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A Generative Artificial Intelligence (GenAI) System for Fashion Design: A Case Study

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***Abstract*—This study employs a Design Science Research approach to propose a foundational information system design theory tailored for Generative Artificial Intelligence (GenAI) applications in the fashion design process. It delineates meta-requirements and design principles that address both the transformative potential of GenAI, and the unique challenges faced by the fashion sector. To validate the practicality of the proposed design theory, a prototype system was developed and evaluated with feedback from 30 experienced fashion practitioners, confirming its feasibility and effectiveness. Insights from case studies conducted with two Hong Kong-based fashion companies further highlight the benefits and challenges of integrating GenAI into fashion design. While GenAI demonstrates promise in enhancing communication, accelerating design processes, and improving customer engagement and satisfaction, key challenges remain, including the need for high-quality datasets, significant computational resources, and ethical considerations related to AI-generated designs. The design principles derived from this study provide a structured guideline for system designers, offering a practical framework for developing GenAI systems that cater to the specific needs of the fashion industry. By contributing both theoretical and practical insights, this study advances understanding of how GenAI can drive innovation in fashion design and lays a foundation for future research in this domain.**

***Index Terms*—Design science research, design theory, design principle, fashion industry, creative industries**

***Managerial Relevant Statement*—Managers and policymakers can gain considerable benefits from the findings of this study, especially in understanding how GenAI can streamline fashion design processes and enhance product innovation. By investing in GenAI technologies, they can empower designers to generate diverse and innovative garment designs quickly, reduce production costs, and enable rapid prototyping. The study's insights also emphasize the importance of integrating GenAI in customer engagement strategies, as demonstrated through virtual try-on and fashion image manipulation, which allow customers to visualize products and personalize their shopping experiences. Managers can establish strategic plans for GenAI adoption, prioritize staff training, and ensure that GenAI workflows integrate seamlessly with existing fashion design process. For policymakers, the research highlights the need to set clear ethical guidelines, develop best practices, and address potential copyright issues associated with AI-generated designs. By doing so, managers and policymakers can responsibly drive technological innovation while meeting industry standards and enhancing customer satisfaction.**

I. INTRODUCTION

THE recent emergence of Generative Artificial Intelligence (GenAI) represents a transformative breakthrough poised to reshape various sectors. GenAI, a specialized subset of AI, generates new content from existing data, producing meaningful, human-like text, images, audio, and videos [1]. Unlike traditional discriminative AI, which analyzes data to establish boundaries for classification or clustering, GenAI's core innovation lies in its ability to generate diverse, unique content through probabilistic modeling. In a survey conducted by Singla, et al. [2] on AI usage in 2024, 65 percent of respondents reported that their organizations were regularly using GenAI, nearly double the percentage from a previous survey conducted 10 months prior. GenAI is characterized by its adaptability to large datasets and its capacity to produce new and varied content that extends beyond classification tasks [3]. This capability has made GenAI a powerful tool across industries, enabling the creation of novel ideas, designs and experiences [4]. For instance, in the healthcare sector, GenAI is used to generate synthetic medical data, aiding in research and training while preserving patient privacy [5]. In the automotive industry, GenAI assists in designing innovative vehicle models and enhancing autonomous driving systems [6]. These examples highlight GenAI's potential to drive innovation and efficiency on a global scale, indicate that research in GenAI holds global and academic importance.

In the fashion industry, leading fashion brands like Adidas, Stella McCartney, Tommy Hilfiger, Carlings, and Zara have integrated GenAI to improve design, production, and customer engagement [7]. Despite these advancements, there is a critical gap in the literature regarding the tailored design and implementation of GenAI systems specifically for fashion. Existing studies primarily focus on the application of GenAI in generating fashion content [8, 9], but few address the comprehensive design principles necessary for effective integration into fashion workflows. This gap is particularly pronounced in areas such as garment-specific innovation, design customization, and the integration of virtual try-on functionalities. This research addresses these gaps by focusing on the design of GenAI systems specifically tailored to fashion. The core research question guiding this study is: How can a GenAI system be effectively designed for fashion applications?

The novelty of this study lies in its dual approach: first, the development of design principles for GenAI systems that ensure both creative potential and trustworthiness within the fashion industry, and second, the demonstration of these principles through the creation of a working prototype. By applying a Design Science Research (DSR) methodology, this study develops a set of practical design principles for GenAI systems in fashion, which have not been thoroughly explored in previous work. These principles are not only informed by the technological potential of GenAI but are also grounded in addressing key trust concerns, which are critical when implementing AI in creative fields.

This study offers both practical and theoretical contributions. On the practical side, the design principles developed provide a framework for fashion industry practitioners to create GenAI systems that are not only innovative but also reliable, usable, and aligned with the sector's needs. These principles ensure that fashion companies can leverage GenAI's creative capabilities while addressing potential concerns about trust and system usability. From a theoretical perspective, this research extends our understanding of GenAI system design, particularly within the context of the fashion industry. It contributes to the broader field of generative AI by introducing a set of design guidelines that are specific to fashion, a sector where the application of GenAI has been limited. This work bridges a gap in the existing body of knowledge and provides a foundation for future research on the intersection of GenAI and fashion, expanding the theoretical framework for AI system design in creative industries.

II. LITERATURE REVIEW

Several GenAI technologies have been used in the fashion domain, including Generative Adversarial Networks (GANs), Transformers or Large Language Models (LLMs), and Diffusion Models. The ability of these technologies to produce photorealistic images has significantly transformed the fashion design process, as demonstrated by the following applications.

A. Fashion Virtual Try-on

Fashion virtual try-on technology overlays garments onto human model images [9], often using conditional GANs (cGANs) guided by inputs like class labels or multimodal data for realistic results [10]. Research primarily focuses on adapting clothing to fit models in various poses, with notable examples including VITON [11] and Flow-Style VTON [12]. Recent advancements, such as TPD [13] and FLDM-VTON [14] have improved image fidelity, garment realism, privacy, and user customization, to address limitations in earlier models and enhancing virtual try-on applications. GarDiff [15] progressively excavates more prior knowledge about fine-grained garment details to improve o improve diffusion process.

B. Fashion Design

The integration of GANs and LLMs in fashion design has led to significant advancements in AI-driven creativity tools. GAN-based tools like DeepWear [16] and Progressive GAN [17] support practical and abstract clothing design with designer high-quality image generation, while desAIner [18] provides surreal inspirations for ideation. StyleGAN [19] enables shape control in garment creation, and models like those by Yang, et al. [20] highlight GAN's versatility across product categories like shoe design. Recently, LLM applications are expanding in fashion to support innovative design processes, including FashionReGen [21] for trends analysis, FashionVLM [22] for item captions, TGNN [23] for outfit creation, and Fashion Matrix [13] for voice-command photo edits.

C. Text-to-Clothes Translation

Text-to-clothes translation generates outfit images from textual descriptions using descriptions [24]. FashionGAN [24] preserve body shape and pose, StackGAN [25] converts text into clothing images, FACT [26] enhance feature alignment, and SeqAttnGAN [27] ensures consistency with sequential text descriptions. Recent diffusion-based models, such as DiffCloth [28] and Ti-MGD [29], enable detailed garment customization using text, body pose, garment sketches, and textures.

