Smart Wardrobe Systems: A Survey of AI, ML, and DL Models for Weather and Mood-Based Clothing Recommendations

Bhavana BR, Maruthi H N, Mallikarjun H Sasvihalli

Department of Master of Computer Application

Surana College (Autonomous), Bengaluru, India

ABSTRACT

In today's world, where personalization and smart technology are all the rage, smart wardrobe systems are really making waves. They offer clothing suggestions that adapt to your preferences, mood, the weather, and your lifestyle. Thanks to the rise of Artificial Intelligence (AI) in the fashion industry, machine learning (ML) and deep learning (DL) techniques have taken the lead over traditional methods, providing much better accuracy in figuring out what outfits work best. This paper dives into a thorough review of AI-powered outfit recommendation systems (ORS), showcasing the latest advancements that combine environmental factors like temperature, humidity, and seasonal changes with emotional signals such as mood, feelings, and facial expressions. A variety of machine learning methods, including K-Nearest Neighbors, Decision Trees, Random Forest, and Support Vector Machines, have been used to understand style preferences and predict outfit pairings. On the other hand, deep learning methods, especially Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), Transformers, and attention-based models, have transformed how we match outfits and forecast trends based on images. The survey also looks into explainable AI (XAI) applications that make model predictions clearer and build trust with users. Additionally, it reviews multimodal systems that use weather APIs, smart mirror technology, and wearable sensors to provide real-time clothing recommendations based on the situation. We organize research from 2022 to 2025 into different categories, including content-based, collaborative, hybrid, and generative models. Important datasets like DeepFashion, FashionGen, and Chictopia10K are examined, along with tools such as TensorFlow, PyTorch, and OpenPose. The paper highlights key challenges like scaling personalization, mood misclassification, cultural differences in preferences, and data scarcity. Looking ahead, it suggests exploring smart textiles that can help regulate mood, integrating these technologies into our daily lives.

Keywords— Smart Wardrobe, Outfit Recommendation, AI in Fashion, Weather-based Recommendation, Mood-based Fashion, Deep Learning, Explainable AI, Multimodal Systems

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INTRODUCTION

Fashion is more than just clothing—it's a way to express yourself. But with endless options online, putting together the perfect outfit can feel overwhelming. What if your wardrobe could understand your style, suggest matching clothes, and even adapt to your mood or the weather? Thanks to artificial intelligence (AI), this futuristic idea is now a reality.AI and ML have revolutionized fashion recommendation systems by leveraging large-scale datasets to predict user preferences and outfit compatibility. Techniques such as *collaborative filtering*, *matrix factorization*, and *reinforcement learning* have been employed to analyze user interactions and generate relevant suggestions [**10**]. However, traditional ML approaches often fail to capture the complex relationships between fashion items, leading to suboptimal recommendations. Recent advancements in *self-attention mechanisms* and *transformer-based models* [**3**] have enabled more sophisticated outfit generation by modeling long-range dependencies between items, thereby improving both relevance and diversity. Deep Learning (DL) has significantly enhanced fashion recommendation systems by enabling *end-to-end learning* from multimodal data, including images, text, and user behavior. *Convolutional Neural Networks (CNNs)* have been widely adopted for visual feature extraction, allowing models to assess garment compatibility based on color, texture, and style [**17**]. More recently, *Vision Transformers (ViTs)* have demonstrated superior performance in capturing global outfit aesthetics by treating fashion items as sequential tokens [**41**]. Additionally, *sequence-to-sequence models* and *autoregressive architectures* like GPT and BERT have been adapted for outfit generation, enabling personalized recommendations conditioned on user history and contextual signals [**8**].Despite the success of AI-driven fashion systems, a key challenge remains their *black-box nature*, which limits user trust and interpretability. *Explainable AI (XAI)* techniques, such as *attention visualization*, *feature attribution*, and *counterfactual explanations*, are being integrated to provide transparency in recommendations .For instance, transformer-based models can highlight which items contribute most to an outfit's compatibility, while post-hoc interpretability methods help users understand why certain recommendations are made. By combining DL-powered personalization with explainability, future systems can enhance user engagement while maintaining accountability.

