A MACHINE LEARNING BASED MULTI-ATTRIBUTE RECOMMENDATION SYSTEM FOR WOMEN'S APPAREL USING RANDOM FOREST

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ABSTRACT

Personalized clothing recommendation is a challenging task due to the complex interactions among body morphology, individual preferences, and usage context. This study proposes a multi-output women's clothing recommendation framework based on a Random Forest (RF) model, utilizing 20 input features including anthropometric characteristics, demographic information, personal desires, consumption behavior, and contextual factors. Five clothing attributes are simultaneously predicted: silhouette, color group, fabric type, fit type, and garment length. Experimental results indicate moderate to good performance, with Accuracy ranging from 0.6339 to 0.8125 and Balanced Accuracy from 0.6724 to 0.8607. Among these attributes, silhouette achieves the highest predictive accuracy (0.8125, Kappa = 0.7136). Apparel length and fabric type show satisfactory results, whereas color group and fit type are more difficult to predict due to their subjective nature. Overall, the findings confirm the potential of Random Forest for multi-attribute clothing recommendation systems that meet personalization requirements.

Keywords: *Fashion recommendation system, Personalized Apparel Recommendation, Machine learning in fashion, Random Forest model.*

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1. INTRODUCTION

In the rapidly evolving context of e-commerce and artificial intelligence, personalized fashion recommendation systems have emerged as a significant research direction aimed at assisting users in selecting clothing that aligns with their preferences, body characteristics, and usage contexts. Recommendation systems represent an important application of artificial intelligence that leverage user data to generate personalized suggestions, thereby enhancing user experience and reducing the time required for decision-making [1, 2]. Within the fashion domain, clothing recommendation research extends beyond simple product suggestions and requires a deeper understanding of aesthetic factors, body morphology, and usage purposes. This necessitates the integration of anthropometric data, individual preferences, and advanced machine learning algorithms [3].

Current fashion recommendation systems typically employ a variety of approaches, including collaborative filtering, hybrid models that combine visual information with product attributes, as well as deep learning networks for extracting image features and personal style representations [2]. Deep neural networks have been applied to outfit recommendation based on individual preferences [3]. Several models have been developed to incorporate semantic attributes in order to improve the interpretability of recommendations [4]. Furthermore, recent studies have utilized deep learning techniques to construct compatibility networks for personalized fashion recommendation [5]. Niveditha S. *et al.* developed a model employing deep learning (DL) and artificial intelligence techniques to recommend outfits that align with fashion trends and user preferences [6]. Meita P. P. S. *et al.* implemented a system based on BERT4Rec (Bidirectional Encoder Representations from Transformers for Sequential Recommendation) to provide personalized women's clothing recommendations using users' interaction sequences [7]. Harisu A. *et al.* proposed a hybrid and deep learning based fashion recommendation system with context-awareness capabilities [8]. Navya *et al.* introduced a deep learning model for personalized fashion recommendation using an image based fashion product dataset [9]. L. C. Wang *et al.* proposed a system designed to select the most suitable clothing design scheme for a specific consumer to achieve personalization [10]. B. Asiroglu *et al.* developed a clothing recommendation system based on a single user image without requiring prior shopping activity data [11]. R. Aoki *et al.* established a fashion style estimation model by enhancing an SVM-based classifier on a small-scale dataset [12]. T. Yamamoto *et al.* proposed a fashion style recognition algorithm using component dependent convolutional neural networks; however, body posture was not considered in their approach [13]. S. Jaradat *et al.* introduced two novel techniques that integrate textual content from Instagram to support fashion image classification [14]. Y. Seo *et al.* applied a pre-trained convolutional neural network based on the GoogLeNet architecture on a small ImageNet dataset for clothing image classification [15]. Y. Li *et al.* proposed a machine learning system for automatic outfit matching but did not incorporate clothing usage context [16]. W. Y. Chen *et al.* presented an approach for fashion image retrieval based on shape features associated with eight facial types [17].