D. Street-to-shop Transfer

Street-to-shop transfer converts images of people wearing clothing into isolated garment images for retrieval or display [30, 31]. rtdGAN [32] generates product images from photos, while CatGAN and TripleGAN [33] improve garment isolation with category attributes. pix2pixHD [34] produced high-resolution, detailed images for improved applications.

E. Garment Transfer

Garment transfer create new clothing items based on reference images. Hobley and Prisacariu [35] used cGAN to adjust garment shape and style, while Jo, et al. [36] created DiscoGAN to apply landscape features to fashion. PISE [37] enables per-region garment control, and more recently, Cao, et al. [38] introduced DiffFashion for structure-aware transfer with diffusion models.

F. Fashion Attribute Editing

Fashion attribute editing modifies specific attributes of fashion items in an image while preserving other details [39]. Fashion-AttGAN [39] targets precise edits, FE-GAN [40] enables sketches and color-based edits, and DesignGAN [41] uses landmark-guided attention for cross-category translation. CFAE [42] combines landmark-based attention with StarGAN and DeepFillv2 for refined edits, while PISE [37] allows selective garment and hairstyle adjustments via parsing maps. More recently, LoopNet [43] refines edited images through two encoder–decoder stages to enable high-fidelity image inversion and fine-grained attribute editing, while FICE [8] includes semantic, pose-related, and image-level constraints when performing text-conditioned fashion-image editing.

While GenAI applications in the fashion industry are rapidly advancing, there remains a significant gap in the literature regarding the tailored design and implementation of GenAI systems specifically for fashion. Few studies have explored the unique design considerations essential to this domain, particularly in addressing industry-specific challenges and integrating GenAI seamlessly into creative fashion design workflows.

III. RESEARCH METHODOLOGY

This study employs the Design Science Research (DSR) methodology by Peffers, et al. [44], a structured approach for conducting design-oriented research in information systems (IS). Consolidates key phases from foundational works (e.g., [45] and [46]), DSR is especially suited to create and validate new artifacts, including conceptual systems. Widely used in recent studies on conceptual system design, DSR is particularly effective for bridging the gap between academic research and practical application, especially within management and IS fields [45]. Its widespread adoption in prior studies (e.g., [47] and [48]) underlines the effectiveness of the DSR methodology in facilitating the design, development, and evaluation of innovative methods that meet the needs of both researchers and practitioners in IS [49]. Its six structured steps (Fig. 1) provide a cohesive and rigorous framework, guiding each phase of this study. Following these clearly defined stages can ensure a systematic approach that rigorously addresses theoretical research gaps while also delivering practical, relevant contributions that align with the needs of the fashion industry. We accomplished each step of the DSR process for developing the design theory to build an effective GenAI systems supporting fashion design process.

A. Identify Problem & Motivation

In this study, we conducted interviews and discussed with 30 experienced professionals from the fashion industry, including designers, merchandisers, and marketers to uncover the challenges and limitations inherent in current fashion design processes. This direct engagement captures a nuanced perspective on the operational hurdles they face, laying a solid foundation for developing a solution that addresses the real needs of the industry.

B. Define Objectives of a Solution

Some researchers explicitly work to translate the problem they are addressing into specific goals or system objectives [46]. These objectives are often referred to as "meta-requirements" (a term used in design science research to describe high-level goals or essential conditions that a system must meet) or simply "requirements." For others, this translation process is less formal and may occur implicitly. For example, it might be integrated into programming and data collection activities or emerge naturally during the process of identifying a relevant and significant problem to address [44]. This study establishes meta-requirements as a strategic framework to categorize goals aligned with industry needs [46] and enhance the solution's potential for meaningful impact in the fashion design field.

C. Design & Development

This research stage involves specifying functions, creating the artifact, and applying design principles derived from the meta-requirements [44]. These principles provide structured guidance for informed design decisions to ensure each element is purposefully crafted to meet the defined needs and address challenges in the fashion design process. This approach not only enhances the coherence and functionality of the artifact but also ensures that it is deeply rooted in the practical requirements of the field.

D. Demonstration

At this stage, the efficacy of the design theory is validated through real-world application, using methods such as experiments, simulations, or case studies [44]. Given the emerging nature of GenAI in fashion, a case-based methodology is ideal for exploring complex, context-driven issues [50]. especially in early research stages [51]. In this study, case studies in two Hong Kong-based fashion companies will implement a prototype based on established design principles. By observing the prototype in practice, stakeholders can directly assess its operational impact and the alignment with industry needs. This validation process can hence solidify the relevance and practical value of the design theory in the fashion sector.

E. Evaluation

The evaluation phase assesses the effectiveness of the artifacts in addressing the identified problem by comparing intended objectives with observed outcomes using performance metrics, satisfaction surveys, and user feedback [44].This study evaluates the proposed solution in three phases: system performance, industry feedback, and real-world application.

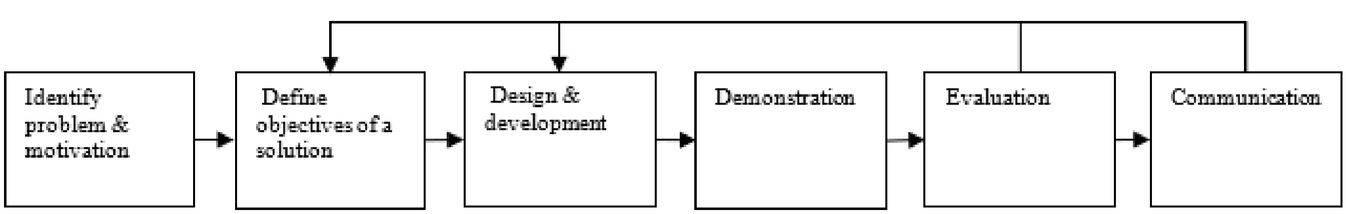

Fig. 1. DSR process proposed by Peffers, et al. [44].

System accuracy is assessed using F1 Score and Mean Average Precision (mAP). Fashion industry professionals evaluate the generated designs for fondness, novelty, complexity, realism, and concept alignment. Potential users assess the system's impact on the fashion design process. This multifaceted approach provides a comprehensive view of the artifacts and ensure they meet industry needs.

F. Communication

Effective communication of the problem, its significance, the developed artifact, its utility, design rigor, and effectiveness is essential for engaging both researchers and practitioners [44]. In this paper, we provide a comprehensive overview of the problem, design theory, artifact, and case study results to share insights with both academic and professional communities. We also emphasized the theoretical and practical contributions in this paper to bridge the gap between theory and practice.

Table I presents an overview of the activities conducted and their corresponding outcomes throughout the six stages of the DSR process in this study.

IV. THE DESIGN THEORY

In this section, we introduce the challenges faced by the fashion industry in the product development process. To address these issues, we propose a set of meta-requirements for an effective GenAI system. Based on these, we develop a list of design principles to guide practitioners in designing an effective GenAI system for the fashion industry.