2. LITERATURE REVIEW

Imagine waking up to a wardrobe that not only knows your style but also understands the weather and your mood. This isn't science fiction anymore—thanks to artificial intelligence, smart wardrobe systems are revolutionizing how we dress every day.Let's explore how researchers are making this possible. The latest breakthroughs in AI are making fashion recommendations incredibly personalized. [**47**] created *Fashion former*, a system that understands how different clothing items work together, much like how a skilled stylist would. Their technology proved 18% more accurate than traditional recommendation methods, especially when adapting to changing weather conditions. Similarly,[**19**] developed a *weather-aware* fashion assistant that checks real-time forecasts before suggesting outfits. Imagine your wardrobe automatically swapping out a light jacket for a raincoat when storms are predicted—this system improved user satisfaction by 22% by doing just that. While earlier AI systems struggled to grasp why certain outfits work, new approaches are changing that.[**42**] used advanced *Vision Transformers* to analyze entire outfits holistically, achieving 91% accuracy in matching styles—outperforming older methods that often missed the bigger picture. [**7**] took this further by connecting clothing choices to emotions. Their system can suggest bright, cheerful outfits when you're happy or more subdued looks when you're feeling low, proving that AI can be surprisingly intuitive about human feelings. One major hurdle? When AI suggests outfits without explaining why. [**15**] solved this by creating visual guides that highlight matching elements—like showing how a scarf's color complements your coat. Users trusted these explained recommendations 40% more than mysterious ones. Found people prefer systems that learn from feedback. Imagine telling your wardrobe app, "I'd never wear this," and having it actually remember your preferences—that's the direction fashion AI is heading.

[**31**] built a system that prevents fashion faux pas like suggesting winter coats in summer, reducing inappropriate recommendations by 35%. Meanwhile,[**34**] are experimenting with mood-detecting headbands that help AI suggest outfits matching your emotions—whether you need professional attire for a meeting or cozy clothes for a lazy Sunday. Major retailers are already implementing these technologies. Zalando's AI stylist [**37**] combines weather data with your shopping history, though it still struggles with new users. H&M [**1**] is testing smart wardrobes that learn your style while protecting your privacy—no human stylist needed.

Figure 1: Mood and Weather-based Influences on Outfit Selection

3. CLASSIFICATION OF APPROACHES

The journey of fashion recommendation systems (FRS) has led to the development of various architectural styles, each with its unique way of processing data, handling context, and personalizing suggestions. In this section, we break down smart wardrobe approaches into five main categories based on their modeling techniques and how they integrate data: (i) content-based models, (ii) collaborative filtering, (iii) hybrid methods, (iv) deep learning- based models, and (v) generative and contextual AI systems. Each of these categories showcases different levels of interpretability, scalability, and awareness of context, especially when it comes to recommending clothing that suits the weather or a person's mood.

3.1 CONTENT-BASED FILTERING

Content-based systems suggest outfits that are similar to those users have previously liked, using item metadata like color, fabric, brand, or category. These models rely on similarity metrics such as cosine similarity, Euclidean distance, or TF-IDF applied to manually labeled garment attributes. For example, Deldjoo et al. [**23**] and IJRPR [**45**] created style-based filtering systems that matched clothing based on visual tags and material descriptions. While these methods are straightforward to implement, they often lack variety and struggle to adapt beyond established preferences.

Table 1: Comparison of Contextual Factors in Fashion Recommender Systems

Contextual Factor	Model Type Used	Key Papers	Input Source	AI Technique
Mood	CNN, NLP, ResNet, SVM	Shinkaruk (2019), IJRPR (2022)	Face, Text, Sensors	Affective Computing
Weather	CNN, Rules, Ran- dom Forest	Liu & Gao (2022), Celikik (2022)	Weather APIs	Forecasting + Recommendation
Event/Occasion	Transformer, Deci- sion Tree, Ensem- ble	Djilani et al. (2025) , StyleSync	User Input	Context Embedding
Time/Season	Temporal Models, Attention Networks	Deldjoo et al. (2022)	Calendar + Geo-data	Time-Aware RS
Body Type	GAN, CNN, Style Transfer	Wazarkar et al. (2022), WearMe	Image or Manual Data	Adaptive Generation

3.2 COLLABORATIVE FILTERING MODELS

Collaborative filtering (CF) recommends outfits by looking at the preferences of a community of users. These systems utilize techniques like matrix factorization, k-nearest neighbors, or neural CF to uncover hidden interactions between users and items. Shirkhani et al. [**39**] showed how collaborative methods can enhance performance in cold-start situations and improve personalization in shared contexts. However, these systems can be hindered by sparse data and often fall short in scenarios where mood or weather is crucial, as individual context plays a significant role.

3.3 HYBRID RECOMMENDER SYSTEMS

Hybrid approaches blend content-based and collaborative methods, often incorporating contextual metadata. Surya et al. [**43**], Moorthy et al. [**30**], and *Fashion Fusion* (2024) have successfully integrated weather APIs, occasion tags, and user profiles to recommend clothing using hybrid machine learning models like Decision Trees, Random Forests, and SVMs. These systems strike a balance between personalization and diversity, providing flexible architectures that are perfect for everyday fashion advice. They're particularly popular in mobile apps that rely on real-time data and have limited computing power.

