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# A Review on Virtual Try-On Systems Using Augmented Reality and Artificial Intelligence in Fashion Retail

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Abstract- Online fashion retail faces persistent challenges in product fit and personalization. The Smart AR Wardrobe concept aims to enhance virtual shopping by integrating Augmented Reality (AR) with Artificial Intelligence (AI) to simulate clothing try-ons, offer accurate sizing, and suggest personalized styles. This paper surveys the underlying technologies enabling such systems, categorizing them by AR rendering, AI-based body modeling, and fashion recommendation engines. Current systems show promise but technical constraints, user privacy, and lack of data standardization remain barriers. This survey consolidates the latest research trends, identifies gaps, and outlines future directions toward more immersive and scalable AR wardrobe experiences.

Keywords- Augmented Reality, Artificial Intelligence, Virtual Try-On, Fashion Technology, 3D Body Modeling, Clothing Simulation

#### I. INTRODUCTION

The digital transformation of retail has made convenience a priority, but fashion buyers still miss the tangibility of trying clothes on. AR-powered tryons offer visual interactivity, while AI models enable personalized and accurate recommendations. The Smart AR Wardrobe concept combines these into a unified experience—users scan themselves, try on clothes virtually, and receive real-time size and style feedback. Such solutions have already shown to increase user engagement and reduce return rates in e-commerce, making them highly attractive to retailers [1], [2].

## **II. LITERATURE SURVEY**

Recent developments in virtual try-on technologies have combined advances in augmented reality (AR), computer vision, and artificial intelligence (AI) to revolutionize fashion e-commerce. Ngo et al. [1]

presented a system that utilizes 3D garment reconstruction and AR to enable interactive virtual try-ons, significantly improving garment visualization accuracy. Companies like Pinterest and Amazon have incorporated Al-based personalization engines that analyze user behavior and image data to suggest outfits tailored to individual preferences [2], [10].

To tackle the challenge of size mismatch in online shopping, Ding et al. [3] introduced diffusion-based models for variable-size virtual try-ons, allowing realistic simulations across different body types. Xu et al. [4] developed ARCloth, a system employing mobile edge computing for real-time AR clothing visualization, enhancing speed and realism even on mobile platforms. However, Park and Jung [6] highlighted the computational complexity of real-time cloth simulation, which remains a bottleneck, particularly on resource-constrained devices.

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Brouwer et al. [5] addressed size recommendation problems through AI models trained on historical fit and return data, showing improved accuracy over traditional size charts. Style and compatibility recommendations have been enhanced using deep learning methods, such as CNN-based visual feature extraction and transformer-based behavioral modeling, as discussed by Liu et al. [7].

Privacy and personalization trade-offs are a recurring concern. Al-Kaff et al. [9] emphasized the ethical implications of Al-driven profiling in virtual dressing rooms, while emerging works on federated learning propose privacy-preserving training methodologies. Multi-scene virtual try-on networks (MS-VTON), as introduced by Lv et al. [13], eliminate the need for personal photos by generating try-on images using only attribute text and clothing data, significantly improving user privacy.

Furthermore, novel visualization methods, like those discussed by Sánchez-Ferrer et al. [14], use dashboards fashion entrepreneurs to help understand consumer behavior and product performance. UVTON [15] leverages UV mapping and DensePose to preserve the 3D structure of the human body in generated images, while Kubo et al. [15] showed that such techniques maintain garment texture and positioning effectively. Single-stage multi-pose try-on networks (SSMTN) introduced by Liu et al. [16] extend these capabilities to handle varied human poses and maintain realism in deformation of garments.

Collectively, these studies form a foundation for understanding the strengths and limitations of current AR-AI-based virtual try-on systems and guide future innovations in smart AR wardrobes.

#### III. METHODOLOGY

The Smart AR Wardrobe system integrates AR rendering, Al-powered personalization, and real-time data processing to create an immersive virtual try-on experience. The methodology begins with computer vision techniques such as pose estimation and semantic segmentation, which help

in accurately tracking user body structure and distinguishing it from the background. This enables virtual garments to drape naturally, accounting for movements, occlusions, and multi-layer clothing interactions. Deep learning-based skeleton extraction models like OpenPose are commonly employed to improve accuracy in body tracking and pose alignment.