However, most existing studies rely mainly on commercial data or product images, with limited integration of anthropometric data, personal preferences, and clothing usage contexts in experimental settings. In addition, many models still show limited predictive accuracy [18]. This creates a research gap in developing fashion recommendation systems based on real user data, particularly within specific cultural contexts such as Vietnamese women. Meanwhile, machine learning methods have been increasingly applied in apparel and fashion research, demonstrating significant advantages [19-23]. Hybrid models combined with parameter optimization have improved performance in applications such as demand forecasting and fashion sales prediction [24-27], attribute selection [28, 29], and customer recommendation tasks involving multiple variables and nonlinear relationships [30]. Therefore, this study develops Random Forest models to build a personalized women's clothing recommendation system based on individual characteristics, personal preferences, and usage context of Vietnamese women. Using survey data from 350 women together with expert labeled clothing recommendations, the study evaluates model performance in predicting key clothing attributes and provides empirical evidence of the effectiveness of Random Forest based approaches in apparel recommendation.

2. METHODS

This study adopts a quantitative research framework integrated with expert knowledge to develop a women's clothing recommendation system based on personal characteristics, individual preferences, and clothing usage contexts. The research procedure consists of four main stages: (i) collecting survey data from the target participants; (ii) encoding and preprocessing input feature variables; (iii) determining suitable clothing attributes using 3 experts based approach; and (iv) constructing, training, and evaluating machine learning models for clothing recommendation. Data on individual characteristics, personal preferences, and contextual factors were treated as input variables, while the recommended clothing attributes, including overall silhouette, fit, length, color group, and fabric type, served as the five output variables. Accordingly, five Random Forest models were developed in parallel to compare their performance in personalized women's clothing attribute recommendation.

2.1. Participants and Survey Data

The study participants consisted of 376 Vietnamese women aged between 18 and 60 years in Northern Vietnam, selected using a controlled convenience sampling approach to ensure diversity in age, occupation, educational level, and annual fashion expenditure. Data were collected through a structured questionnaire combining quantitative items and standardized scale-based questions. The survey information comprised: (i) anthropometric and body related characteristics; (ii) personal clothing styles and preferences; and (iii) clothing usage contexts. All collected data were validated, incomplete records were removed, and the dataset was standardized prior to subsequent analysis and model development.

2.2. Encoding of Personal Anthropometric, Body Characteristics and Preferences Variables

The anthropometric variables include *age, height, weight,* body mass index (*BMI*, defined as weight divided by the square of height), shoulder width (*shoulder*), and leg length (*leg_length*). Overall body shape (*body_shape*) is categorized into five groups, *A-line, H-line, X-line, T-line,* and *O-line*, and encoded as integer values from 1 to 5, respectively. Fashion spending (*fashion_spending*) is quantified as the annual amount (in million VND) that a participant spends on fashion products. User occupation is encoded as a categorical variable (*occ*), including student, worker, freelancer/office staff, teacher/manager, and businessperson/artist, represented by integer values from 1 to 4. Personal clothing preferences are assessed using five criteria: perceived elegance (*desire_elegant*), comfort (*desire_comfort*), confidence (*desire_confident*), attention attraction (*desire_attention*), and youthfulness (*desire_youthful*), all measured on a five-point Likert scale. The use of Likert scales enables the quantification of subjective factors while facilitating machine learning models in learning the relationships between personal preferences and the recommended clothing attributes.

2.3. Clothing Usage Context

Clothing usage context is described through a set of variables, including *season*, time of day (*time_day*), and usage purpose (*occasion*). The season and time variables are encoded as categorical features, with *Spring, Summer, Autumn*, and *Winter* and *Morning/Noon/Evening*. Clothing usage purposes are expressed as binary variables, including work (*occ_work*), daily activities (*occ_daily*), party (*occ_party*), and formal occasions (*occ_formal*). This encoding scheme allows a single outfit to simultaneously accommodate multiple usage contexts.

