A Holistic Hybrid Adaptive Geometric Deep Learning and Perceptual Fashion Recommender System with Applied Metaverse for size-fit problems in online shopping

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***Abstract*—Clothing is the most frequently returned item on e-commerce platforms. Most of the garments are returned due to a poor fit or poor appearance on the customer's body. Returning purchased items often not only has an impact on the carbon footprint but also leads to an unsatisfied customer experience. In India alone, the return rate for purchases online is 25-40% and the key contributor is size-fit. Our system not only makes recommendations based on the user's style preferences but also takes into account how the garment fits and looks on the user's body ensuring a more personalized fashion recommendation for the user. Previous research on fashion recommendation systems has focused on modelling recommendations based on user history, item-item compatibility, body shape, or styling preferences using social media or user history patterns. We introduce a Holistic Hybrid Adaptive Geometric and Perceptual (HHAGP) Recommender System for individualized fashion recommendations. Our proposed system addresses the lack of cross-brand standardisation of clothing sizes and the lack of a fashion recommendation methodology that takes into account both users' physical characteristics and style preferences. The HHAGP recommender system complements the existing class of content-based and collaborative fashion recommender systems by evaluating the recommendations geometrically and perceptually in order to further subset them so that they are highly individualized and user-specific. To achieve this goal, the recommendations obtained from the implicit content-based and collaborative recommender system are passed through a Monocular-to-3D Virtual Try-On Network (M3D-VTON) to visualize the recommendation on the user's body and then filtered by a Visual Geometry Group model (VGG) that assigns a perception score to the recommendation. The measurements for the different sizes of the filtered recommendations are geometrically matched to the user's physical characteristics in order to obtain the best-fit recommendation size. An explicit feedback loop continuously adapts the system to the user's preferences. The results demonstrate a robust user-centric system that provides user-specific fashion recommendations considering both qualitative and quantitative characteristics. Our system combines traditional user history-based collaborative recommendation systems with user-clothing fit and user-clothing perception combined with a hybrid feedback loop to model accurate clothing recommendations. The augmented reality-based meta-virtual surrounding helps the consumer to visualise different environments with the recommended apparel. This paper presents a novel solution that provides user preference-based fashion recommendations that are perceptually appealing and complement the user's body shape and size. This approach when applied will result not only in reducing the returns of the apparel but also help in developing an immersive dataset for Indian body fits by size.**

***Keywords*—Geometric Deep Learning, Applied Perception, Metaverse, Recommender System**

I. Introduction

The following key factors influence the decision to purchase fashion items: 1) the appearance of the garment on the user's body, 2) the fit and how well the garment complements the user's body, and 3) compatibility with the user's fashion preferences. The current online shopping experience lacks a methodology that allows a user to obtain information about these key factors influencing the clothing purchase decision. There is a lack of standardization of sizes across brands and locations, and size charts assume that a user has tailored body measurements available, so a user cannot get a clear idea of how the garment will fit on their body. The only way for a user to visualize how the garment will look and fit their body is to purchase the garment and physically try it on. This leads to a poor user experience when the item doesn't look or fit right, as well as wasted capital and resources for the e-commerce platform.

In India alone, the return rate for online purchases is 25-40%, with clothing fit issues being a major contributor [1]. 19% of users purchase clothing in different sizes, shapes and fits with the intention of keeping the best size and fit that complements their body and returning the rest [2]. Such frequent returns have a significant impact on the environment as they increase the carbon footprint of the e-commerce platform as well as waste capital and resources. Fashion e-commerce in India is growing at a rate of 18.92% (CAGR 2022-2025) [3] and unless a methodology to solve the problem is implemented, the number of returned items and therefore the negative economic and environmental impacts will increase proportionately. Reducing returns is critical for e-commerce platforms because even a 5% reduction in returns has a direct impact on improving the platform's net margin significantly [4]. Indirect effects include improved user experience and, as a result, increased clothing purchases on the platform.

We introduce a Holistic Hybrid Adaptive Geometric and Perceptual (HHAGP) Recommender System for individualized fashion recommendations. Our proposed solution consists of three modules: 1) Fashion Preference (FP) Module, 2) Virtual Try On (VTON) Module, and 3) the Geometric and Perceptual Fit (GPF) Module.

