.2 Style clustering. In order to further populate the fashion image dataset labeled with attributes, we crawled a total of 302,772 images from 8,121 fashion shows from U.S. Vogue between 2010 and 2019. The fashion images cover 987 brand names ranging from mega couture (e.g., Gucci, Chanel) to high street brands (e.g., JCrew, Topshop) [30]. We labeled attributes in each image using our attribute detection model. Finally, we obtained 302,772 images with 146 attributes.

We used a non-negative factorization (NMF) algorithm [82] for style clustering. It has benefits because each axis in the space derived by the NMF has a straightforward correspondence with each document cluster, and document clustering results can be directly derived without additional clustering operations.

In NMF, the entire data V is divided into matrix parameters and expressed in times of matrix W (Weight Matrix), and matrix H (Feature Matrix) [46]. Data V, which consists of attribute i which is the number of attributes (146) and u which is the number of images (302,722) (Equation 1).

$$V \approx WH \ \ where \ \ V \in \mathbb{R}^{i \times u}, W \in \mathbb{R}^{i \times a}, H \in \mathbb{R}^{a \times u} \tag{1}$$

[4]Our work that details the deep-learning algorithms and model performance is currently under review at a different venue.

Data V is decomposed r (the number of styles) times via matrix decomposition into W consisting of attributes i and style a, and feature matrix consisting of a and image u (Equation 2).

$$\boldsymbol{V_{iu}} \approx (\boldsymbol{W H_{iu}}) = \sum_{\boldsymbol{a}=1}^{\boldsymbol{r}} \boldsymbol{W_{ia} H_{au}} \tag{2}$$

In the feature, for matrix H, the style group is labeled according to the attributes of a particular image, and the specific attributes and their importance that make up that style can be seen in W.

From collaboration with with fashion design professionals, we identified the appropriate number of groups (clusters), and verified that each style group accurately represents a fashion style. We narrowed down the number of clusters by merging similar style clusters into one cluster. The process consists of the followings.

- Range identification: In the interview with fashion design professionals, they suggested the range of the proper number of clusters to be between 25 to 40.[5]
- Creation of the first style group: Initially, 40 style clusters which is based on the maximum number were created based on NMF.
- Selection of representative images: We took 25 images based on the descending order of having the top 10 attributes in each group and prepared a 1,000 sample dataset.
- Merging style: We asked three fashion design professionals who participated in the previous interviews to merge style clusters. As a result, we obtained 25 style clusters. This number seemed quite appropriate, given the results of the previous studies (14 groups [72]; 30 groups [1]), hence we finally extracted 25 style groups using the NMF results.

5.2 TrendQ: Quantitative definition of trends for 25 styles (Goal 2)

TrendQ defines "popularity" based on the ratio of the number of style frequencies in the four fashion cities over a 10-year period (2010-2019). The 25 styles were grouped into four categories–Trending, Declining, Comeback, and Steady–depending on the changes in popularity. Using the group selection button, selecting a specific popularity group presents three representative styles of that group. The y-axis refers to the percentage of a certain style's frequency in a given year, and the x-axis refers to the season of the fashion show.

5.2.1 Trend. A fashion style trend can be defined as a change in popularity of a particular style over time [36]. The fashion trend index determines how many times a style is shown in a given year. As the number of images shown on runways varies across years, we used the relative frequency of each style in a given year ($\boldsymbol{y_t^s}$). The number of images I of a particular style s, divided by the total number of images Q in a given year t, was used as the fashion style trend indicator (Equation 3).

$$\boldsymbol{y_t^s} = \frac{\boldsymbol{I_t^s}}{\boldsymbol{Q_t}} \tag{3}$$

[5]We used some algorithmic methods to set the number of clusters based on distance or using the elbow test to remove clusters in PCA based on eigenvalues. However those algorithms generated 5-10 clusters, which were not in the range that the professionals suggested; thus, we employed NMF instead.