2.4. Expert-Based Clothing Recommendation Framework

The output clothing attributes include overall *silhouette, fit_type, length, color_group*, and *fabric_type*. These attributes are determined using an expert based approach grounded in practical experience in women's fashion design and styling consultation. The clothing recommendation framework is constructed through the integration of body characteristics, individual preferences, and usage contexts. For instance, individuals with *X-line* body shapes are typically recommended *X-line* silhouettes to emphasize natural curves; participants prioritizing comfort or exhibiting higher BMI values are advised to select garments with regular or loose fit; whereas those seeking prominence or attending evening events are often suggested warm color palettes and waist accentuating silhouettes. Fabric types are selected in accordance with seasonal conditions and comfort requirements. These recommendation rules are established by fashion experts and consistently applied across the entire dataset to generate output labels that are logical, stable, and reflective of real world fashion consulting practices.

2.5. Design and Implementation of the Clothing Recommendation System

The recommendation system was designed with five independent Random Forest models, each taking 20 input features comprising anthropometric characteristics, body morphology, personal preferences, and clothing usage context. The outputs of the five models correspond to the five recommended clothing attributes: overall silhouette, color group, fabric type, fit type, and apparel length.

Random Forest is an ensemble learning method that combines multiple decision trees to improve predictive accuracy and reduce overfitting. This model is particularly well suited for mixed datasets containing both continuous and categorical variables and additionally enables the assessment of input feature importance. For the multiclass clothing attribute recommendation task in this study, RF generated final predictions based on majority voting across all trees in the forest. The Random Forest optimization procedure was conducted as follows: (1) identification of key hyperparameters, including *ntree* (number of trees in the forest), *mtry* (number of variables randomly selected at each split), and *nodesize* or minimum tree depth; (2) hyperparameter tuning using *k-fold cross-validation* on the training set, with the parameter combination achieving the highest *Balanced Accuracy* selected for the final RF model; and (3) training of the optimized Random Forest model on the training set and evaluation on an independent test set using *Accuracy, Kappa,* and *Balanced Accuracy* metrics [31].

After completing the dataset and defining the input and output variable sets, the models were established to evaluate the performance of the five recommendation models corresponding to the five clothing attributes: *silhouette, color_group, fabric_type, fit_type, and length*. The dataset comprising 376 samples is divided into two subsets: a training set accounting for 80% of the data and a test set comprising the remaining 20% and using *createDataPartition* function in R software. The data split is conducted randomly but in a controlled manner to maintain relatively balanced class distributions across both subsets. The training set is utilized for model construction and hyperparameter tuning, while the independent test set is used to assess the generalization performance of the models. Prior to training, continuous variables were normalized to a common scale to improve model convergence. Categorical variables were appropriately encoded using one-hot encoding or label encoding. Although normalization is not strictly required for Random Forest models, it was applied to ensure consistency across the data processing pipeline. Each model was trained independently for its corresponding clothing attribute. The final recommendation results were aggregated and compared with expert-labeled ground truth in test set.

To evaluate the effectiveness of the clothing recommendation models, this study employs primary metrics: *Accuracy*, *Cohen's Kappa* coefficient and *Balanced Accuracy*. These metrics are selected to reflect not only the proportion of correct predictions but also the level of agreement between model outputs and expert recommendations. *Accuracy* is defined as the ratio of correctly predicted instances to the total number of samples in the test set. This metric indicates the overall predictive capability of the model in providing appropriate recommendations. However, in multiclass classification tasks with potentially slight class imbalance, Accuracy alone may not fully capture model quality. Therefore, *Cohen's Kappa* coefficient is additionally utilized to measure the degree of agreement between model predictions and expert labeled outputs while accounting for agreement occurring by chance. Given the multiclass and imbalanced nature of the dataset, *Balanced Accuracy* was employed as the primary evaluation metric, as it equally weights class wise recall and avoids dominance of majority classes. *Cohen's Kappa* was reported to assess agreement beyond chance, while overall accuracy was provided for reference. The combination of these metrics enables a comprehensive evaluation of model performance, ensuring both high predictive accuracy and effective learning of expert fashion knowledge. The best performing model is selected based on evaluation results on the test set, while also considering model stability and practical applicability within the personalized women's clothing recommendation system.