The FP module consists of content-based and collaborative recommender systems (holistic) that model implicit and explicit user data and feedback (hybrid) to model user fashion and styling preferences to provide personalized and adaptive clothing recommendations. The FP module models clothing attributes to ensure item-item compatibility, and also uses user transaction, wishlist, history, screen time, and interaction data, as well as user ratings, reviews, and returns to predict users' fashion, styling, and fit preferences. Explicit feedback after the user physically tries on the clothing is taken into account to further adjust the recommendations according to the user's body.

The recommendations from the FP Module are passed on to the VTON module. The VTON module is inspired by Monocular-to-3D Virtual Try-On Network (M3D-VTON) [5] architecture and uses a full body image of the user and target clothing item to conduct two-dimensional (2D) and three-dimensional (3D) virtual try-on. The VTON module further uses Open3D [6] to post-process the 3D virtual try-on into a point cloud.

The GPF module uses a VGG-inspired [7] classification architecture to perceptually score the 2D virtual try-on images based on the type of fit (slim, regular or relaxed fit). The GPF module determines the measurements of the user from their full body image using an OpenPose [8] inspired architecture and geometrically matches them to the clothing measurements to rate the geometric fitness of the clothing item based on the type of fit (slim, regular or relaxed fit). The geometrical and perceptual fitness scores are combined while also accounting for any explicit user feedback to obtain the goodness of fit score.

We also propose a data collection methodology that uses social media and fashion e-commerce as a source to retrieve clothing images on a user's body. A variation of ClothingOut [9] is used to receive body-agnostic clothing images and a PIFuHD [10] inspired architecture is used to develop 3D models from the clothing images on a user's body.

Our methodology combined with Augmented Reality (AR) based applications and Internet of Things (IoT) mirrors can revolutionise the offline trial room experience. The VTON module can serve as a framework for continuous and adaptive metaverse character updates in conjunction with IoT mirrors or mobile applications.

In summary, the contributions of this paper are:

- A new HHAGP system that models recommendations based on user size, and fit preferences while also allowing users to virtually try garments.
- A holistic and hybrid FP module that adaptively models user fashion preferences while maintaining item compatibility.
- A VTON module that allows 2D and 3D full-body virtual try-on of clothing.
- A GPF module that enables the scoring of clothing fit and compatibility based on perceptual and geometric heuristics.
- A data collection methodology for developing an immersive fashion dataset for the Indian body size and fit.

II. Related Work

A. Fashion Recommenders

Previous work on fashion recommenders model recommendations based on fashion item representation [11]–[16] recommending garments based on photos, videos and ratings and fashion item compatibility [17]–[22] recommending items based on item-item or region-specific compatibility in the same outfit. However, such an implementation does not address the sizing issue and a user's inability to visualize the garment prior to purchase. Research on fashion recommendations based on personalization and fit [22]–[36] addresses the fit problem and models user preferences but does not enable the visualization of clothing on the user's body and does not account for compatibility between recommended items. Fashion recommendation research, which focuses on interpretability and explainability [37]–[42], explains the approval or disapproval of a fashion outfit, allowing a user to make an informed decision before purchasing clothing, but does not take into account the user's fashion and size preferences. Another research direction of fashion recommendations focuses on discovering trends [27], [28], [43]–[48] to understand consumers' fashion preferences but does not address the fit and visualization of clothing.

B. Virtual Try-On

Research on 2D virtual try-on [49]–[60] and 3D virtual try-on [5], [61], [62] addresses the problem of visualization of clothing on the user's body but does not focus on fitness, compatibility and user preferences of the clothing items.

III. Methodology

In this section, we introduce our methodology in detail. The Holistic Hybrid Adaptive Geometric and Perceptual (HHAGP) Recommender System consists of three modules that function in succession: 1) Fashion Preference (FP) Module, 2) Virtual Try On (VTON) Module, and 3) the Geometric and Perceptual Fit (GPF) Module.