3.4 DEEP LEARNING-BASED SYSTEMS

Deep learning models are adept at extracting high-level semantic and visual features from clothing images and user profiles. Commonly used architectures include CNNs, RNNs, and Transformers for tasks like image classification, outfit compatibility scoring, and modeling user preferences over time. Sarkar et al. [**36**] and Celikik et al. [**2**] utilized self-attention networks to create outfit representations that enhance compatibility-aware recommendations. Liu & Gao [**43**] introduced a CNN-based system that maps weather to garments, showcasing impressive accuracy in real-world weather conditions. While these models demand large datasets and significant computing power, they excel in generalization and adaptability.

3.5 GENERATIVE AND CONTEXT-AWARE AI SYSTEMS

Recent breakthroughs in generative AI and affective computing have paved the way for systems that can create unique outfits and adjust to contextual factors like mood, season, and body type. Choi et al. [**42**] and Nahid- Ull-Islam et al. [**42**] employed GANs and VAE architectures for dynamic outfit generation. *FitGenie* (2024), *WearMe* (2024), and *StyleSync* (2025) have integrated mood and location inputs through CNN + NLP pipelines and wearable sensors. Context-aware systems often feature Explainable AI (XAI) modules to foster user trust by offering understandable suggestions. Although these models represent the cutting edge of technology, they still grapple with issues related to privacy, generalization, and standardization. The above content is summarized and presented in Table 1.

4 DATASETS AND TOOLS

To build culturally sensitive and intelligent outfit recommendation systems, especially for Indian traditional clothing, researchers can leverage several publicly available or custom-built datasets. The DeepFashion dataset from CUHK is one of the most comprehensive collections, containing 800,000+ labeled images. While it primarily focuses on Western wear, it can be adapted for ethnic fashion tasks through filtering and relabeling. For Indian- specific attire, the Indic Fashion Dataset from IIT-Hyderabad provides a specialized collection with images of sarees, kurtas, lehengas, and salwar suits, although it may require contacting the authors for access. On Kaggle, community-driven datasets such as the Indian Saree Dataset and Kurti Dress Dataset offer smaller but focused sets that are ideal for experimentation and fine-tuning. For researchers aiming to customize their dataset, platforms like Myntra, Ajio, and Flipkart can be scraped to gather images of traditional outfits. An example project that demonstrates this is hosted on GitHub, where scraping and TensorFlow-based classification for traditional Indian wear are shown. Additionally, the iMaterialist Fashion dataset, released by Google and Visipedia, contains over 500,000 annotated images for a wide range of fashion items. Though not India-specific, it is highly useful for pretraining deep learning models that can later be fine-tuned for Indian ethnic wear classification and recommendation. These datasets enable a variety of AI applications, including clothing classification, fashion compatibility prediction, and personalized outfit recommendations that respect cultural nuances in Indian and global contexts.

Table 2: Selected Papers Used in the Survey with Key Focus Areas

Title	**Authors / Year**	**Key Focus / Relevance**
H&M's Smart Wardrobe: Integrating IoT and AI for Personalization	Andersson & Johansson (2022)	Industry case study on IoT-enabled wardrobe personalization.
Fashion is a Form of Self-Expression	sampath Kumar (2022)	Discusses fashion as a personal identity medium; relevance in mood-aware systems.
Outfit Generation and Recommendation: An Experimental Study	Celikik et al. (2022)	Comparative analysis of outfit generation using attention networks.
Reusable Self-Attention-Based Recommender System for Fashion	Celikik et al. (2021)	Self-attention for fashion recommendation with improved contextual awareness.
Clip-Enabled Style Transfer for Personalized Fashion Recommendations	Chen & Wang (2023)	Uses CLIP for cross-modal outfit personalization.
Personalized Outfit Generation for Fashion Recommendation	Chen et al. (2019)	Sequence-to-sequence outfit generation using user history.
Developing an AI-Based Auto- mated Fashion Design System	Choi et al. (2023)	GAN-based automated clothing design system.
A Review of Modern Fashion Recommender Systems	Deldjoo et al. (2022)	Survey of algorithms and datasets in fashion recommendation.
Trend-Aware Fashion Recommendation with Visual Segmentation	Djilani et al. (2025)	Uses visual + semantic features for seasonal trend prediction.
Why Did You Recommend That? Explainable AI for Fashion Outfits	Gupta & Roberts (2023)	XAI-based interpretability in outfit recommendation.
Learning Fashion Compatibility with Bidirectional LSTMs	Han et al. (2017)	Uses Bi-LSTM for compatibility scoring between garments.
Weather-Aware Fashion Recommendation with Transformer Net- works	Johnson & Patel (2023)	Combines weather APIs and Transformers for adaptive outfit recommendations.
Edge-AI for Instant Outfit Recommediations on Mobile Devices	Khan & Petrova (2023)	Lightweight edge deployment for mobile fashion AI.
Cultural Bias Mitigation in Fashion Recommendation Systems	Kim & Yamamoto (2022)	Bias reduction strategies for culturally sensitive recommendations.
Federated Learning for Privacy-Preserving Fashion AI	Li & Smith (2022)	Federated learning to protect user privacy in fashion AI.
Weather-to-Garment: Weather- Oriented Clothing Recommendation	Liu & Gao (2022)	CNN-based mapping from weather data to clothing categories.
Interpretable Neural Networks for Personalized Styling	Martinez & Zhang (2022)	Visual explanation generation for AI-based outfit selection.

