



# Chapter 5

## AI Generative Models for the Fashion Industry

**A. Firos**

 <https://orcid.org/0000-0003-4207-713X>  
Rajiv Gandhi University, India

**Seema Khanum**

 <https://orcid.org/0000-0002-2933-2717>  
Indian Computer Emergency Response Team (ICERT), MeitY, Electronics Niketan, India

### ABSTRACT

*Fashion designers and brands use GANs to create new and unique patterns, styles, and textures. GANs consist of a generator and a discriminator, which work together to produce high-quality, realistic outputs. VAEs are another type of generative model that is applied to generate new fashion designs. VAEs are known for their ability to generate diverse outputs by sampling from a learned latent space. Fashion designers can use VAEs to explore different design variations and styles. StyleGAN and its successor, StyleGAN2, are advancements of GANs that specifically focus on generating high-resolution and realistic images with control over different style elements. These models have been employed in fashion to create detailed and visually appealing designs. These AI generative models have the potential to revolutionize the fashion industry by facilitating creativity and providing new avenues for artistic expression. However, it's essential to consider ethical implications, intellectual property rights, and the responsible use of AI technologies in the context of fashion design.*

### INTRODUCTION

#### Generative Models for Fashion Industry Using Artificial Neural Network

Generative models, particularly those based on deep neural networks, have found significant applications in the fashion industry (Sohn et al., 2020). These models can create new and realistic designs, assist in trend forecasting, and streamline various aspects of the fashion production pipeline. Here are several types of generative models commonly employed in the fashion industry are Generative Adver-

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sarial Networks (GANs), Variational Autoencoders (VAEs), Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs) Conditional Generative Models and StyleGAN.

Generative Adversarial Networks (GANs) are widely used for generating realistic and novel fashion designs (Yan et al., 2022). They consist of a generator network that creates synthetic data and a discriminator network that evaluates the authenticity of the generated samples. Generative Adversarial Networks (GANs) can generate new clothing designs, patterns, and textures (Sun et al., 2019). GANs can simulate how a garment looks on a person, facilitating virtual try-on experiences. GANs can transfer styles between different images, allowing for creative adaptations of fashion elements.

Variational Autoencoders (VAEs) are used for generating new samples while also learning a structured latent space (Yuan et al., 2020). This makes them suitable for generating diverse and meaningful fashion designs. VAEs can generate diverse styles within a particular fashion category. VAEs can learn individual preferences and generate personalized fashion recommendations (Simian et al., 2022).

Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs) are used for sequence generation and can be applied to generate fashion-related sequences such as clothing designs, patterns, or even fashion-related text. RNNs/LSTMs can generate intricate textile patterns (Lee, 2022). It can also be used for generating descriptive captions for fashion images or designs.

Transformer-based architectures like GPT (Generative Pre-trained Transformer) can be fine-tuned for various fashion-related tasks, including design generation, trend analysis, and fashion language understanding (Särmäkari et al., 2022). It can be used for Trend Forecasting where we use it for analyzing large volumes of fashion-related text to identify emerging trends. It can be also used for Generating creative and appealing product descriptions for fashion items.

Conditional Generative Models generate samples based on specific conditions (Guo et al., 2023). In the fashion industry, this could include generating designs conditioned on certain style preferences or user characteristics (Kang et al., 2017). It can be used Personalized Design Generation where we create designs based on user input or preferences. It can also be used for generating Seasonal Collections where we Generate designs tailored to specific seasons or themes.

An extension of GANs, StyleGAN focuses on controlling the style of generated images (Kato et al., 2018). This can be applied to generate diverse and realistic fashion styles. StyleGAN is used for Creating models that allow users to control specific aspects of style in generated fashion designs.

These generative models contribute to various stages of the fashion industry, from design conceptualization to trend forecasting and personalized shopping experiences. They enhance creativity, reduce design iteration times, and enable more efficient and personalized interactions with consumers. Additionally, the continual evolution of generative models and deep learning techniques contributes to ongoing advancements in the field (Wu et al., 2021).

## **Deep Neural Network for Giving Suggestions**

Deep Neural Networks (DNNs) are often used in recommendation systems to provide personalized suggestions (Boussiou et al., 2023). Deep Neural Networks will do the Data Collection first, where it will do the user data collection and item data collection. For User Data it gathers information about users, their preferences, behaviors, historical interactions, and any other relevant data. For Item Data it

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