The FP module learns the user's fashion preferences and narrows down the recommendations for the VTON module. The VTON module allows the user to visualize the garments. The GPF module evaluates the fit of the garment on the user's body geometrically and perceptually. The three modules work in conjunction to allow a user to obtain recommendations based on their fashion preferences, ensuring a visually and physically pleasing fit while also allowing the user to visualize the garment in 2D and 3D prior to purchase.

A. Fashion Preference Module

The Fashion Preference (FP) module (see Fig. 1) focuses on learning item-item compatibility and user fashion preferences to filter, sort and subset the comprehensive catalogue of a fashion e-commerce platform.

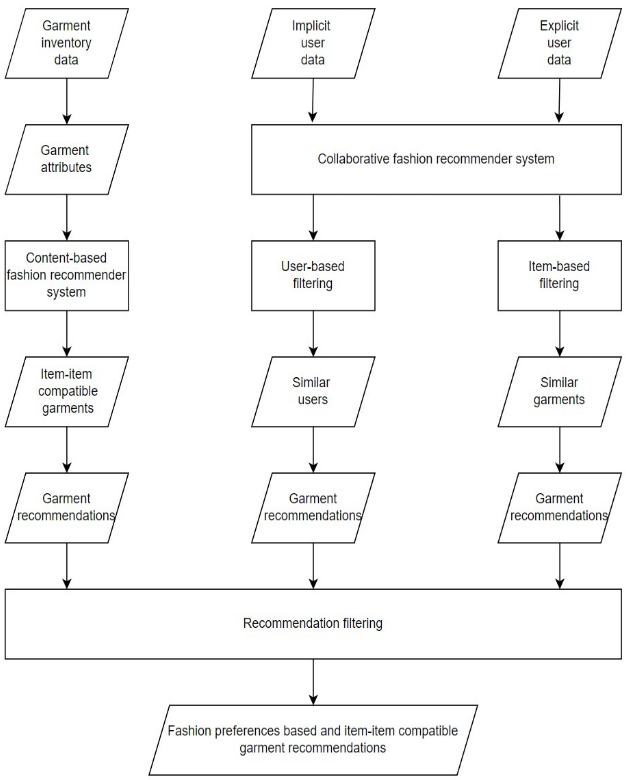

Fig. 1. Flowchart of FP module.

The garment inventory data includes information about the various garment attributes (e.g. images, style, colour, texture, type etc.), and a content-based fashion recommendation system finds similar items which are filtered to find similar compatible items. The content-based fashion recommender system is formed by modifying and ensembling modern fashion item representation [11]–[16] and fashion item compatibility [17]–[22] architectures. Implicit user data (e.g., items searched, user actions, items visited, wishlist items, items purchased, etc.) and explicit user data (e.g., comments, ratings, reviews, etc.) are used by user-based and item-based collaborative recommender systems, to model users' fashion and styling preferences. The collaborative fashion recommendation system is an ensemble architecture of modern user-based and item-based recommendation systems [63]–[65]. The recommendation filtering algorithm takes the garment recommendations from the content-based and collaborative recommender systems and filters and sorts to find an ordered set of recommendations attributing the user fashion preferences, item similarity and compatibility.

For a user, the set of garment recommendations can be formulated as follows:

$$R_i = R_i^{content-based} \cap R_i^{user-based} \cap R_i^{item-based} \quad (1)$$

where R_i is the set of garment recommendations for the i^{th} item bought by the user; $R_i^{content-based}$, $R_i^{user-based}$ and $R_i^{item-based}$ are the sets of garment recommendations for the i^{th} item bought by the user given by the content-based, user-based collaborative and item-based collaborative recommender systems.

The set R_i is ordered according to s_{ij} given by:

$$s_{ij} = \frac{\delta s_{ij}^{content-based} + \sigma s_{ij}^{user-based} + \rho s_{ij}^{item-based}}{\delta + \sigma + \rho} \quad (2)$$

where s_{ij} is the similarity score of the i^{th} item bought by the user and j^{th} item of R_i;$s_{ij}^{content-based}$, $s_{ij}^{user-based}$ and $s_{ij}^{item-based}$ are the similarity scores of the i^{th} item bought by the user and j^{th} item of R_i given by content-based, user-based collaborative and item-based collaborative recommender systems; and δ, σ, ρ are constants.