For AR rendering, mobile-optimized rendering pipelines or edge computing resources are used to perform real-time cloth simulations. These simulations rely on physics-based models that capture the realistic motion of garments, including wrinkles, shadows, and dynamic folds, while minimizing latency on mobile devices. Platforms like ARKit and ARCore serve as the base for markerless tracking and real-time garment visualization.

Al plays a central role in size prediction and personalization. Machine learning models are trained on user-uploaded images, return data, and fashion metadata to accurately estimate body dimensions and recommend optimal Convolutional neural networks (CNNs) collaborative filtering methods are used to identify user style preferences based on visual patterns, behavioral data, and historical choices. Reinforcement learning is also applied in some systems to dynamically refine outfit suggestions based on real-time user interactions.

The Smart AR Wardrobe further integrates data from various sources—user reviews, browsing behavior, garment attributes—and synthesizes it through centralized or edge-based Al models. Due to growing concerns about data privacy, techniques like federated learning are proposed to keep user data on-device while still allowing the central model to learn effectively. These privacy-preserving models ensure that personalization does not come at the cost of user confidentiality.

Overall, the system design prioritizes responsiveness, realism, and personalization while minimizing computational overhead and ensuring

fashion retail experience.

#### IV. FINDINGS AND TRENDS

Increased Retailer Adoption: Major fashion retailers and platforms (e.g., Zara, Amazon, Farfetch) are investing in AR and Al-driven virtual try-on systems to enhance user experience, reduce product returns, and gain competitive advantage.

Hybrid Shopping Experiences: There is a growing trend of combining online and in-store experiences using AR mirrors or kiosks, allowing customers to virtually try garments in physical stores without needing fitting rooms.

User Engagement and Conversion Boost: Studies show that virtual try-on features significantly increase time spent on product pages and improve conversion rates, especially among Gen Z and millennial consumers.

Cross-Platform Synchronization: Emerging systems are enabling synchronization of user wardrobes across platforms (e.g., e-commerce, social media, gaming avatars), contributing to a cohesive digital fashion identity.

Rise of Virtual Influencers and Avatars: Digital models and influencers are being integrated into AR platforms to promote try-on experiences, helping brands reach wider audiences and drive engagement via social media.

Integration with Voice and Gesture Interfaces: are incorporating Advanced systems commands or gesture-based interactions to provide a more intuitive, hands-free try-on experience.

Sustainability and Conscious Consumption: Virtual try-ons are helping reduce environmental impacts by lowering return rates and minimizing overproduction, aligning with sustainable fashion goals.

ethical data use, aiming to deliver a seamless virtual Localization and Cultural Adaptation: Al models are being trained to recommend culturally appropriate or seasonally relevant styles, helping brands localize their offerings in global markets.

> Real-Time Feedback and Emotion Recognition: Some systems are testing integration of real-time facial expression analysis to assess user satisfaction and tailor recommendations accordingly.

> Expansion into Accessories and Cosmetics: Beyond garments, AR try-ons are now extending into virtual fitting of eyewear, shoes, handbags, makeup, and even hairstyles.

> Consumer Education via AR: Retailers are using AR to explain fabric types, garment care, and sustainable sourcing, helping consumers make more informed purchasing decisions.

# **Challenges and Gaps Technical Barriers**

High Computational Demands: Realistic garment simulation, including dynamic folds and fabric response, requires substantial GPU resources, making it difficult to achieve high fidelity on mobile or edge devices [6].

Real-Time Performance Constraints: Maintaining smooth, real-time performance across diverse network and device conditions is still a challenge, especially for remote rendering and AR streaming. Inconsistent Lighting and Background Conditions: Variability in user environments (e.g., lighting, camera angles, room clutter) reduces AR realism and can degrade model accuracy [4].