3. RESULTS AND DESCUSSIONS

The performance metrics of the five Random Forest models for recommending women's overall silhouette, color group, fabric type, fit type, and garment length in test set are presented in Table 1.

Table 1. RF Model's Performance for women clothing recommendation

Model's output	*Accuracy*	*Kappa*	*Balanced_accuracy*
Silhouette	0.8125	0.7136	0.8607
Color_type	0.6339	0.4302	0.7080
Fabric_type	0.7946	0.4009	0.6878
Fit_type	0.7054	0.3285	0.6724
Length	0.7297	0.4363	0.6973

The results in Table 1 indicate that the Random Forest model achieves reasonably strong performance in the women's outfit recommendation task, using anthropometric characteristics, personal preferences, and usage context as input variables, together with five garment related output attributes. Overall, Accuracy ranges from 0.6339 to 0.8125, while Balanced Accuracy lies between 0.6724 and 0.8607, reflecting relatively stable generalization capability on the unseen dataset.

Among the output attributes, the RF model for *silhouette* achieves the best performance (Accuracy = 0.8125, Kappa = 0.7136, Balanced Accuracy = 0.8607). The high Kappa value indicates strong agreement between model predictions and ground truth labels, well beyond chance. This suggests that anthropometric features and personal preferences (e.g., height, weight, BMI, and body shape) are closely associated with silhouette selection, and that Random Forest effectively captures nonlinear relationships and feature interactions in this task. These results confirm that silhouette is the most learnable attribute from personalized data and plays a foundational role in the outfit recommendation system. For *fabric_type* and *length*, the model achieves Accuracies of 0.7946 and 0.7297, respectively, with Balanced Accuracy values of approximately 0.69 ÷ 0.70. Although Accuracy is relatively high, the moderate Kappa values (0.4009 and 0.4363) indicate the presence of class imbalance or feature overlap between groups (despite these being realistic attributes). This reflects the fact that fabric choice and garment length depend not only on anthropometric characteristics but are also strongly influenced by usage context, seasonality, and fashion trends factors that may not yet be fully represented in the current feature set. The two attributes *color_type* and *fit_type* yield lower performance, particularly in terms of Kappa (0.4302 and 0.3285, respectively). Although *color_type* attains a Balanced Accuracy of 0.7080, its Accuracy remains at 0.6339, indicating difficulties in discriminating color classes, which are highly subjective and strongly dependent on individual taste as well as cultural factors. Similarly, *fit_type* exhibits the lowest Balanced Accuracy (0.6724), reflecting the complexity of mapping body characteristics and user preferences to perceived "fit," which is often shaped by wearing habits and personal experience.

Overall, the experimental results demonstrate that Random Forest is a suitable approach for multioutput outfit recommendation systems, particularly for attributes closely tied to body morphology such as *silhouette* and *length*. However, performance remains limited for highly perceptual and aesthetic attributes (*color_group* and *fit_type*). This suggests that future studies may benefit from incorporating additional psycho-aesthetic user features or integrating Random Forest with deep learning or hybrid models to better represent usage context and personal preferences. Furthermore, addressing class imbalance and expanding the dataset scale may further enhance the reliability and practical applicability of personalized fashion recommendation systems.