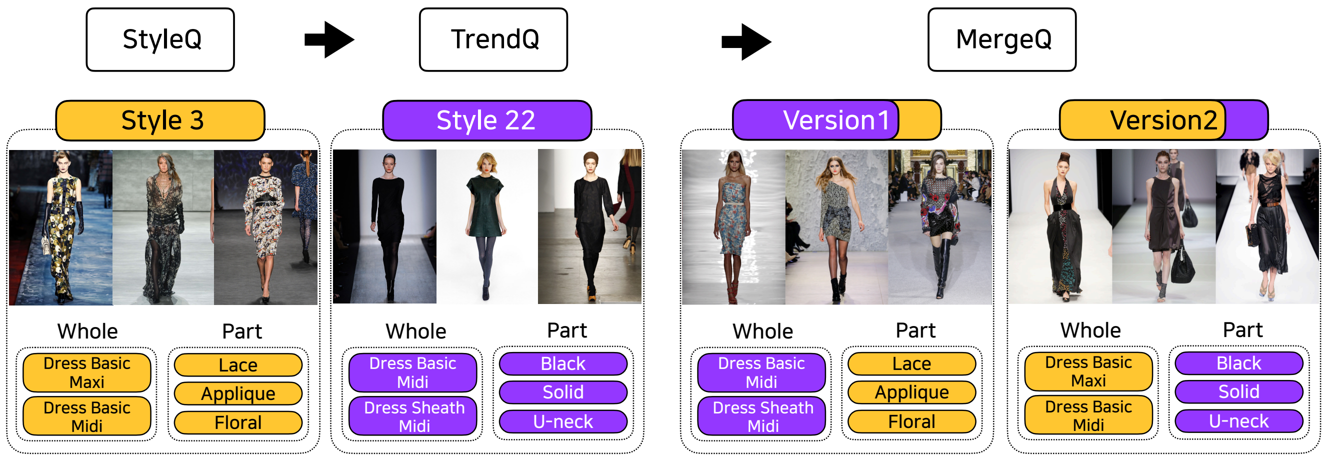

Figure 6: The procedure of merging two styles in MergeQ. In this example, a designer chose Style 3 from the images that he/she uploaded (StyleQ) and Style 22 from style trend interface (TrendQ). A style consists of whole attributes and part attributes. When merging two styles, the whole attributes from one style and the part attributes from another style (vice versa) will be mixed and extracting the most relevant style with those attributes will be suggested (MergeQ).

For the purpose of developing the forecasting model, we used the data between 2010 and 2017 for training, those in 2018 for validation, and those in 2019 for testing. We used an auto-regressive integrated moving average model (ARIMA) [10] which has a convincing performance in a prediction task with a relatively simple structure, and the mean absolute error (MAE) of our model is 0.0254. Given the number of samples, this was a reasonable performance considering prior work [1] predicting style popularity with ARIMA with a large number of samples (MAE=0.0186).[6]

In summary, TrendQ has the order of usage as follows.

- *Trend group selection* (Figure 5-T1) provides four trend groups based on the frequency of the style's appearance at the four major fashion shows by year.
- *Style selection* (Figure 5-T2) provides three styles for each trend group. Each style includes the information about trend changes and the six representative looks. The two styles chosen from StyleQ and TrendQ are considered in MergeQ.

5.3 MergeQ: Style combinations (Goal 3)

MergeQ proposes a style to the user that contains the styles that the user selected from StyleQ and TrendQ. The purpose of this function is to support the creation of a new combination of attributes by providing a proper combination of the two selected styles of the attributes. By suggesting a style that the designer had not thought of before, MergeQ is expected to expose a designer to more design possibilities and facilitate more divergent and convergent thinking opportunities in the fashion design ideation process.

For style combinations, 146 attributes were divided into two groups: "Whole" (60 attributes) representing the form of the garment and "Part" (86 attributes), representing the details of the garment. Then, the Whole of one style and a Part of another style are mixed, and vice versa. Through this process, two types of combinations are generated. For example (Figure 6, MergeQ-Style Version 1), if the Part attributes of StyleQ are lace, applique, and floral and the representative Whole attributes of the TrendQ style are midi basic dress and short sheath dress, the creation of a midi basic dress and a short sheath dress decorated with laces, appliques, and a floral pattern become the representative intersection attribute. Furthermore, the opposite case is also conducted (Figure 6, MergeQ-Style Version 2). We can clearly see the different image suggested between two style versions.

MergeQ offers 10 representative looks related to the combination of attribute information, as well as a link to a fashion show with designs that include many combinations of fashion attributes and detailed explanations of each style. In this way, we hoped to support designers in effectively developing and expanding upon their ideas.

MergeQ uses the information about whole and part attributes from the object detection model and about styles from the clustering model to suggest a style with the best match.

In summary, MergeQ has the order of usage as fellows.

- *Intersection attributes* (Figure 5-M1) presents styles that combine whole attributes from one style and the part attributes from another style (or vice versa).
- *Intersection looks* (Figure 5-M2) shows 10 representative looks from the fashion shows.
- *Intersection shows* (Figure 5-M3) provides web links to the fashion shows. A user can check more representative looks from the shows.

6 USER STUDY

The goal of our user study was to determine whether FashionQ supports divergent and convergent thinking, practical usability, and ideation for fashion design.

[6]Since the sample size in our work is not large enough to be used with a more advanced deep learning model such as LSTM [32], we used another popularly used algorithm, ARIMA [10], that is more appropriate for analyzing our dataset.

6.1 Participants

We conducted a user study with 10 fashion design professionals (7 females and 3 males) who are currently working in the fashion design industry. Note that these participants were newly recruited for the FashionQ evaluation study different from those in the formative study. Career experience of the professionals ranged from 2 to 11 years (mean=7.0, SD=3.3). Each participant was invited to a university laboratory for the study. Our study was approved by the Institutional Review Board (IRB), and the consent of the participants was sought before the study. Each participant was given a $30 gift certificate after the study.