Garment-Body Misalignment: Even advanced pose estimation can result in occasional clipping, floating garments, or inaccurate fitting when users move quickly or assume uncommon poses.

Limited Multi-Layer Try-On Support: Accurate layering of garments (e.g., shirt + jacket + accessories) remains technically difficult due to occlusion handling and cloth interaction physics.

#### **Privacy & Ethical Concerns**

Lack of Transparency in Data Usage: Many platforms do not clearly disclose how body measurements, photos, or behavioral data are stored or used, raising privacy and consent concerns [9].

Potential for Body Shaming or Bias: Al-based body modeling and style recommendations may unintentionally reinforce beauty stereotypes or create discomfort for users with non-standard body types.

Bias in Training Data: Most Al models are trained on limited and often biased datasets, which can lead to exclusion or poor performance for diverse users in terms of skin tone, body shape, or cultural attire.

Consent and Child Safety: Ensuring proper safeguards for minors using virtual try-on apps remains under-addressed, particularly in apps popular with younger demographics.

#### Standardization and Interoperability Issues

Lack of Industry-Wide Garment Metadata Standards: Attributes like fabric elasticity, drape coefficient, or sleeve type are not standardized across brands, hindering consistent Al interpretation [1], [5].

Inconsistent Size Labels Across Regions: Variability in sizing systems (US, EU, Asia) makes it difficult for Al models to offer globally reliable size recommendations.

Platform Fragmentation: No universal infrastructure exists to integrate AR wardrobe data across different e-commerce platforms, apps, or digital fashion ecosystems.

#### **User Experience Limitations**

Steep Learning Curve for Non-Tech Users: Some users find the scanning or setup processes complex or unintuitive, leading to low adoption despite technological capability.

Poor Feedback Loop: Current systems lack effective mechanisms to learn from failed recommendations (e.g., a user disagrees with the suggested size or dislikes the outfit style).

Low Trust in Accuracy: If early attempts deliver subpar results (e.g., unrealistic visuals or bad fit), users may lose confidence and avoid using the tool again.

#### **Commercial and Integration Hurdles**

High Implementation Costs: Integrating highquality virtual try-on features into retail platforms can be expensive, particularly for small or medium fashion brands.

Inventory and Data Integration Challenges: Mapping large product catalogs to virtual try-on systems requires significant backend changes, including digitization of garments and rich metadata tagging.

Legal and Copyright Issues: Digitally modeling branded clothing or styles may raise IP concerns, especially when AR avatars or influencers wear high-end fashion in virtual environments.

#### **Future Directions**

#### **Real-Time AR on Edge Devices**

Research is optimizing mobile rendering through neural compression and on-device ML [4].

#### **Garment Data Standards**

Open metadata formats for garments could improve fit predictions and recommendation accuracy [5].

### **Emotion-Aware Outfit Suggestions**

Emerging models may soon combine facial emotion recognition with contextual outfit curation [10].

#### **Integration with Digital Avatars**

AR wardrobes will likely sync with users' metaverse avatars, enabling digital-physical fashion crossover [8].

#### V. CONCLUSION

The evolution of the fashion retail landscape is increasingly being shaped by immersive technologies, and the Smart AR Wardrobe stands at the forefront of this transformation. By integrating Augmented Reality (AR) with Artificial Intelligence (AI), these systems offer a highly interactive, personalized, and efficient way for consumers to engage with clothing products virtually. The convergence of pose estimation, cloth simulation, style recommendation engines, and real-time rendering has the potential to redefine how users shop online—not just by allowing them to see how a garment fits, but by predicting how it will feel, move, and express their individual style.

Our review highlights that current virtual try-on systems have significantly progressed in realism and personalization, thanks to deep learning and neural rendering techniques. Commercial platforms have already started reaping the benefits, with increased user engagement, reduced return rates, and enhanced customer satisfaction. Furthermore, the integration of mobile edge computing and cross-platform compatibility is paving the way for real-time experiences on consumer-grade devices, making this technology increasingly accessible.

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