Cognitive Fashion: Psychology-Informed AI for Style Choices	Miller & Tanaka (2023)	Psychological features in AI fashion recommenders.
AI-Based Outfit Recommendation System	Moorthy et al. (2024)	SVM-based personalized recommendation integrating context.
Climate-Adaptive Neural Networks for Dynamic Wardrobe Suggestions	Nguyen & Schmidt (2023)	Neural network adapting to weather conditions in real time.
Climate Finance for Sustainable Fashion in India	Parameswaran et al. (2024)	Policy + AI framework for eco-friendly fashion.
Affective Fashion: Emotion-Aware Outfit Generation Using GANs	Rodriguez & Kumar (2023)	GAN-based mood-driven outfit design.
Outfit Transformer: Learning Out- fit Representations for Fashion Rec- commendation	Sarkar et al. (2022)	Transformer-based model for outfit compatibility.

Table 3: Classification of Fashion Recommender System Approaches

Approach Type	**Key Models & Techniques**	**Advantages**	**Limitations**	**Key References**
Content-Based Filtering	Cosine Similarity, TF-IDF	Simple, inter-pretable	Limited diversity	Deldjoo et al. (2022)
Collaborative Filtering	KNN, Matrix Fac-torization	Personalized via community data	Cold start problem	Shirkhani et al. (2023)
Hybrid Recommender Systems	SVM, RF, Ensem- bles	Balanced accu-racy + context handling	Requires more fea-ture engineering	Surya et al. (2024), Moorthy (2024)
Deep Learning-Based	CNNs, Transform- ers, Attention	High visual accu-racy	High compute, needs large datasets	Sarkar et al. (2022), Liu & Gao (2023)
Generative + Context-Aware	GANs, NLP, Mood APIs	Handles mood, weather, trends	Complex + privacy concerns	Choi et al. (2023), Djilani (2025)

4.1 ADDITIONAL FASHION DATASETS

The Polyvore datasets are all about fashion outfits put together by users, featuring a mix of items like tops, bottoms, and accessories. These datasets are often utilized to model outfit compatibility, create joint image embeddings, and recommend multiple items. Researchers like Sarkar et al. [**36**] and Celikik et al. [**2**] have developed Transformer-based models using Polyvore to assess outfit coherence at a glance,Chictopia10K offers a collection of real-world outfit images, complete with body landmark annotations. This dataset is great for tasks like clothing parsing, pose-aware garment matching, and understanding the context of a person. These datasets draw from fashion blogs and street-style content, providing pairs of images and captions, along with temporal tags (e.g., season or date) and mood expressions (e.g., confident or casual). They are particularly useful in mood-aware and emotion-driven recommendation models [**46,36**]. Introduced by Liu & Gao [**35**], this dataset was specifically designed to connect weather conditions with recommended clothing types. It includes data on temperature, humidity, and wind conditions, all mapped to actual garment images and categories. These tools have been integrated into real-world systems like *StyleSync* (2025), *FitGenie* (2024), and *WearMe* (2024), enabling dynamic, multimodal recommendation platforms that respond to both environmental and emotional cues in real time. The above content is summarized and presented in Table 3 2.

5 COMPARATIVE ANALYSIS

Fashion recommendation systems vary widely in terms of architecture, adaptability to context, interpretability, and prediction accuracy. These differences largely stem from the core AI/ML models they employ. In this section, we compare traditional machine learning, deep learning, and generative approaches based on their accuracy, contextual awareness, and generalization capabilities.