6.2 Study procedure

We asked the participants to assume that they were a designer of famous brands and were asked to conduct ideation for fashion design and perform the following three tasks: (1) identify the brand style that represents their own, (2) examine style trend to reflect, and (3) generate new fashion design ideas. We selected 15 popular brands (e.g., Burberry, Prada, Chanel) that are highly influential in the fashion industry (these brands participated in all four major fashion shows between 2010 and 2019). We prepared 15 fashion show images for each brand's latest fashion show (2020FW). None of the participants worked at nor had close business relationships with those 15 fashion brands so that we were able to minimize the effect of any understanding or experience that they might have of those brands in performing the user study tasks.

We conducted a within-subjects study. Participants were asked to be in both the experimental and control groups, and the order was randomly assigned. Participants in the experimental group were asked to use FashionQ to complete three tasks as follows: (1) identify the brand style, (2) identify a style trend to reflect, and (3) generate a new fashion design by combining the brand style and the trend style. The control group relied on the participants' own experience and ability without using FashionQ. This is considered to be the appropriate baseline condition based on the findings of our formative study. The tasks to complete were the same as those in the experimental group: (1) brand style identification (select a picture of their favorite brand from among 15 pictures and determine the style of the picture), (2) style trend identification (proceed with the search work, such as by using social media, fashion magazine webpages, and fashion blogs, in the way they usually would), and (3) new fashion design generation (they were allowed to refer to the U.S. VOGUE homepage, which has information about fashion show collections, and then select fashion images, and make a simple sketch).

The study proceeded as follows:

- Step 1: The participants provided demographic (age, gender) and background (length in years of career as fashion design professional) information.
- Step 2: The participants were randomly assigned to either the experimental or control group, and asked to complete the task in 30 minutes. For the participants who were in the experimental group were instructed for 10 minutes on how to use FashionQ. After the task, they were asked to answer the survey questions.
- Step 3: After a five-minute break, the participants switched groups (from experimental to control or vice versa) and completed the task again for 30 minutes in accordance with the instructions for their new group. They then completed the same survey as in Step 2.
- Step 4: The participants were asked to be interviewed by the researchers about the degree of divergent and convergent thinking support offered by FashionQ and and its practical use.

6.3 Survey questions

The survey questions consisted of two themes. The first focused on divergent and convergent thinking support and was used only for the evaluation of FashionQ. In the first question set, we used 7-point Likert scales for all questions (1: Strongly Disagree; 7: Strongly Agree). The questions are as follows.

- Q1-1: Did StyleQ help you explore more fashion designs in a particular style? (extending—divergent thinking)
- Q1-2: Did TrendQ help you learn about popular styles from current and historical fashion trends? (constraining—convergent thinking)
- Q1-3: Did MergeQ help you think of other styles through attribute combinations? (blending—divergent thinking)
- Q1-4: Did MergeQ help you consider possible future design directions through attribute combinations? (blending—convergent thinking)

The second theme refers to one's perceived confidence in AI-based results. This type was used in both the experimental and control groups. In the second question set, we used 7-point Likert scales for all questions (1: Not confident at all; 7: Very confident). The questions are as follows.

- Q2-1: How confident were you about the style you have labeled?
- Q2-2: How confident were you about the trend information you found?
- Q2-3: How confident were you about the ideation results of the style and trend you combined?
- Q2-4: How confident were you about the overall design process?

6.4 Statistical analysis

For the questions about divergent and convergent thinking, we computed descriptive summary statistics. For the questions about perceived confidence in the AI results, we used a paired sampled t-test to determine the statistical significance of the survey responses between the two groups.

First, we confirmed that the three cognitive operations for divergent and convergent thinking are generally well supported. The average scores for StyleQ (divergent thinking), TrendQ (convergent thinking), and MergeQ (divergent thinking), MergeQ (convergent thinking) were 5.4, 5.8, 5.6, and 4.1, respectively (Figure 7). We noted that the score of MergeQ-convergent was the lowest.

Second, we found that the experimental group showed significantly higher scores than the control group for all five questions ($p < 0.05$; Figure 8). This indicates that FashionQ supported the fashion design ideation outcomes quite well.

6.5 Interview analysis

During the interview, the participants explained in detail how AI externalized the three cognitive operations and influenced ways of divergent and convergent thinking. Table 2 summarizes the interview results and implications. When reporting interview quotes, we use P_u^X to denote participant number X in the user study.

6.5.1 Fashion design ideation with AI-based CST. All participants answered that FashionQ provided sufficient support in promoting divergent and convergent thinking.