A. Challenges

In collaboration with a Hong Kong fashion association, we conducted interviews and discussions with 30 fashion industry practitioners to gain insights into the challenges they face in product development process. These interviews highlighted several key challenges, summarized as follows:

1) Challenge 1 (C1). Overcoming Workload and Resource Constraints: The fashion product development process is complex, involving roles such as merchandisers, designers, and buyers. In many small and medium-sized enterprises (SMEs), a shortage of specialized designers forces merchandisers to take on multiple roles, increasing workload and stress. High employee turnover exacerbates this, resulting in lost expertise and reduced efficiency. The industry's fast pace demands a responsive supply chain with short lead times to quickly adapt to shifting trends and mitigate forecasting errors. For instance, Zara swiftly transforms designs into store-ready products within four weeks [52], showcasing the importance of efficient workload and resource management to maintain productivity and drive innovation.

2) Challenge 2 (C2). Inefficient Fashion Image Management: In the product development process, fashion professionals frequently need quick access to images for tasks such as gathering style inspiration, analyzing trends, and conveying design concepts. However, the lack of a systematic approach to organizing and managing these images often results in a tedious, time-consuming search process. Without an efficient image management system, designers and merchandisers spend significant time manually searching through disorganized collections, which hampers creativity and delays their ability to respond swiftly to changing trends and market demands.

3) Challenge 3 (C3). Disputes and Communication Breakdowns: Disputes among collaborators are common during the fashion development process, often arising from differing perspectives among designers, merchandisers, and production teams. Each stakeholder brings unique insights and opinions on product designs, which, if not promptly documented and shared, can be overlooked or misinterpreted. This lack of systematic communication frequently leads to misunderstandings and disagreements, disrupting collaboration and negatively impacting productivity and efficiency.

4) Challenge 4 (C4). Visual Communication Gap: The fashion product development process is inherently complex, requiring both verbal and visual elements—such as sketches and images—to convey creative concepts accurately. Often, ideas cannot be fully expressed in words alone, making visual representation essential for alignment and design refinement. However, effective participation in these visual discussions often hinges on sketching abilities or proficiency with design software, creating a barrier for team members who are not trained designers. This skill disparity can hinder collaboration and limit contributions from individuals with valuable insights but without the means to express them visually.

TABLE I
ACTIVITIES AND OUTCOMES FOR EACH STEP OF THE DSR PROCESS IN THIS STUDY

Stage	Activity	Outcome
Identify problem & motivation	• Conduct interview with practitioners in the fashion industry	Challenges in fashion design process (Section IV.A)
Define objectives of a solution	• Establish meta-requirements that serve as design specifications to address the identified challenges	Meta-requirement (Section IV.B)
Design & development	• Formulate design principles based on the meta-requirements	Design principles (Section IV.C)
Demonstration	• Implement the design principles in a prototype system and incorporates the design features • Conduct a case study within a fashion company	A system prototype (Section V.B)
Evaluation	• Conduct experiments and system evaluation	Experiment and evaluation result (Section V.C)
Communication	• Disseminate the design theory including meta-requirements and design principles that guide the development of GenAI-based systems for fashion design	This paper

B. Meta-Requirements

Building on the challenges outlined in the previous sub-section, we have formulated a list of meta-requirements (MR) for the GenAI system. These meta-requirements serve as critical criteria that must be met to effectively address the identified challenges within the fashion product development process.

1) MR1. Automated Design Generation: The system should employ GenAI algorithms to automatically generate innovative fashion designs based on specified input parameters, such as style, season, color, material, and current trends. By enabling rapid prototyping, the system converts initial concepts into detailed, executable designs, significantly reducing manual effort and accelerating the design process. This automation is especially advantageous for managing high workloads, supporting SMEs with limited staff, and allowing for swift conversion of ideas into review-ready designs. This directly addresses Challenge C1.

2) MR2. Intelligent Image Management: The system should include an intelligence image management module capable of automatically categorizing, tagging, and indexing fashion images based on design elements like patterns, colors, and styles. This module should enable quick and accurate image organization, to streamline the retrieval process and reduce the time spent searching for visual inspiration. By enhancing the management of large image databases, this solution directly addresses Challenge C2.

3) MR3. Enhanced Communication and Documentation: The system should include a feature that logs all communications, decisions, and design changes throughout the project timeline. This documentation capability ensures transparency and accountability by providing a comprehensive audit trail, which helps resolve disputes and prevent miscommunications by clearly illustrating the evolution of design decisions and modifications. By fostering alignment and efficiency among team members, this feature directly addresses Challenge C3.

4) MR4. Visual Collaboration: The system should provide robust tools for real-time design sharing and modification, enabling all team members to contribute visually throughout the design process. By minimizing reliance on physical samples and reducing production timelines, these tools will support rapid design iterations, improving decision-making and coordination, especially in remote settings. This functionality is critical for bridging the visual communication gap identified in Challenge C4.

Table II summarizes the proposed meta-requirements and illustrates the connections between each meta-requirement and its associated challenges. This table demonstrates how the meta-requirements were strategically designed to address the specific challenges identified within the fashion product development process, highlighting the intentional alignment between challenges and their corresponding solutions.

TABLE II
META-REQUIREMENTS AND THE RELATED CHALLENGES

Meta-Requirement	Challenges
R1. Automated design generation	C1
R2. Intelligent image management	C2
R3. Enhanced communication and documentation	C3
R4. Visual collaboration	C4

B. Design Principles

Derived from the meta-requirements established in the previous sub-section, the following design principles serve as guiding concepts for the development process of the GenAI system.

1) DP1. Design for Flexibility: Adapt to various fashion genres and styles to fulfill the requirements of automated design generation (MR1). It must integrate a broad spectrum of fashion styles and historical design influences, enabling designers to create innovative and unique designs. To achieve this, the system should support an extensive palette of design parameters—such as cuts, colors, and textiles—allowing for diverse combinations that produce trend-setting designs. This adaptability is essential for catering to different market segments and personalizing designs to meet specific client demands.

2) DP2. Design for Popularity Prediction: Utilize advanced analytical technologies to proactively analyze and predict the popularity of fashion items based on extensive datasets, thereby guiding the creative process and strategic decision-making (MR1). By scanning vast arrays of data, ranging from current market trends and social media activity to historical collections and consumer behavior, the system can generate actionable insights. These insights will empower designers to stay ahead of market demands by anticipating which designs are likely to resonate with consumers.

3) DP3. Design for Data Integration and Management: Implement robust mechanisms for efficient data management to ensure that fashion images and design data are well-organized and easily accessible. This principle supports advanced image retrieval systems that enhance creativity and productivity, addressing the requirement of intelligent image management (MR2). The system must be capable of handling, organizing, and retrieving large volumes of fashion-related data to ensure that users can quickly access the information they need.

4) DP4. Design for Transparency and Traceability: Establish a system where all modifications, decisions, and communications are traceable and transparent. This principle promotes accountability and facilitates dispute resolution, enhancing communication and documentation (MR3). The system should document every action taken during the design process, making this information readily accessible to all team members. By fostering a transparent work environment, this principle ensures accountability at each stage of the fashion design process, from conceptualization to final production.