The final recommendations for the FP module for a user are determined by:

$$R = \bigcap_{i=1}^{n} R_i \quad (3)$$

where R is the final set of ordered recommendations and n is the total number of items previously bought by the user.

B. Virtual Try-on Module

The Virtual Try-On (VTON) module (see Fig. 2) allows the user to visualize the garment in 2D and 3D on their body. Recommendations from the FP module are processed by the VTON module to obtain 2D and 3D virtual try-on representations of the garments.

The user's full body image is passed through a pose estimation architecture based on OpenPose [8] and an image parsing algorithm based on 2D Human Parsing [66] to give pose key points and a parsed image of the user respectively. The target garment image and user image are pre-processed and pre-aligned to obtain the garment image mask, user image sobel, user image palm mask and aligned user & garment images. All the preprocessed data is fed to an M3D-VTON [5] inspired architecture to develop 2D virtual try-on representation and consecutively 3D virtual try-on representation. The 3D virtual try-on representation is post-processed with Open3D [6] to obtain the final 3D virtual try-on representation.

C. Geometric and Perceptual Fit Module

The Geometric and Perceptual Fit (GPF) module (see Fig. 3) is used to geometrically and visually assess the fit of the garments on the user's body.

The user's full body image is passed through an OpenPose [8] based architecture to obtain the key points of their pose. The key points of the pose are processed to determine 21 human body measurements (see Fig. 4), which, considering the type of fit (tight, regular or relaxed fit), are matched to the

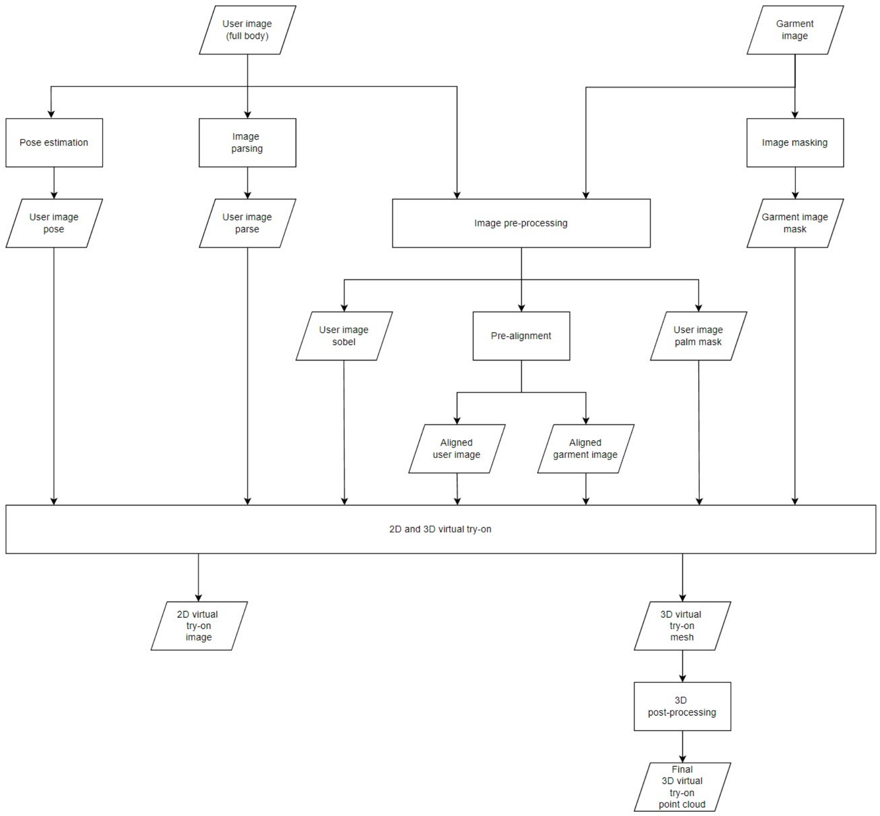

Fig. 2. Flowchart of VTON module.

measurements of the garment to evaluate the geometric fit of the garment on the user's body.