StyleQ provides attributes-based style clustering information to support the *extending* cognitive operation in divergent thinking. This helped designers determine and expand the range of styles in their repertoire. Participants mentioned that they were able to expand the scope of concepts or increase the number of concepts in a specific style by means of StyleQ. For example: *"In the representative photo of the style, there was a design that I hadn't usually thought of, but it was a recommendation in an understandable range, which expanded the range of the style I was thinking of"* (P_u^1). *"The style I chose is a sexy style. Looking at the attribute information, such as the representative blazer and boxy sweater, which are far from the sexy style standard I thought of. It seemed necessary to distinguish the sexy style boundary that I already knew in greater detail. I was able to come up with a style group that I hadn't thought of"* (P_u^4).

Participants answered that the attributes in FashionQ are all used by designers in the field and seem adequate for use in analysis. They mentioned that creating fashion styles based on those attributes seems accurate, for example: *"Since the 146 attributes used in FashionQ are quite essential in fashion design work, I think there is a high possibility of covering all styles"* (P_u^7). In addition, all participants appreciated the number of fashion images (302,772) used in modeling because accessing and analyzing such a large number of images individually is almost impossible. *"The fact that it was centered on 300,000 images of the four major fashion shows over 10 years gave us great confidence in the system"* (P_u^1). *"The data from*

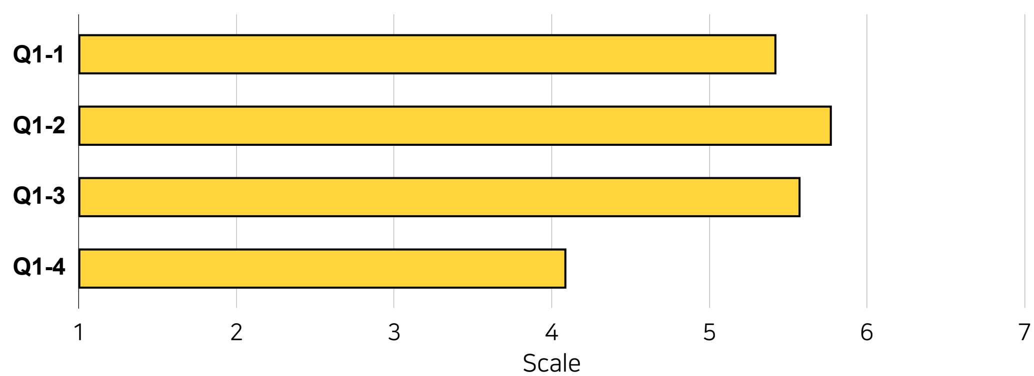

Figure 7: Support for divergent and convergent thinking.

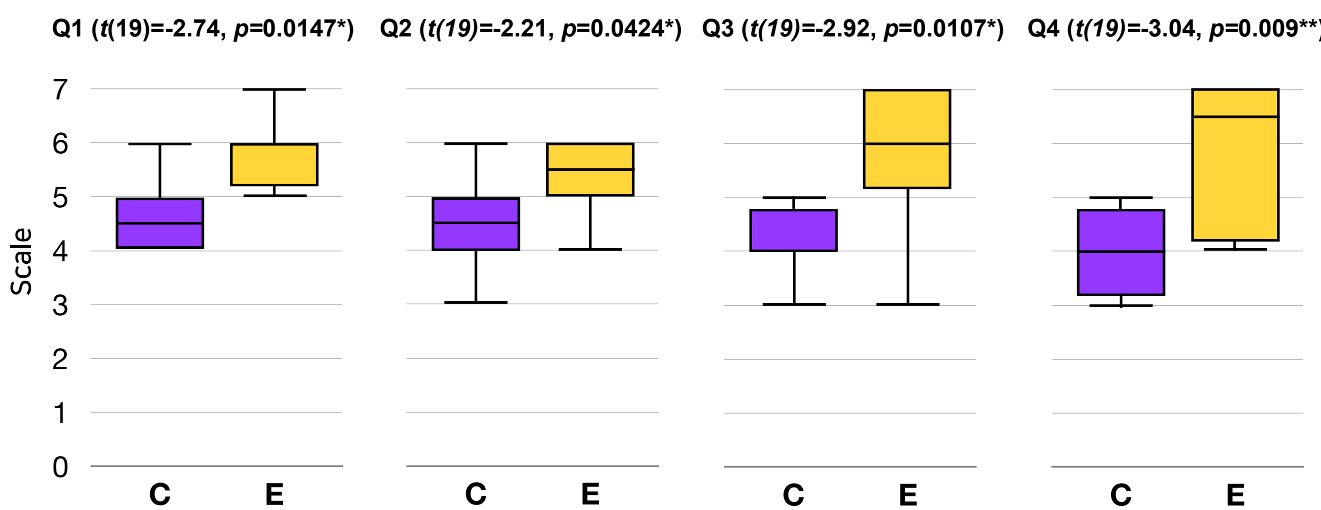

Figure 8: Fashion design ideation outcomes between the no-FashionQ (C = Control) and FashionQ (E = Experimental) conditions ($^*p < 0.05$, $^{**}p < 0.01$).