5) DP5. Design for Inclusivity: Create inclusive tools that are accessible to all users, regardless of their technical skills or artistic capabilities. By providing user-friendly design tools, every team member can contribute their unique perspectives directly to the design process, facilitating visual collaboration (MR4). For example, these tools should empower merchandisers with limited graphic design skills to visually articulate changes they envision for a product to enhance collaborative input and creativity.

6) DP6. Design for Immersive Virtual Experiences: Develop immersive, realistic experiences that allow detailed previews of how newly generated or modified garments will look and fit on actual human bodies to eliminate the need for physical prototypes (MR1). This capability not only accelerates the development process but also enhances remote collaboration, enabling adjustments and fittings to be conducted virtually (MR4). Such an approach effectively bridges geographical gaps between designers, manufacturers, and clients.

Table III illustrates how each design principle contributes to fulfilling the identified meta-requirements, reinforcing the strategic alignment between the principles and the challenges faced within the fashion product development process.

TABLE III
DESIGN PRINCIPLES AND THE RELATED META-REQUIREMENTS

Design Principle	**Meta-Requirement**
DP1. Design for flexibility	MR1
DP2. Design for proactive trend analysis	MR1
DP3. Design for data integration and management	MR2
DP4. Design for transparency and traceability	MR3
DP5. Design for inclusivity	MR4
DP6. Design for image generation and immersive virtual experiences	MR1, MR4

V. CASE STUDIES IN THE FASHION SECTOR

To effectively demonstrate the efficacy of the developed design theory, comprehensive case studies were conducted in collaboration with fashion companies based in Hong Kong. This practical application allowed for the implementation of the design principles and the observation of their impact in a real-world setting.

A. Background of Cases

Founded in 2017, Company A has quickly risen to prominence as one of the top fashion brands in Hong Kong, specializing in both ready-to-wear and tailor-made cheongsams, as well as antique and modern jewelry. The brand focuses on contemporary interpretations of the traditional cheongsam, a classic Chinese dress inspired by the qizhuang of the Manchu people, infusing modern aesthetics into these iconic garments.

Company B, established in the 1980s, quickly expanded into Mainland China by the 1990s, offerings knitwear, leather, suede, wool, and accessories, and becoming a household name in the casual apparel sector. The brand has developed a robust global network of outlets and maintains a strong online presence across major Chinese e-commerce platforms, including Tmall, Taobao, Jingdong, Douyin, and Dangdang.

To enhance operational efficiencies and deepen customer interactions, both Company A and Company B are eager to integrate cutting-edge technologies. As a result, they initiated a collaborative research project with the research team, which recommends leveraging GenAI technologies to innovate the garment product design process and enrich customer engagement strategies.

B. System Implementation

The research team developed a GenAI-based platform to support the garment design process, with its functionalities and features defined and implemented based on the proposed design principles. The platform, named the Intelligent Inspiration Image Generation Platform (I3GP), leverages GANs and other AI technologies to facilitate the design process and enhance customer engagement for fashion companies. As illustrated in Fig. 2, the platform comprises several interconnected components that work collaboratively.

1) Data Acquisition and Preprocessing Layer: The Fashion Data Collector continuously collects fashion-related data from predefined sources, including both images and text, to build and update the garment product database. Then, the Fashion Data prepares data for further analysis. This involves a text pre-processor that handles tasks such as segmentation and stop word removal, and a visual pre-processor that filters, enhances, and cleans images of clothing items to optimize them for subsequent steps. Once pre-processing is complete, the data is forwarded to the Fashion Data Feature Extractor, which has two specialized engines to extract text and visual features.

TABLE IV
DATA SOURCE AND THE TRAINING SET FOR VIRTUAL TRY-ON

Sources	**Number of images**
Farfetch	17,677
Zara	500
M&S	148
Total	**18,325**

2) Model and Algorithm Layer: This layer consists of four core components: (1) NLP Engine. This component includes tools for text segmentation and sentiment analysis, which are used for feature extraction and text pre-processing, (2) Image Recognition and Segmentation (IRS) Engine. Equipped with tools for image segmentation and garment detection, this engine facilitates visual feature extraction and data pre-processing, (3) Pre-trained GAN Models. These models are used for generating fashion images, modifying attributes, transferring styles, and enabling virtual try-ons. They are *selected based on a thorough* evaluation of their performance and feasibility, and (4) Additional AI Models. These models enhance fashion image classification and support predictive and analytic tasks. The research team conducted evaluations of existing GAN models to identify and implement those that demonstrate strong performance and practical feasibility.

a) New garment image generation: StyleGAN2 [53], an advanced GAN model, was used to create diverse and realistic garment designs. Trained over 800,000 iterations over five days, it produces high-quality fashion images by refining generator normalization,

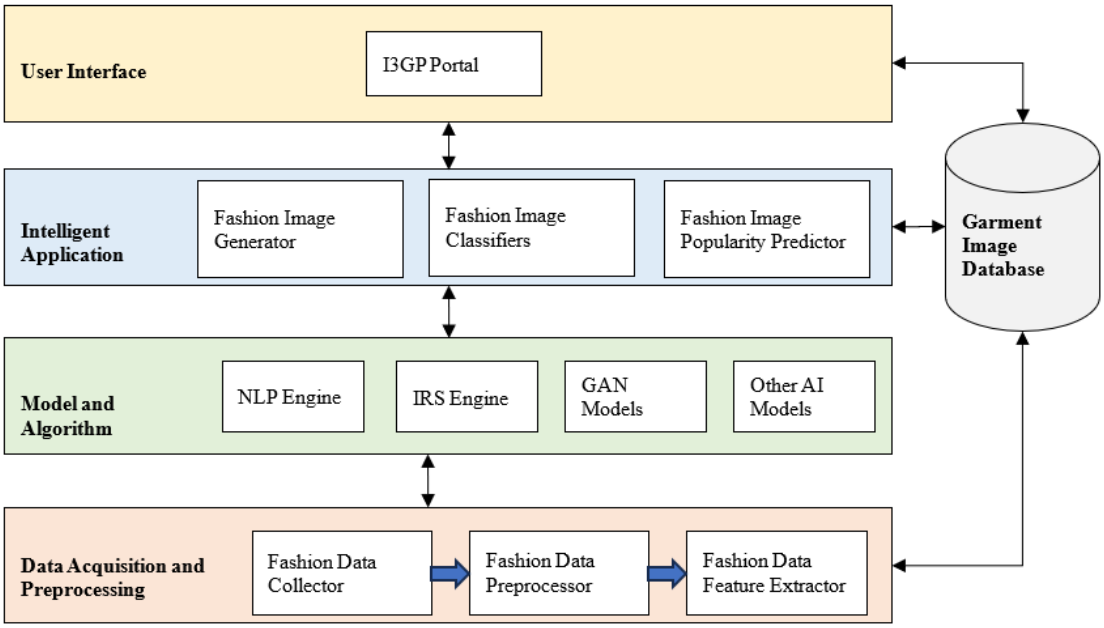

Fig. 2. Architecture of the proposed I3GP.

removing progressive growing, and minimizing artifacts

b) Fashion image manipulation: SOAT (StyleGAN of All Trades) [54] was employed for attribute transfer (e.g., modifying collars) and style adaptation, to enhance design exploration and customer engagement. Fine-tuned across 84 SOAT models, SOAT supports a wide range of attributes, including pattern and styles. By leveraging garment and landmark detectors, SOAT ensures precision while maintaining image quality.

c) Virtual try-on: Flow-Style VTON [12], a StyleGAN-based model, generates realistic try-on visuals by aligning garments with user body images using an appearance flow map. The model was trained using resized data from publicly accessible datasets from Farfetch.com, Zara and M&S (256 x 192 pixels) (Table IV). The data was processed for human parsing and pose estimation.