The geometric fit matching can be formulated as follows:

$$I_j^{adj} = I_j + \beta_j \tag{4}$$

$$L^{geometric} = \frac{\sum_{j=1}^{m} \mathbb{1}_j^{garment} \frac{\left|I_j^{adj} - G_j\right|}{1+\left|I_j^{adj} - G_j\right|}}{\sum_{j=1}^{m} \mathbb{1}_j^{garment}} \tag{5}$$

$$S^{geometric} = 1 - L^{geometric} \tag{6}$$

where j ranges from 1 to m ($m = 21$, see Fig. 4); I_j is the j^{th} measurement of the user's body; β_j is the adjustment factor (depends on the type of fit); I_j^{adj} is the adjusted j^{th} measurement of the user's body; $L^{geometric}$ is the geometric matching loss; G_j is the j^{th} measurement of the garment; $\mathbb{1}_j^{garment}$ is the correction coefficent which takes the value 1 if the j^{th} measurement exists for the garment else it takes the value 0 and $S^{geometric}$ is the geometric fit score.

Three VGG [7] inspired classification models (based on the type of fit) are trained to perceptual score a clothing try-on image as fit or unfit given the type of fit of the garment. The 2D virtual try-on representation from the VTON module is perceptually evaluated by the classification model to give the perceptual fit score.

The aggregate of the geometric and perceptual fit score while also accounting for explicit feedback by the user on previously purchased similar garments (if any) is taken to obtain the goodness of fit score. The goodness of fit score is representative of the overall fit of the garment on the user's body and is formulated as follows:

$$S^{fit} = \left(\frac{S^{geometric} + S^{perceptual}}{2}\right) + \gamma \tag{7}$$

where $S^{geometric}$ and $S^{perceptual}$ are the geometric fit and perceptual fit scores;γ is the feedback factor which takes the value 0 if no feedback exists; S^{fit} is the goodness of fit score.

IV. Dataset

The FP module is trained on a combination of the H&M Personalized Fashion Recommendations dataset [67] and the Amazon Reviews dataset [68]. Our data collection methodology uses social media and fashion e-commerce platforms to collect images of users physically wearing garments. These images are then processed by a clothing retrieval architecture inspired by ClothingOut [9] to retrieve body-agnostic garment images. The physical try-on image is fed to an architecture based on PIFuHD [10] to generate a 3D physical try-on representation. The garment image with the 2D and 3D physical