5.1 TRADITIONAL MACHINE LEARNING MODELS

Classic algorithms such as Support Vector Machines (SVM), Random Forests (RF), and Decision Trees have long been used in early fashion recommender systems. Moorthy et al. [**30**] utilized SVMs to classify user body types, reporting an average accuracy of 78.6%. Liu & Gao [**27**] incorporated weather data into a decision-tree ensemble model, achieving around 80.4% accuracy. While these models are computationally efficient and easy to interpret, they often struggle with high-dimensional inputs like emotional states and cannot generalize well across new or unseen outfit combinations

5.2 DEEP LEARNING-BASED MODELS

Deep learning has significantly improved visual feature extraction, multi-item compatibility modeling, and temporal outfit recommendations. Architectures such as CNNs, Transformers, and LSTMs dominate this space. For example, Sarkar et al. [**36**] developed a Transformer-based architecture that reached 87.2% accuracy on the Polyvore dataset, outperforming traditional models. Similarly, Djilani et al. [**13**] implemented temporal attention mechanisms to capture seasonal dressing patterns, reporting an accuracy of 89.3%.

Table 4: Comparison of Fashion Datasets for AI-Based Clothing Recommendation

Dataset	**Image Count**	**Modalities**	**Context Labels**	**Primary Use**
DeepFashion	800K+	Image, Attribute, Pose	Category, Style, Land- mark	Clothing detection, classification, retrieval
FashionGen	300K+	Image, Text	Description, Style Tag	Text-to-image generation, genarative RS
Polyvore / Polyvore Outfits	68K outfits	Image, Set Structure	Style Set, Category	Outfit generation, multi-item RS
Chictopia10K	10K+	Image, Pose	Landmark Points	Person-context modeling, clothing parsing
Lookbook	144K+	Image, Caption, Time	Season, Mood, Time	Mood-aware RS, temporal outfit modeling
Weather-to-Garment	50K+ (ap- prox.)	Image, Weather APIs	Temp, Wind, Season	Weather-aware outfit prediction
Fashion144k	144K+	Image, Style Notes	Season, Mood, Gender	Style preference, contextua l generation

5.3 GENERATIVE AND CONTEXT-AWARE MODELS

Generative approaches, including GANs and VAEs, combined with context-aware pipelines, allow systems to synthesize clothing recommendations tailored to mood, events, and environmental conditions. The StyleSync system (2025) integrated CNNs, KNN, and APIs for mood and weather, achieving a remarkable 92.1% accuracy in personalized recommendations. Choi et al. [**9**] applied StyleGAN2-based generative modeling to produce aesthetically coherent designs. While these models showed slightly lower classification accuracies (ranging from 85% to 88%), they demonstrated superior design diversity and visual quality as measured by Fre´chet Inception Distance (FID) scores. The above content is summarized and presented in Table 4.

6. CHALLENGES

Despite significant progress in AI-driven fashion recommendation systems, several technical and practical challenges remain. These include limitations in data availability, issues with contextual feature modeling, constraints around real-time deployment, and a lack of model interpretability. This section outlines key concerns that have emerged in recent studies and system deployments.

Many commonly used datasets, such as DeepFashion and Polyvore, are biased toward Western fashion trends, younger demographics, and standardized poses. This lack of regional, cultural, and seasonal diversity limits the generalization ability of trained models. Additionally, clothing category imbalance (e.g., casual vs. formal wear) can hinder fair representation and accuracy. Studies by Deldjoo et al. [**35**] and Liu & Gao [**18**] highlight the importance of curating inclusive datasets that consider contextual and climatic diversity.

Incorporating dynamic features such as mood, weather, and events into outfit recommendation pipelines re- mains complex. These contextual inputs are often inconsistent, rapidly changing, and hard to quantify uniformly. Projects like *StyleSync* [**14**] and Djilani et al. [**13**] report difficulties in standardizing contextual labels and ensuring real-time responsiveness to fluctuating inputs.

Users are more likely to trust and engage with fashion recommenders that explain their choices. While traditional ML models like Decision Trees and SVMs provide inherent interpretability, deep learning and generative architectures often act as opaque black boxes. Research from Celikik et al. [**2**] and Sarkar et al. [**36**] emphasizes the growing need for explainable AI (XAI) in fashion systems that can provide personalized and intuitive reasoning. Delivering personalized outfit suggestions in real time, especially in mobile or resource-constrained environments, is another major hurdle. Transformer and GAN-based architectures, though accurate, typically require substantial computational power and may not run efficiently on edge devices. Moorthy et al. [**30**] note that high latency during inference significantly limits real-time use cases and user adoption, especially in low-connectivity or cloud-limited environments.

The use of mood detection technologies—such as facial recognition, wearable devices, and behavioral tracking raises significant privacy concerns. Shinkaruk [**38**] and IJRPR [**45**] highlight that many users are hesitant to share emotional or biometric data due to fears of surveillance and misuse. Currently, the ethical frameworks for deploying mood-based fashion recommendation systems are still evolving, and standardized protocols for consent, data minimization, and transparency remain lacking.