Table 2: Strengths and weaknesses of AI output. Strengths highlight efficiency and objectivity of data analysis. Weaknesses highlight accuracy, explainability, and interpretability issues. Possible solutions through human-in-the-loop, crowdsourcing, and initiative provision were proposed to address the weaknesses.

AI	Strengths of AI	Weaknesses of AI	Possible solutions
Attribute detection	AI detects fashion attributes from the image with high accuracy.	Inaccurate prediction of AI decreases designers' trust of the results.	Allow designers to revise the data used in detection modeling (e.g., attribute re-labeling).
Style clustering	AI employs fashion attributes as criteria to cluster styles quantitatively and provides results from large-scale data analysis.	Unclear explanation of clustering results (e.g., number of the clusters, meaning of the cluster).	Allows designers to make new clusters based on combinations of attributes they want to see and to compare them with others' clusters to find reasonable combinations.
Trend prediction	AI provides results from multi-year, large-scale data analysis and helps designers understand fashion trends.	Unclear explanation of AI decreases designers' trust of the results.	Provide fashion designers with other designers' evaluations of prediction results or allow them to see the forecast accuracy of the same model in different timeframes of past years.
Style merging	AI provides style intersections and helps designers understand the style merging process.	Inaccurate and uninterpretable prediction of AI that conflicts with designers' expertise and experience decreases their trust of the results	Provide an opportunity for designers to reflect their intention toward AI (e.g., attribute weight manipulation, interdomain materials).

the four major fashion shows are familiar to designers, who always refer them in the ideation process. The familiar data gave me a sense of confidence in the overall results for AI" (P_u^{10}).

TrendQ was designed to help fashion design professionals recognize the particular styles that designers should consider for ideation by providing information on the popularity of styles. This supports the *constraining* cognitive operation in convergent thinking. Participants stated that they were able to focus on the salient styles based on the types of temporal variations and compare their existing knowledge with the changes in long-term trends, for example: *"Based on the number-based popularity trend information for each style, I was able to identify six styles that I should consider for ideation. Personally, I tend to find many trends for ideation work, but by using styleQ, I was able to materialize the particular styles to refer to"* (P_u^5). *"It was helpful to show the style that is currently trending in a trend group and an upcoming group. I think the ideas can be focused more. Also, I can exclude styles in the declining group during ideation"* (P_u^8).

Participants mentioned that the trend forecasting model in TrendQ gave them a sense of confidence derived from the number-based trend information. Their knowledge or idea of historical information for a certain fashion style was somewhat vague, but TrendQ helped them shape style concepts. For example: *"This was the first time I encountered trend data based on frequency of 10 years! The popularity of the style in 2020, which was predicted based on the number of changes in the popularity of a particular style over the years, was also very meaningful"* (P_u^2). *"The 10-year data covers all the designs we need to refer to"* (P_u^3).

MergeQ was designed to support the *blending* cognitive operation in both divergent and convergent thinking. By providing information on the intersection of two styles, MergeQ shows users new style information and style combinations that have not been tried before. This helps the users think of new ideation methods related to design applications and gives them an opportunity to use forgotten old designs as ideation materials. The following responses were collected: *"The suggested merged styles were beyond my expectation. These styles are quite interesting. I need to take a closer look"* (P_u^1). *"When I combined style 1 and style 4, the system suggested a look that partially used the pattern of style 4 on the bottom. I personally like to use the pattern on tops or all over the clothes, but looking at the suggested results, it was interesting to see that I had the opportunity to try different ideations and compared with the existing styles that I am interested in"* (P_u^3). *"MergeQ recommended to me the 2019 Missoni show and the 2010 Rodarte show based on my selection in style merging. The Missoni brand itself is famous, and I personally remember several designs because they were recently announced. Rodarte is a brand I've never heard of, and was announced 10 years ago. It was old and unfamiliar, but I found quite a few interesting points to refer to that could blend with my own design. I see the possibility of a new ideation method in a forgotten design"* (P_u^2).

6.5.2 Weaknesses of AI in CST. One of the critical aspects in AI is its accuracy. We asked the participants about their concerns or reservations when accessing the AI results. First, inaccurate results from the attribute detection model made certain results in TrendQ and MergeQ somewhat questionable. Second, some participants were not sure about the number of styles used in clustering and whether this number covers all fashion styles. Third, when there was a conflict between the prediction of style trends and the participants' expectations, they were not sure whether they could trust the prediction results. Lastly, when the suggested results in MergeQ were completely different from what was expected, the participants found the results confusing. Overall, it is important to note that all of these cases pertain to the accuracy, explainability, and interpretability of AI models.

6.5.3 Different evaluation criteria. Our interview results highlight one interesting aspect. Although the participants mentioned their perceived issues with the AI models and results, the evaluation criteria were different for each of the ideation phases, and this aspect was quite salient among the participants. In other words, the level of tolerance toward AI was different in different phases.