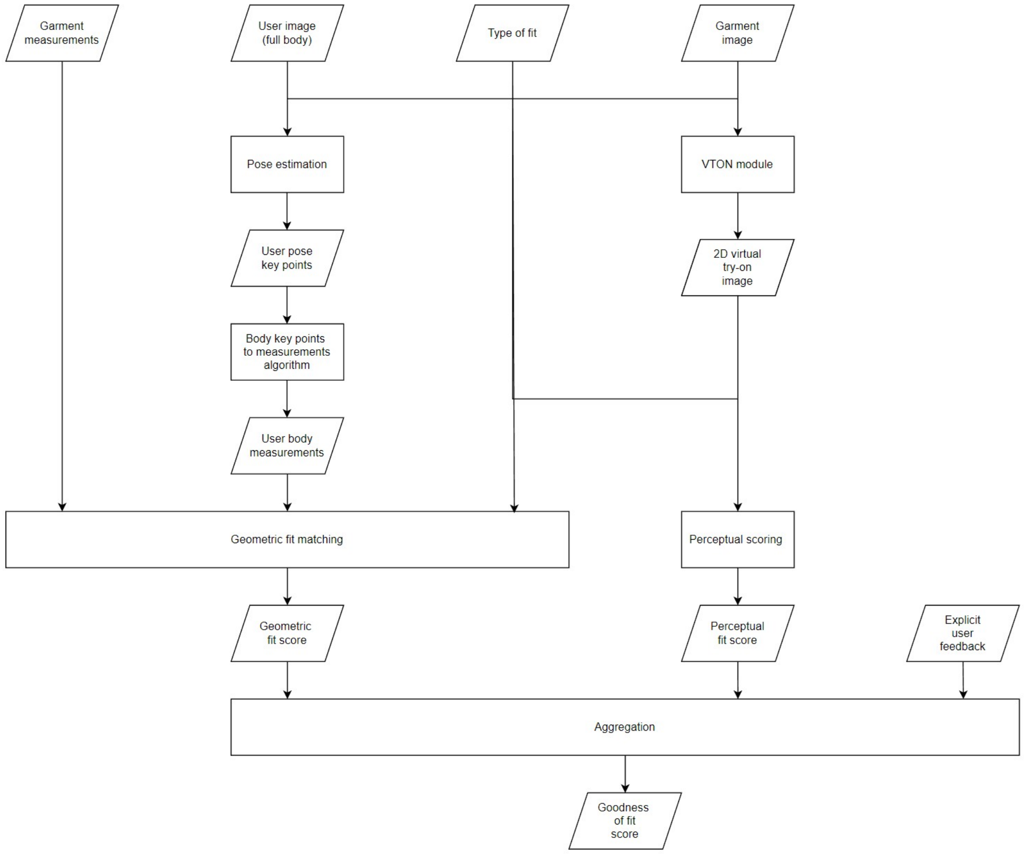

Fig. 3. Flowchart of GPF module.

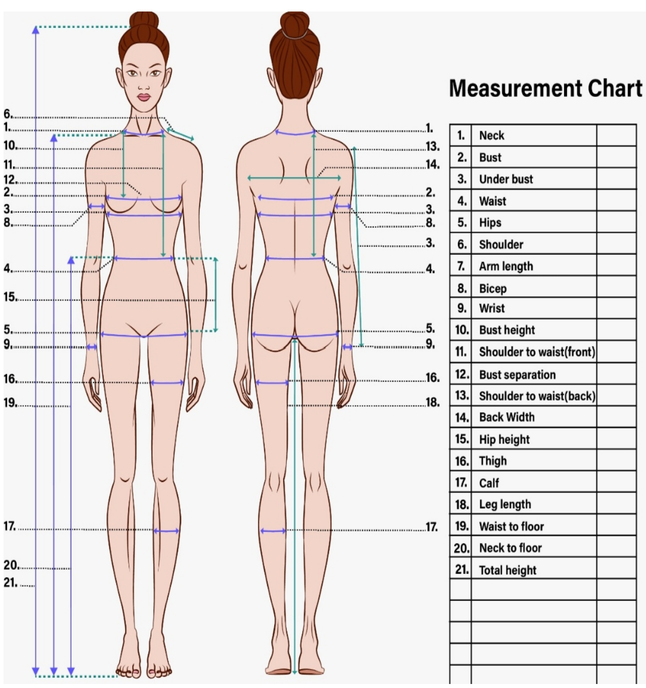

Fig. 4. Body measurements chart.

try-on representations is used to train the VTON module. The user image is further labelled for the fit type and as fit or unfit (based on the fit type). The classification dataset is therefore used to train the GPF module's perceptual scoring models.

V. Applications

The HHAGP system, when applied to fashion e-commerce, can drastically reduce the return rate and improve the user experience while also developing a comprehensive fashion dataset of user size-fit. The HHAGP system can also be applied to physical stores with IoT mirrors which can reduce store crowding and provide instant clothing trials with fashion recommendations.

The HHAGP system, in combination with IoT mirrors and AR applications, can serve as a framework for continuous updates of metaverse character models. Whenever a user uses the IoT mirror or AR application for the virtual try-on of clothing, the HHAGP system can use the generated 3D virtual try-on representation as the user's updated metaverse character. The use of IoT mirrors in homes can further make this update frequency even shorter allowing users' metaverse characters to be a one-to-one representation of their real-world bodies.

VI. Conclusion

In this work, we propose a Holistic Hybrid Adaptive Geometric and Perceptual (HHAGP) Recommender System for individualized fashion recommendations that builds on the merits of the various modern fashion recommender and 2D & 3D virtual try-on approaches. Our HHAGP system models the fashion preferences of the user and allows the user to virtually try on clothing while also providing heuristics regarding the fit and look of the garment on the user's body. For future work, we propose a streamlined architecture of the HHAGP system for computationally effective fashion recommendations.

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