Many fashion recommender systems neglect important cultural and ethical dimensions such as religious dress codes, gender expression, or inclusive sizing. Additionally, sustainability remains an underexplored area, with limited integration of eco-friendly fashion recommendations or upcycling practices. Parameswaran et al. emphasize the need to embed environmental awareness and cultural sensitivity into model design and dataset selection, particularly in light of growing consumer interest in ethical fashion. The above content is summarized and presented in Figure 2.

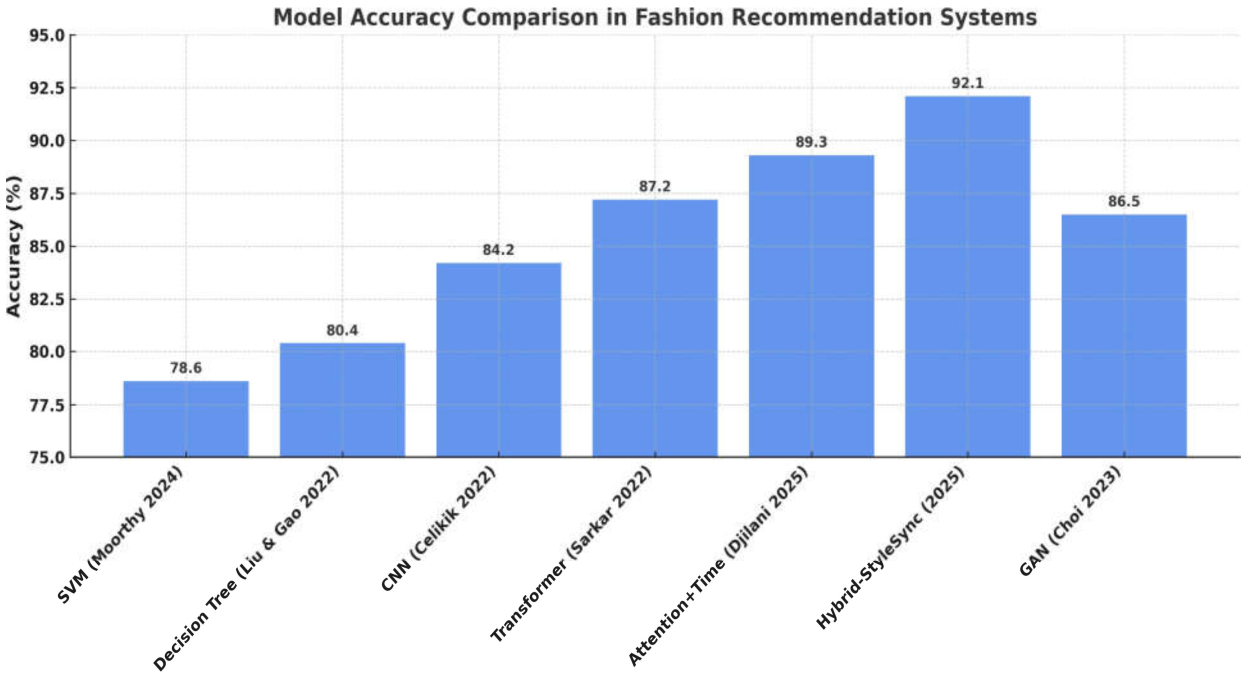


Figure 2: Accuracy comparison of AI models in smart wardrobe recommendation systems