First, the participants were quite flexible in accepting the results of StyleQ (*extending*) and TrendQ (*constraining*). They mentioned that they often exchange many design ideas or opinions at work, which is helpful in coming up with new design ideas, refining ideas, or making design decisions. Thus, for them, the StyleQ and TrendQ results provided additional design information or insights that could facilitate design discussions and assist in making better design decisions. *"There were times when the accuracy of StyleQ and TrendQ was low, but that was not a big problem. At least we could get some additional insights"* (P_u^4). *"Design work requires a great deal of collaboration, so communication with others is very important. I feel like FashionQ is another collaborator who gives quantitative insights. Our team doesn't have such a person"* (P_u^7).

Second, on the other hand, the participants exhibited high standards when evaluating MergeQ (*blending*) outcomes. Participants responded that compared to StyleQ and TrendQ, the involvement based on their own experience was necessary in the process of deriving results from MergeQ. *"Unlike recognizing brand style and understanding trends, the ideation stage is very important for designers because it is a process that requires creating a brand new direction"* (P_u^5). We noted that seven participants indicated their high standard or more strict decision over the MergeQ outcomes. For example, *"It seems like MergeQ has more creativity components, but my trust in it is a bit low. If I can select the attribute I want to emphasize in MergeQ, might be able to trust it more"* (P_u^4). *"Analyzing big data that humans cannot cover is very impressive and meaningful, but the creative ability is difficult to trust. I still think people are more creative than AI"* (P_u^2). Therefore, our participants are more satisfied with MergeQ's ability to generate novel style combinations for expanding the design possibilities (*blending—divergent thinking*) but they have reservations when using MergeQ outcomes for setting future design directions (*blending—convergent thinking*) compared to the style combinations that they could generate on their own. This explains the relatively lower rating of survey item Q1-4 compared to the other cognitive operations that FashionQ aims to facilitate.

7 DISCUSSION

In this section, we summarize the findings of the study and discuss its implications. We also report the limitations of the study and our plans for future work.

7.1 CST for creativity support

Both the quantitative and qualitative results of our user study confirmed the possibility of externalizing cognitive operations (i.e., extending, constraining, and blending) to support divergent and convergent thinking using an AI-based CST. FashionQ supports *extending* designer's idea space by revealing styles, attributes, popularity variations (StyleQ), *constraining* styles based on their trend and popularity information, and *blending* two styles by presenting the possibility of new style design through style combinations.

FashionQ presented various paths that could support creative tasks. Participants responded that they discovered the possibility of creative ideation work through divergent thinking supported by our CST. Accessing declining styles in TrendQ helped the participants focus on other trendy styles by excluding those declining ones. Participants also chose steady styles to ideate styles that could be generally acceptable to the public for a long period of time.

7.2 Human and AI interaction for creativity support

One of our study results highlighted the application of AI to cognitive operations, based on the characteristics of tasks, and human evaluation on it. This means that in CST, it is necessary to carefully consider design implications to increase the user-perceived accuracy, explainability, and interpretability of AI. In the following subsections, we will discuss the implications of these findings and how to better use AI results in the context of creativity support.

7.2.1 High level of tolerance for inaccuracy in extending and constraining tasks. In recognizing brand style (StyleQ) and understanding trends (TrendQ), users' tolerance for AI in accuracy was quite high. When developing an AI model that supports the tasks at ideation phases that require *extending* and *constraining* , focusing on developing an AI model that provides perfect prediction accuracy may not be entirely necessary. This may be due to the fact that the primary objectives of divergent thinking and constraint discovery ideation processes are to maximize fashion designers' exposure to diverse style and attributes and market trend and popularity constraints that could help them explore, shape, and redefine design possibilities in order to generate more creative design ideas. In our user study, participants placed high value of being presented with out-of-the-box styles and trends that they were unfamiliar with or had not previously thought of without the assistance of FashionQ. This means that slightly inaccurate predictions of style or trend outcomes will not negatively impact the ideation process, and in some cases might even benefit it because the bewildering predictions could sometimes inspire creative outcomes. Even if the predictions are completely inaccurate, the designers could quickly discard those ideas and move onto the next concepts.