This project leverages advanced AI algorithms to enhance fashion image classification and support a predictive and analytic task. These models are for their effectiveness in specific classification contexts and optimized for performance. As shown in Table V, multiple AI models are used to perform various classification tasks ([55-57]). This project also introduces a popularity prediction approach by using MLP regression with Inception v3 for feature extraction [58]. Trained on fashion datasets from Amazon and Instagram, this approach predicts item popularity based on visual and contextual features. This allows designers and manufacturers to confidentially evaluate the potential of their designs without public exposure.

3) Intelligent Application Layer: This layer consists of three key modules. (1) Fashion Image Classifier. This module leverages pre-trained AI models and the IRS engine to categorize and label fashion images by identifying specific clothing attributes. This employs robust classification methodologies as detailed in Table V and Appendix A. (2) Fashion Image Generator. This module employs GAN models to create new designs, modify existing ones, and produce virtual try-on images. (3) Fashion Image Popularity Predictor. This module uses an MLP regression model to forecast the popularity of newly generated designs, providing insights into consumer interest without public exposure or comparison to existing items

4) Garment Product Database: This database stores both collected and generated fashion images, along with their associated labels, such as theme, texture, shape, and season. This organization facilitates efficient retrieval and analysis.

5) User Interface (IG3P Portal): The IG3P portal features an

TABLE V

APPROACHES EMPLOYED FOR ATTRIBUTE CLASSIFICATION

Approach	Description	Classification
ResNet50 [55]	It excels in classifying global features such as color and pattern, utilizing residual learning to handle deep network up to 152 layers without accuracy loss.	Image type, Color, Pattern, Fabric, Skirt Style, fashion Style
Yolov5 [56]	The YOLOv5l6 variant, trained on 31,440 images and tested on 7,860 images, was employed for precise garment region detection. Known for its speed and precision, YOLOv5 is ideal for dynamic, real-time garment detection tasks.	Garment type
OSNet [57]	It uses attention mechanisms to detect key local features, making it ideal for fashion attributes in small areas such as sleeve length or neckline, where ResNet50 may lag. With a lightweight 2.2 million parameters and multi-scale feature detection, OSNet processes 1,000 images in under 3.8 seconds on a GPU, and achieves high accuracy in tasks like neckline classification.	Sleeve Length, Neck Design, Dress Style, Pants Type

intuitive user interface that enables users to modify existing concepts by defining parameters and attributes to generate new fashion design images. Users can also search the fashion image database and virtually try on garments. Screenshots of the interface are provided in Appendix B.

C. System Evaluation

The evaluation of the proposed system was conducted in three phases: evaluation of system performance, feedback from industry professionals and real-world applications.

1) Attribute Classification Metrics: For tasks related to attribute classification, we evaluated the effectiveness of our classifiers in identifying image types, garment types, and specific clothing attributes (as outlined in Table VI). These evaluations employed widely accepted quantitative metrics, namely:

a) *F1 Score*: It is a harmonic mean of precision and recall, making it particularly useful in scenarios with imbalanced datasets, which are common in fashion design. This metric ensures a balanced evaluation of classifier performance, taking both false positives and false negatives into account. A higher *F1 Score* indicates that the classifier is effectively capturing the true positive classifications while minimizing errors in attribute classification. It is calculated as:

$$F1\,Score = \frac{2 \times \frac{TP}{TP+FP} \times \frac{TP}{TP+FN}}{\frac{TP}{TP+FP} + \frac{TP}{TP+FN}} \tag{1}$$

where *TP* is True Positive; *FP* is False Positive; TN is True Negative; and *FN* is False Negative.

b) Mean Average Precision (*mAP*): *mAP* is frequently used in object detection tasks and provides a comprehensive measure of precision across multiple categories. In the context of fashion design, mAP is particularly relevant as it measures the accuracy of detecting various garment-related attributes, such as fabric type, color, or style. This metric ensures that the system's classifier performs effectively across diverse and sometimes overlapping categories. It is calculated as follows:

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k \tag{2}$$

where n is the number of classes, AP_k is the average precision of class k.

The evaluation results, presented in Table VI, indicate that the classifiers achieve accuracy scores ranging from 0.80 to 0.97, with an average accuracy of 0.94. These results demonstrate that the classifiers developed in this project perform at a high level of reliability, ensuring robust and accurate attribute classification across diverse fashion images.

2) Evaluation of New Design Generation: To evaluate the quality of fashion design images generated by the GAN-based models, a human preference assessment was conducted. The evaluation involved 30 seasoned professionals from the fashion industry, including 22 designers, four merchandisers, and four fashion production managers. These participants provided perceptual feedback on the generated designs. Each participant had over five years of experience in fashion design and/or production, with a gender distribution of 22 females and eight males. The criteria for evaluation included originality, aesthetic appeal, and feasibility of the designs within current industry trends. During the evaluation, participants were presented with 100 randomly selected fashion design images. They rated these images using a scoring scale ranging from 1 (lowest) to 5 (highest), based on following specific criteria:

- **Fondness**: Evaluates the emotional appeal and aesthetic preference users feel toward the design, reflecting how much they like or connect with it.
- **Novelty**: Measures the originality and uniqueness of the design, assessing how fresh and innovative it appears compared to existing styles.
- **Complexity**: Assesses the level of detail and intricacy in the design, including patterns, textures, and structural richness.
- **Realism**: Evaluates how lifelike and visually convincing the generated image appears, focusing on its resemblance to a real photograph.
- **Alignment with concept**: Evaluates how well the generated design matches the intended design concept, reflecting its consistency with the original idea or theme.

TABLE VI
ACCURACY OF FASHION ATTRIBUTE CLASSIFICATION

Classifier	**Metric**	**Accuracy**
Image Type	*F1 score*	0.97
Garment Type	*mAP*	0.96
Color	*F1 score*	0.92
Pattern	*F1 score*	0.96
Sleeve Length	*F1 score*	0.80
Neck Design	*F1 score*	0.94
Fabric	*F1 score*	0.95
Skirt Style	*F1 score*	0.95
Dress Style	*F1 score*	0.95
Fashion Style	*F1 score*	0.96
Pants Type	*F1 score*	0.95
	Average:	0.94

The results demonstrated that the average score for each criterion consistently hovered around or above 3.5, with an overall average score of 4.01. This favorable feedback suggests that industry practitioners found the GAN-generated fashion designs to be visually appealing and practically valuable, reflecting a high level of satisfaction with the system's capability to produce diverse and high-quality design outputs.