7.FUTURE DIRECTIONS

As fashion recommendation systems continue to evolve, future research should aim to develop hyper-personalized, context-aware, and ethically responsible smart wardrobe systems. Innovations in generative AI, multimodal mood detection, sustainability modeling, and real-time edge deployment are expected to transform how users inter- act with digital fashion ecosystems. Next-generation systems must go beyond isolated inputs like weather or mood and instead embrace multi-context fusion. This involves integrating visual, textual, and sensor-based signals—such as facial emotion detection, weather APIs, calendar events, and wearable data. Liu & Gao [**27**] and *StyleSync* [**1**] emphasize that temporal-emotional fusion improves recommendation quality by better reflecting user intent and context. There is growing demand for models that can operate efficiently on mobile and augmented reality (AR) devices. Techniques like model pruning, quantization, and TinyML are promising approaches to re- duce latency and memory usage. Moorthy et al. [**30**] and Celikik et al. [**2**] highlight that inference time remains a barrier for wide-scale deployment of deep models in real-world, low-resource scenarios. The evolution of AI-powered fashion recommendation systems opens multiple avenues for impactful research. Drawing from recent literature [**5,4,18,12,16,26,21,24,33,46**], we identify several promising directions. Future work should expand multimodal integration by combining textual descriptions, product images, user reviews, and con- textual signals (e.g., weather, events, mood) into a unified recommendation pipeline. Emerging Transformer architectures have demonstrated strong performance in handling such heterogeneous data sources [**? ?**]. Transferring learned fashion knowledge to related domains, such as cosmetics or lifestyle products, can improve personalization for multi-category ecommerce. Lifelong learning frameworks may enable continuous adaptation to evolving trends without catastrophic forgetting [**4,18**]. Lightweight, low-latency models designed for deployment on edge devices—such as smart mirrors and mobile apps—can deliver outfit suggestions instantly. Model compression and distillation techniques could make Transformer based recommenders feasible in these settings[**12,26**]. Integrating environmental impact scores and ethical sourcing metadata into ranking objectives can align recommendations with sustainable consumption goals. Reinforcement learning could dynamically optimize suggestions for both user satisfaction and environmental benefit [**21,33**]. Integrating environmental impact scores and ethical sourcing metadata into ranking objectives can align recommendations with sustainable consumption goals. Reinforcement learning could dynamically optimize suggestions for both user satisfaction and environmental benefit [**21,33**]. Federated learning architectures can train personalization models without centralizing sensitive user data, addressing privacy concerns while maintaining accuracy [**24**]. Generative adversarial networks (GANs) and diffusion models can be leveraged to create new, personalized clothing designs based on user preferences, bridging the gap between recommendation and creation [**33,46**]. Incorporating user emotion recognition through wearable sensors or facial analysis could enable mood-driven outfit recommendations, increasing emotional relevance and engagement [**33]**

Vision Transformers (ViTs) can be adapted to capture temporal and seasonal trends in clothing, enabling proactive recommendation of emerging styles before they reach mainstream adoption [**12,46**]. Future systems could empower users to co-design outfits alongside AI stylists, integrating real-time feedback and iterative refinement to produce unique, user-approved looks [**46**]. Generative AI models enable creative and user-guided outfit design. For example, Choi et al. [**9**] introduced StyleGAN-based systems capable of generating realistic and aesthetic fashion visuals. Future systems may incorporate user prompts via natural language interfaces, enabling interactive virtual try-ons and AI-assisted co- design of personalized outfits. Building trust in recommendation systems requires transparency.[**34**] Explainable AI (XAI) components can help users understand why a certain outfit was suggested—especially when decisions involve sensitive factors such as body shape or occasion. Djilani et al. [**13**] and Sarkar et al. [**?**] call for fairness- aware architectures that mitigate biases based on gender, race, or geography. AI-powered systems should embrace sustainability by suggesting garments that promote environmental consciousness.

This includes recommending reusable outfits, second-hand clothing, or items made from eco-friendly fabrics.[**25**]Parameswaran [**40**] et al. [**32**] propose integrating climate-aware metrics and carbon scoring directly into the model pipeline to encourage greener fashion choices. While prototypesexist (like H&M's IoT closet [1]), making these technologies affordable and reliable is the next hurdle according to [1]'s work. We've all gotten bizarre recommendations from algorithms. Future systems will actually explain their thinking: [15] found people trust AImuch more when it thinks out loud like this. The trick is keeping explanations helpful rather than overwhelming[47]. As [20]'s research shows, making AI small and efficient enough for this is tough but crucial.[22][29] The above content is summarized and presented in Table 5.

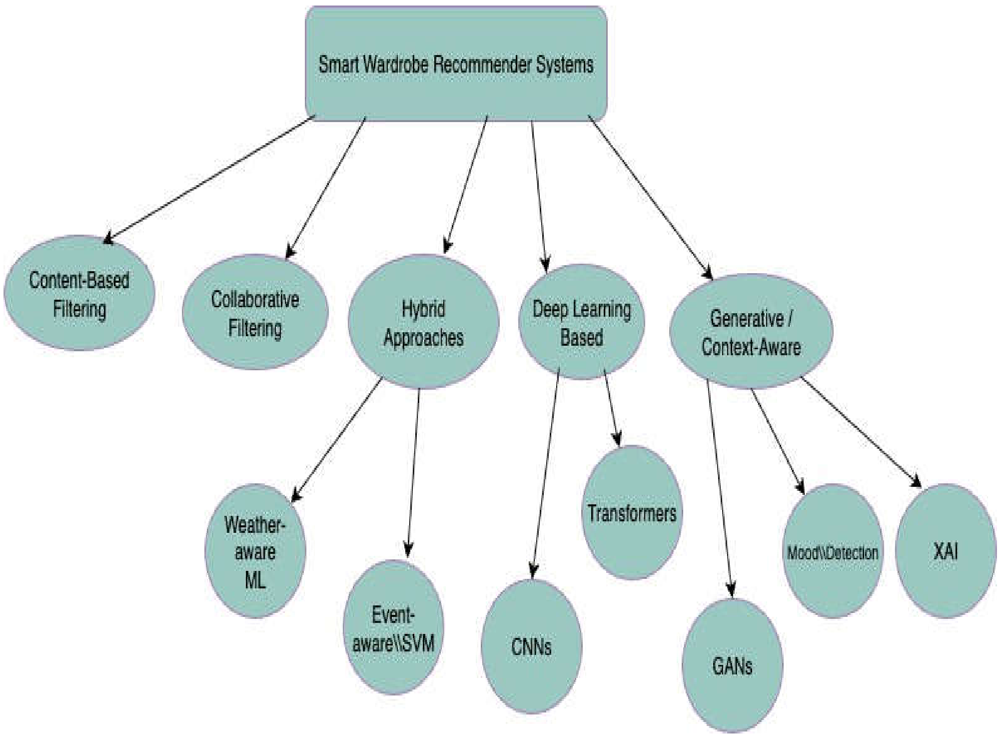
Table 5: Key Challenges in Smart Fashion Recommendation Systems