7.2.2 Demand for high customizeability in blending tasks to support convergent thinking. On the other hand, when setting design directions (MergeQ), participants demanded high level of customizeability when they engaged in style combinations, which involves the *blending* cognitive operation that supports both divergent and convergent thinking. Designers wanted to take the lead in the ideation work of customizing combination attributes when creating new style concepts. Regarding the attribute interaction information in MergeQ, this would mean providing the designers with the authority to manipulate the weight of the attribute for a fashion image and corresponding style. For example, if a user wants to see the intersection information in which the flower pattern is more emphasized, there could be an added feature that allows the designer to increase the attribute weight of the flower pattern or tweak the weight of other pattern attributes. Research has emphasized the importance of granting humans the initiative or control to generate creative outcomes when they co-work with AI. For example, in the case of collaborative drawing with AI, previous research has found that giving humans more control over a major portion of the figure and allowing AI to

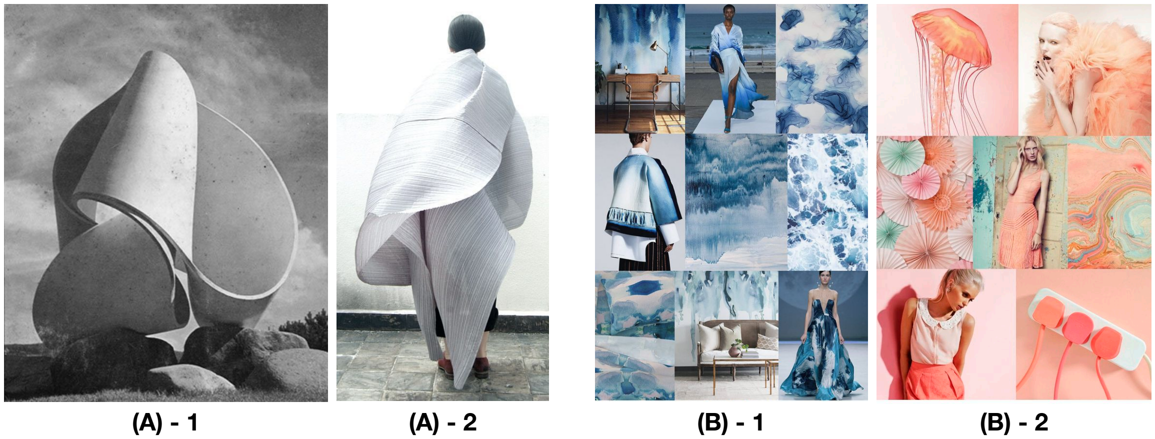

Figure 9: Examples of interdomain materials suggested by fashion design professionals. (A)-1 and (A)-2 are cases of inspiration derived from focusing on a single feature. (B)-1, and (B)-2 are cases of inspiration derived from focusing on multiple features (source: Pinterest).[7]

supplement the rest will lead to significantly higher usability than the case without such considerations [54].

7.2.3 Provide non-fashion-related material in blending tasks to support divergent thinking. The fashion designers[7] also wanted a proactive and fundamental approach to divergent thinking beyond manipulating the weight of the attributes in MergeQ. *"For divergent thinking to be more active, it would be great if we could provide not only fashion product photos but also material information that is not a fashion product that could offer additional inspirations. It would be nice to present a picture of a building that is similar in shape to a fashion product picture, or a picture with a similar color combination used in fashion products"* (P_u^2). Some participants recommended pictures used in ideation (Figure 9) for this purpose. They wanted to be provided with various interdomain materials (non-fashion) that represent possible designs of the selected style combinations. Depending on the feature(s) of interdomain materials, fashion design professionals find opportunities for ideation from various sources. In Figure 9, (A)-1 and (A)-2 are cases of inspiration derived from the silhouette of a work of architecture (a single feature), and (B)-1 and (B)-2 are cases of inspiration derived from various features, such as mood, color, fabric, and pattern (multiple features). Providing interdomain materials corresponds to moving. Bonnardel and Marmèche [9] found that when supporting the ideation of a furniture designer, supporting interdomain materials plays an important role in creativity support.

In summary, our study findings indicate that the participants found AI-based CST to be highly valuable for supporting divergent thinking and constraint discovery, but demands additional customizeability features to support convergent thinking and further expansion of creative non-fashion interdomain source materials to facilitate divergent thinking. This can be explained by the fact that the objective of divergent thinking is to be exposed to as many possible ideas as possible (whether they are good or bad), whereas in convergent thinking the goal is to filter down to the "best" ideas, and therefore the requirement of customizeability is important in refining the ideas into more desirable ones. And given the highly iterative nature of the ideation process in blending, designers further require additional source materials to help them expand the design possibilities when combining multiple styles, attributes, materials, and colors into design ideas. In the following section, we discuss some of the challenges in developing AI models for AI-based CST.

7.3 Challenges in developing AI-based CST

To help researchers, practitioners, and designers in a variety of domains that engage in highly creative processes by utilizing AI-based CST presented in our study, we discuss challenges and key lessons that need to be considered in future AI-based CST research and development.