3) Real-World Application: The GenAI system was implemented in a real-world fashion industry setting through a collaboration with Company A and Company B. Potential users participated in a trial of the I3GP system, after which feedback was collected using both structured surveys and open-ended interviews to evaluate its impact on the fashion design workflow. Six potential users from both companies assessed the efficiency of their current fashion design process (without I3GP) and the anticipated improvements with I3GP across various aspects, using a satisfaction scale of 1 (least satisfied) to 10 (most satisfied). As shown. As shown in Table VII, potential users indicated that I3GP would significantly improve their fashion design process.

TABLE VII
PROTOTYPE EVALUATION RESULTS

Aspect	Mean (Standard Dev.)	p-value	Significant?
Communication in meetings	Not using = 3.00 (1. 26) Using = 7.50 (1.97)	<0.001	Yes
Generating new ideas from initial concepts	Not using = 2.33 (0.52) Using = 6.83 (1.83)	<0.001	Yes
Modifying a design (e.g., sleeve length, collar)	Not using = 3.00 (1.26) Using = 7.00 (2.28)	<0.005	Yes
Converting sketches to images	Not using = 3.50 (1.05) Using = 7.00 (1.67)	<0.005	Yes
Searching reference images	Not using = 3.33 (1.37) Using = 7.67 (1.63)	<0.0005	Yes

VI. DISCUSSION

In this study, we proposed a design theory for developing generative AI (GenAI) systems tailored to the fashion design process, accompanied by a comprehensive set of design principles. The design principles we have established serve as a valuable framework for system designers and fashion industry practitioners, offering clear guidance on creating GenAI-based systems to enhance the fashion design process. By articulating these principles, we directly address the core research question: How can a GenAI system be effectively designed for fashion applications? Following these principles, we developed a platform known as I3PG, which serves as a practical case study. As outlined in Table VIII, the features of the proposed platform were meticulously crafted to align with the established design principles. This alignment ensures that the system not only addresses the specific needs of the fashion brand but also exemplifies the theoretical framework underpinning the study, reinforcing the integration of theory and practice in the design of GenAI systems.

Guided by DP1, the fashion image generator of I3GP enables designers to dynamically select and combine a variety of design elements, including colors, patterns, and shapes. This functionality supports the generation and modification of garment images tailored to diverse fashion genres and styles. In alignment with DP2, the fashion image popularity predictor is designed to analyze data from social media and eCommerce platforms, allowing it to forecast the popularity of generated fashion items. This feature provides designers with valuable insights to inform their creative decisions.

To address DP3, we developed a comprehensive garment image database that organizes and stores extensive design data, including images and their associated attributes. Additionally, AI-powered fashion image classifiers are employed to automatically categorize garment attributes stored in the database, significantly enhancing data retrieval and utilization.

The I3GP platform also includes a detailed log of fashion image modifications, promoting enhanced transparency and traceability as outlined in DP4. Furthermore, the user interface is designed to be intuitive, easy to navigate, and accessible to individuals of all skill levels. This ensures that all team members can effectively contribute to the design process, reflecting the principles of DP5.

Finally, the platform offers the capability for newly generated or modified garment items to be fitted on virtual models, providing an immersive experience for both designers and customers. This feature enhances engagement and facilitates a deeper understanding of how designs will appear in real-world contexts.

A. Potential Benefits

Following a thorough review and evaluation of the proposed platform by potential users and industry practitioners, we have identified several key benefits that the integration of this GenAI system could bring to the fashion industry:

1) Enhanced Communication: The proposed system is designed to streamline communication between various internal and external stakeholders involved in the fashion design

TABLE VIII
MAPPING OF DESIGN PRINCIPLES TO DESIGN FEATURES

Design Principle	Design Features
DP1. Design for Flexibility	Generates fashion images based on diverse user-defined criteria, supporting customized and adaptable design outputs.
DP2. Design for Popularity Prediction	Evaluates and forecasts the potential popularity of newly created garment items, empowering brands to make data-driven design decisions.
DP3. Design for Data Integration and Management	Organizes and integrates extensive collections of fashion images and datasets, ensuring seamless access and efficient management. By consolidating diverse data sources, the system automates the classification of key clothing attributes to enhance processing accuracy.
DP4. Design for Transparency and Traceability	Offers a detailed history of image modifications, fostering accountability and transparency throughout the design process.
DP5. Design for Inclusivity	Features an intuitive, user-friendly interface to improve accessibility for a diverse range of users, fostering inclusivity in the design experience.
DP6. Design for Image Generation and Immersive Virtual Experiences	Enables virtual try-ons of newly generated or modified garments, creating an engaging and interactive shopping experience that enhances user engagement. Leverages automated, rapid image generation to support on-demand creation of fashion visuals, empowering designers to experiment and iterate efficiently.

process. Users can modify designs collaboratively during face-to-face or virtual meetings, enabling them to demonstrate ideas in real-time and facilitating more effective discussions.

2) Accelerated Fashion Design Cycle: By utilizing the platform, the fashion design cycle can be significantly shortened. Merchandisers, even those without extensive experience in professional design software, can make modifications directly on the platform. This capability eliminates the need to wait for overloaded designers to implement minor changes, thereby speeding up the overall design process.

3) Increased Customer Engagement and Satisfaction: The platform transforms the way fashion brands interact with their customers by providing a highly personalized and engaging experience. It allows customers to design their garments by transferring styles from other images and customizing various attributes such as colors, patterns, and fits, ensuing the final products aligns with their individual preferences. Through direct manipulation of garment images, customers can effectively communicate their unique preferences and specific requirements to designers, bridging the gap between creative vision and execution. Additionally, the virtual try-on feature provides customers with a realistic preview of how different garments will look and fit, helping them make more confident purchasing decisions. By offering this immersive and interactive experience, the system fosters deeper engagement, as customers can experiment with styles and visualize outcomes in real-time. This tailored approach not only boosts customer satisfaction but also enables brands to gather valuable data on preferences and trends, which can be used to refine product offerings and marketing strategies. Ultimately, this fusion of personalization, creativity, and advanced technology elevates the overall shopping experience, creating stronger, more meaningful relationships between fashion brands and their customers.

B. Challenges and Barriers

Through this case study, we identified several technological and managerial challenges and barriers that may arise when implementing GenAI in the fashion industry.

1) Technological Challenges

a) Data collection: High-quality and diverse datasets are essential for training GenAI models to generate realistic and varied fashion designs. However, obtaining a large and representative dataset that accurately reflects different styles, materials, and body types poses significant challenges. Furthermore, as fashion trends evolve rapidly, it is crucial to continuously update these datasets. The system employs web crawling technology to collect data from various webpages regularly, utilizing a proxy server to navigate the virtual environment. However, frequent access to certain web servers can result in the web crawler being blocked, hindering the collection of necessary data. Therefore, the technical team must regularly review and update the crawler to ensure it operates effectively without encountering access issues.

b) Data quality: While numerous websites and social media platforms offer a wealth of fashion-related data, not all sources are reliable or of high quality. A search may yield numerous results, but many websites contain subpar data that cannot be utilized effectively. For instance, certain social media platforms may feature a plethora of fashion images, but if these images do not display the complete garment, they become unusable for training purposes. Consequently, the project team must invest considerable effort in identifying and vetting reliable data sources that provide accurate and relevant information.

c) Training stability and model collapse: GenAI models, particularly GANs, are often plagued by training instability. Issues such as model collapse, where the generator produces a limited variety of outputs, can be especially detrimental when striving for a diverse array of fashion designs. This limitation may result in a homogeneity of generated designs, potentially stifling innovation, and creativity, as the models may fail to explore the full spectrum of possible design spaces. To mitigate these issues, continuous monitoring and adjustment of the training process are necessary to identify and address any training instabilities early on.

d) Generalization across different styles and trends: GenAI models trained on specific datasets may struggle to generalize across diverse fashion styles or rapidly changing trends. The learning of these models is confined to the data they were trained on, which may not encompass future trends or a wide array of cultural styles. Consequently, users aiming to leverage GenAI for designing across various styles or for anticipating emerging trends may find their models quickly becoming outdated or irrelevant. To enhance the generalization capabilities of GenAI models, it is crucial to curate diverse and comprehensive datasets that cover a wide range of styles and trends. Additionally, continuously updating the dataset to incorporate new trends and employing few-shot learning techniques can significantly improve the model's adaptability to emerging styles.