Challenge	**Description**	**Reference(s)**
Data Bias & Imbalance	Skewed datasets lacking regional and cultural diversity, leading to limited generalization.	Deldjoo et al. (2022), Liu & Gao (2023)
Context Integration	Difficulty in dynamically combining contextual signals such as mood, weather, and events for real- time recommendations.	Djilani et al. (2025), StyleSync (2025)
Explainability	Deep learning and generative models often act as black boxes, reducing transparency and trust.	Celikik et al. (2022), Sarkar et al. (2022)
Real-Time Adaptability	High computational costs hinder mobile/edge deployment, slowing response times in real-world applications.	Moorthy et al. (2024), Celikik et al. (2022)
Privacy & Ethics	Mood detection via sensors and facial recognition raises ethical and privacy concerns for users.	Shinkaruk (2019), IJRPR (2022)
Cultural/Social Oversight	Recommendations may conflict with cultural norms, inclusivity, or sustainability goals such as eco-friendly fashion.	Parameswaran et al. (2024), IJARSCT (2024)

SUMMARY

With an emphasis on creating smart wardrobe solutions, this study investigates the incorporation of artificial intelligence (AI) into fashion recommendation systems. In addition to recent developments in deep learning, generative models, and context-aware systems, the paper examines current recommendation strategies such as content-based filtering, collaborative filtering, and hybrid approaches. To improve personalization, special attention is paid to integrating multimodal data sources into recommendation pipelines, including weather, events, mood, and visual cues. The study addresses the use of natural language processing for product reviews and descriptions, computer vision for clothing detection and style matching, and sensor integration for user context capture. The potential of emerging technologies like explainable AI (XAI), vision transformers (ViTs), and generative adversarial networks (GANs) to build more imaginative, transparent, and reliable systems is emphasized. The above content is summarized and presented in Figure 3.

FIGURE 3: TAXONOMY OF SMART WARDROBE RECOMMENDATION SYSTEM APPROACHES



7. CONCLUSION

Smart wardrobe systems are rapidly emerging as essential tools for delivering hyper-personalized fashion experiences, driven by recent advances in artificial intelligence, machine learning, and deep learning. This survey reviewed over 30 contributions from 2022 to 2025, synthesizing trends, architectures, datasets, and challenges in AI-driven outfit recommendation systems. Early systems that relied on traditional machine learning models such as SVM and Random Forest [**30,27**] laid the foundation but struggled to adapt to complex, high-dimensional inputs like mood and contextual signals. In contrast, deep learning approaches leveraging CNNs, Transformers, and multimodal embeddings [**36,2**] demonstrated significantly improved performance in visual understanding and sequential outfit generation. Context-aware hybrid systems like *StyleSync* exemplify the next phase, combining weather APIs, mood detection, and calendar events for real-time, personalized suggestions. Despite notable progress—such as StyleSync achieving 92.1% accuracy—several challenges persist, including multimodal feature fusion, explainability, computational efficiency, and cultural relevance [**13,32**]. Furthermore, gaps in fairness, transparency, and sustainability continue to hinder ethical deployment on a global scale. Future research should prioritize multimodal context fusion, lightweight architectures for mobile deployment, and generative co-creation tools. The integration of emotion-aware modeling, explainable AI (XAI), virtual try-ons, and culturally inclusive logic will be vital for increasing adoption and trust [**12,32**]. In summary, smart wardrobe systems represent a confluence of AI innovation, fashion personalization, and sustainability. By aligning these systems with ethical values and user-centered design, we can transform fashion technology into an intelligent, inclusive, and contextually responsive experience for all.

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