During our design and development of FashionQ, we worked closely with fashion design professionals to articulate and define the design processes and fashion attributes. We also asked fashion design students to annotate a dataset of 25,470 images for constructing FashionQ's object-detection and clustering models. These steps are highly time-consuming and labor-intensive and took us over a period of 2-months. Recruiting and securing fashion design professionals and students for this work was not easy, as they still face high workload demands while they assisted us with this study. For this reason, we propose utilizing algorithm-generated attributes in future development of AI-based CST. For example, Banaei et al. [2] summarized 1,104 attributes used in an interior CAD program. Liu et al. [49] used the naming data of the online fashion market and obtained 1,000 attributes. Given that designers expressed a high level of tolerance of AI prediction outcomes in extending and constraining tasks, an AI-based CST that incorporates algorithm-generated attributes should not drastically lower user experience. However, image annotation may vary highly depending on the design domain of inquiry. Therefore, plans for data collection and annotation should be made carefully.

There is another challenge when determining the number of conceptual instances (in our case, the number of style clusters). This was also highlighted by some of the participants, who were

[7]http://www.pinterest.com/

not sure whether 25 is representative enough. Number of styles varied drastically in prior fashion design research (e.g., 30 styles [1], 14 styles [72], 5 styles [40]). In this work, we initially applied a clustering algorithm that automatically determine the number of clusters (i.e, using the elbow test to remove clusters in principal component analysis based on eigenvalues) and generate a small number of clusters, and worked with fashion designers in an iterative design process that ultimately arrived at a desired number of 25 clusters. Other design domains may have different design constraints, and other clustering methods can be considered and employed in the AI-based CST depending on the specific context. Adhering to the expressed desires for high customizeability by our study participants and the general spirit of promoting transparent AI that could improve explainability and interpretability, future AI-based CST could consider preparing the results by different cluster counts and giving users the option to navigate the cluster results and select a cluster number that is deemed appropriate to their use and context.

7.4 Limitations and future work

Although our study results provide many insights, there still exist some limitations that we plan to address in future studies.

First, the attributes used in our study did not include all possible attributes. We intentionally excluded some of the attributes, such as fabric type due to an attribute detection accuracy issue of the model. Since the fashion design professionals in our study exhibited a high tolerance of receiving suggestions based on a wide range of AI prediction accuracy when performing extending (StyleQ) and constraining (TrendQ) tasks, it would be reasonable for us to include some of the challenging attributes at the tradeoff of further increasing their exposure to more design possibilities in order to facilitate divergent thinking. In addition, future AI-model development could include other types of time series data for additional analytical insights in trend forecasting. For example, Al-Halah et al. [1] expanded the range of use of forecasting data by combining Amazon sales and style concepts. FashionQ can also be expanded using these data, which can be useful for fashion design professionals when they perform the constraining tasks to come up with new and creative design ideas.

Second, our user study was limited to 30-min of ideation tasks comparing the ideation outcomes and user experiences between the use and nonuse of FashionQ conditions. A more realistic experiment would be a randomized controlled, longitudinal field trial with real fashion designer teams throughout an actual ideation design life cycle, which could span a period of several months. A longitudinal field-based study will allow us to further understand how fashion designers perceive, adopt, and incorporate FashionQ into their existing workflow. Despite the experimental nature of the study, we believe that our study results clearly contributed to a better understanding of AI-based tool for creativity support, which also advances the body of knowledge in human-AI research.

Third, although our research has been framed based on close work with 20 fashion professionals (10 participants for the interviews and 10 for the user study), their insights may not represent the perspectives of all professionals nor all the dynamics of the fashion industry. Thus, the attributes or styles derived from our study may not be applicable to some case. In addition, the study results could be influenced by the carry-over effect derived from the within-subjects design [31].

As future work, we plan to conduct future AI-based CST research on idea implementation, which is the step that follows ideation (Figure 2). Research has demonstrated that utilizing a model that provides design suggestions [33] through attribute conversion based on generative adversarial networks (GAN) [28] can support rapid prototyping [20]. Applying the FashionQ framework could further contribute to creative research in the idea implementation phase. In addition, we will consider applying the CSI (Creativity Support Index) [13] to assess the overall creativity outcomes and usability of FashionQ in future studies. Finally, we plan to apply the FashionQ framework to other design domains beyond the fashion design industry.

8 CONCLUSION

Modern AI is constantly developing and expanding. Its value and importance are increasing as it is applied to many environments for various purposes. This paper aims to investigate how AI can support creativity and to uncover salient aspects that need to be considered in designing AI-based CST in the context of ideation in the fashion design domain. Creativity is a subjective concept that is applied differently depending on people and environments. In this work, we engaged fashion design professionals to understand their current design practices, goals, and challenges. Through an iterative process with the fashion designers, we carefully designed and developed an AI-based CST that externalizes three cognitive operations — extending, constraining, and blending — in overcoming design fixation during the fashion design ideation process. Our user study showed many promising results and important insights for improving future designs of AI-based CST. We propose future work that could improve FashionQ AI models and interactive features to further support divergent thinking, constraint discovery, and convergent thinking creative processes, apply FashionQ to the idea implementation phase and longitudinal field deployment studies, and expand the FashionQ framework to other creative domains beyond the fashion design industry.

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