2) Managerial Challenge

a) Cost and resource allocation: Implementing GenAI models necessitates considerable computational resources for training, including high-performance GPUs and substantial memory capacity. This requirement can pose a significant barrier for small to medium-sized fashion companies that may lack access to the necessary computational infrastructure. For example, training GANs to generate fashion images entails not only initial computational expenses but also ongoing costs associated with model updates, infrastructure maintenance, and potentially cloud computing services if local resources are inadequate. These financial burdens can be particularly daunting for smaller organizations, making it difficult for them to absorb such technological investments without straining their budgets.

b) Ethical and legal issues: The deployment of GenAI raises several ethical concerns, particularly regarding design originality and copyright compliance. Since GenAI models learn from existing data, there is an inherent risk of generating designs that closely resemble copyrighted works. This situation necessitates careful navigation of ethical and legal challenges to avoid infringement issues, which could limit the creative freedom associated with using GenAI technologies for design inspiration. To address these concerns, it is essential to establish clear guidelines and best practices for employing GenAI in fashion design, emphasizing respect for copyright and ensuring the originality of generated outputs. Utilizing GenAI as a tool for inspiration rather than direct design generation can help mitigate some of these issues. Moreover, integrating legal and ethical consultations into the development and deployment processes can further safeguard against potential violations and promote responsible usage of GenAI technologies.

VII. Conclusion

A. Theoretical Implications

This study makes significant contributions to the existing body of knowledge by developing a design theory for GenAI systems tailored for fashion design and providing empirical evidence regarding the effectiveness and challenges associated with integrating GenAI into the fashion industry. Specifically, this study contributes to the following aspects.

Firstly, this research advances theoretical contributions by presenting a robust design theory and a specialized set of principles tailored to the unique requirements and challenges of implementing GenAI systems in the fashion design industry. In contrast to prior literature, which often focuses on the use of GenAI solutions in the fashion industry (e.g., [8], [28] and [34]), this study provides a structured approach for implementing GenAI, that goes beyond mere adoption. By aligning GenAI solutions with the operational demands of fashion design, our study offers a comprehensive framework that addresses both technological and practical aspects, thereby filling a critical gap in the literature. Additionally, this study contributes concrete design artifacts, a GenAI system architecture and a functional prototype, that serve as practical frameworks for integrating GenAI into fashion.

Our study distinguishes itself from traditional theoretical AI adoption frameworks by incorporating real-world validation through case studies and a functional prototype. These contributions not only provide empirical evidence supporting the proposed framework but also offer actionable guidance for practitioners. By bridging theoretical insights with practical implementation, our design theory advances theoretical understanding while providing practical insights for integrating GenAI into fashion design.

Traditional AI frameworks often focus on barriers and drivers to adopting AI [59], AI readiness [60]. Our study goes further by addressing how GenAI systems should be designed and operationalized to meet creative and practical demands of fashion design process. Unlike standard frameworks (e.g., [61]) that provide generalized approaches to AI adoption across industries, our design theory is tailored to the unique needs of the fashion industry. It explicitly addresses challenges such as garment-specific innovation, design customization, and the integration of virtual try-on functionalities, which are not typically considered in generic AI adoption models.

Secondly, this study underscores the vital role of cross-disciplinary research that bridges information systems and fashion design. It offers theoretical validation for integrating GenAI technologies, within creative industries. By demonstrating how this integration drives innovation and improve design processes, the research highlights the profound impacts of merging cutting-edge technology with creative disciplines. This intersection is particularly significant as it paves the way for further interdisciplinary collaborations, enriching both fields and facilitating a more comprehensive understanding of how technology can drive creative expression while providing valuable cross-disciplinary insights.

B. Managerial Implications

The findings of this study offer actionable insights for fashion practitioners seeking to leverage GenAI to enhance their design processes. Specifically, this study yields the following managerial implications for industry managers and practitioners:

Firstly, for managers and strategists in the fashion industry, the study illustrates the significant benefits of investing in GenAI technologies. The real-life case study provides concrete, relatable evidence of how GenAI can be applied successfully in practice. It demonstrates how GenAI can be leveraged to generate innovative garment designs, empowering designers to explore a broader array of creative possibilities without the constraints imposed by traditional design methods. The findings here suggest that GenAI offers a substantial shift toward speed and efficiency, which can speed up the fashion design process to fulfill the need of the fashion industry [62]. Furthermore, the case study showcasing the implementation of GenAI-based methods for virtual try-on and fashion image manipulation highlights the potential of these technologies to enhance customer engagement. By enabling customers to visualize how garments would look on them or experiment with different styles, fashion brands can offer a more personalized shopping experience, which is an emerging trend within the fashion industry.

Secondly, through this study, managers gain valuable insights into the specific challenges of implementing GenAI, enabling them to anticipate and plan for both technological and managerial obstacles. For example, the need for high-quality, continually updated datasets and model stability highlights the complexity of maintaining realistic and relevant designs [63]. Additionally, understanding the substantial computational costs and resource demands, especially for smaller companies, prepares managers to allocate budgets effectively and assess infrastructure requirements. The study also emphasizes the importance of addressing ethical and legal concerns, such as copyright and originality, highlighting the need for clear guidelines and best practices. Equipped with this knowledge, managers can make more informed decisions, strategize for sustainable GenAI integration, and navigate the industry's evolving technological landscape responsibly.

C. Alignment with Engineering Management Practices

The proposed GenAI system aligns with key engineering management practices by:

1) Promoting Agility and Adaptability: The platform enables rapid adjustments to designs and processes, helping organizations stay responsive to evolving market conditions and technological advances. This supports engineering management's need to be agile in a dynamic business environment.

2) Supporting Workforce Development: By simplifying design tasks, the system reduces the need for specialized skills, allowing for easier onboarding and employee training. This aligns with policies focused on workforce inclusivity, upskilling, and empowering a broader group of employees to contribute to engineering tasks.

3) Enhancing Resource Efficiency: The system optimizes resource utilization by reducing dependency on professional designers for minor modifications, thereby aligning with sustainability and cost-efficiency goals.

4) Facilitating Strategic Decision-making: By providing actionable insights through user interactions and design data, the system aids managers in making informed decisions about product development, resource allocation, and customer engagement strategies.

D. Limitations and Future Study

This study offers valuable insights into GenAI applications in the fashion sector but has several limitations. The case study focuses on two fashion companies, primarily based in Hong Kong and Mainland China, which may limit the generalizability of the findings across different regions and cultures. Future studies could explore additional companies and regions to broaden the practical utility of GenAI in the fashion industry. This includes developing concrete implementation steps for small and medium-sized enterprises (SMEs) with limited resources. Additionally, incorporating real-time customer feedback loops to dynamically refine AI-generated designs and examining the role of GenAI in promoting sustainable fashion practices are promising areas for further exploration. To improve the generalizability of our findings, future research should prioritize cross-regional testing. This approach will help validate the insights across diverse geographic and cultural contexts, thereby making the results more universally applicable.

As ethical and legal issues are identified as key challenges in adopting GenAI within the fashion industry, these considerations warrant further attention. Specifically, addressing copyright and originality concerns is essential. Future research should focus on developing mechanisms to ensure the originality of AI-generated designs while mitigating copyright infringement risks, which would be both theoretically enriching and practically valuable for industry practitioners.

E. Concluding Remarks

This study presents a tailored design theory and guiding principles for implementing GenAI in the fashion industry, highlighting both its potential benefits and associated challenges. The insights gain from case studies emphasize the need for the industry to navigate technical complexities, address ethical concerns, and keep pace with rapid GenAI advancements. By merging theory with practical insights, this research contributes to academic discourse and offers actionable strategies for practitioners to effectively and responsibly integrate GenAI into fashion design.

APPENDIX

A. Classifiers and the Corresponding Attributes

Classifier	**Group**	**Attributes**
Color (12)	Color (12)	Black, blue, brown, cyan, green, gray, pink, purple, orange, yellow, white, red
Pattern (22)	Pattern	Plain, vertical stripes, horizontal stripes, argyle, checkered, chevron, geometric, houndstooth, letters, zebra, polka dot, camouflage, floral, galaxy, leopard and cheetah, tie dye, graphic, paisley, ripped quilted, sequin, embroidery
Sleeve Length (8)	Sleeve Length (8)	Sleeveless, cap sleeves, short sleeves, elbow length sleeves, 3/4 sleeves, wrist length sleeves, long sleeves, extra long sleeves
Neck Design (23)	Neckline (11)	Turtleneck, strapless neck, deep v neckline, straight neck, v neckline, square neckline, off shoulder, round neckline, sweetheart neck, one shoulder neckline, halter
	Collar (9)	Collarless, ruffle semi-high collar, draped collar, shirt collar, peter pan, puritan collar, rib collar, hooded, pussy bow
	Lapel (3)	Notched, shawl, plus size shawl
Fabric (4)	Fabric (4)	Lace, fur, leather, denim
Skirt Style (9)	Skirt Style (9)	A-line, draped, godet, mermaid, pencil, pleated, skater, tiered, tulip
Dress Style (17)	Dress Style (17)	Halter dress, Bardot dress, high-low dress, mermaid dress, pinafore dress, pencil dress, peplum dress, shirt dress, smock dress, t-shirt dress, tube dress, A-line dress, ball gown, blouson dress, strappy dress, wrap dress, shift dress
Fashion Style (6)	Fashion Style (6)	Gothic, rococo, regency, bohemian, pinup, sporty
Pants Style (6)	Pants Style (6)	Straight, skinny, boot-cut, wide leg, sweatpants, peg leg

B. SCREENSHOT FOR I3GP

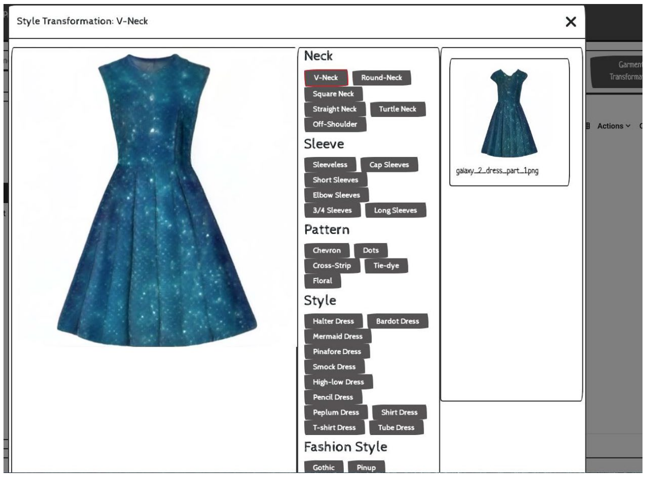

Fig. B.1. Screenshot for modifying parts of a garment design.

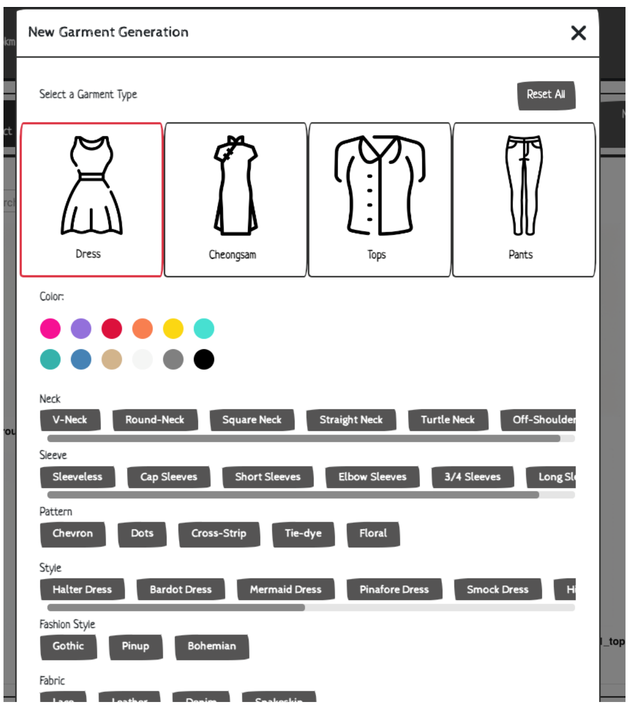

Fig. B.2. Screenshot for selecting attributes for new garment design generation.

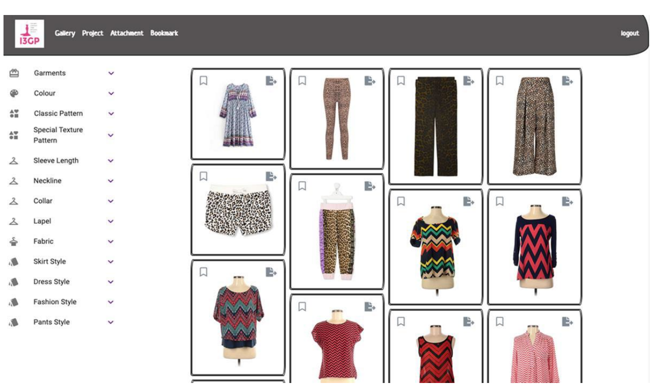

Fig. B.3. Screenshot for the search in the fashion image database.

Fig. B.4. Screenshot for putting different garment item on the model.

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