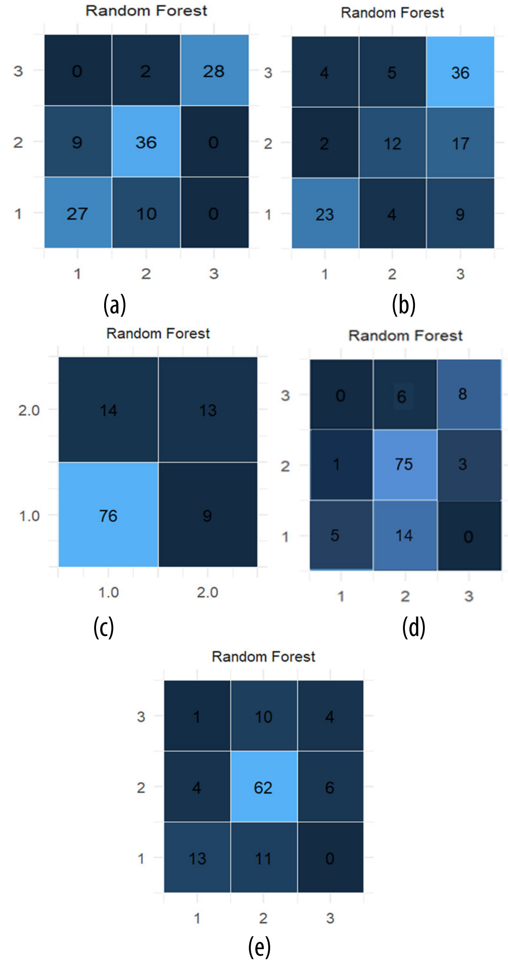
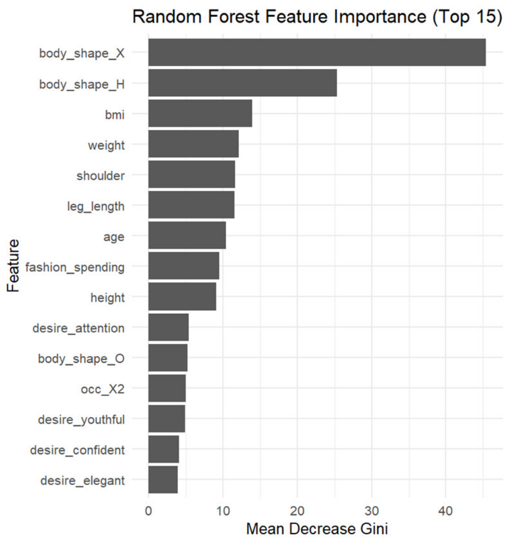


Figure 1. Confusion matrices of the clothing *silhouette* (a), *color_group* (b), *fabric_type* (c), *fit_type* (d) and *length* (e) recommendation models on the test set

Figure 1 presents the confusion matrices of the Random Forest models for five output attributes in the women's outfit recommendation system: *silhouette, color_group, fabric_type, fit_type*, and *length*, evaluated on the test set. Overall, the models classify dominant classes more effectively but show greater difficulty with boundary or low sample classes, reflecting typical characteristics of real world personalized fashion data. For *silhouette*, class 2 is classified relatively well (36 correct predictions), while classes 1 and 3 show substantial confusion toward class 2, with 27 and 28 samples misclassified respectively. This indicates that the intermediate silhouette acts as a morphological "overlap zone," where anthropometric features do not clearly separate extreme body types, consistent with practical garment classification. For *color_group,* confusion among the three groups is relatively high, especially between classes 1 and 3. Although class 3 achieves the highest correct predictions (36 samples), several samples from other classes are cross classified. This reflects the subjective nature of color recommendation, where similar anthropometric and preference profiles may correspond to multiple suitable color choices. For *fabric_type* (binary classification), the model correctly predicts most class 1 samples (76), while class 2 shows higher misclassification (13 predicted as class 1). This suggests a bias toward the dominant class and reflects the increasing functional overlap between woven and knitted fabrics. For *fit_type*, class 2 is strongly recognized (75 correct predictions), while the other classes are frequently assigned to the central class. This suggests that perceived "fit" is highly subjective, with most users concentrated around a medium fit level. For *length*, class 2 again achieves the highest accuracy (62 samples), while classes 1 and 3 often shift toward the middle class. Similar to silhouette, medium length appears as a default option when anthropometric cues are insufficient. Overall, the models perform better for central classes and attributes closely linked to body morphology, but face challenges with boundary classes and perceptual attributes such as color and fit. These results suggest that anthropometric data are effective for recommending silhouette and length but insufficient for fully modeling color preference and perceived fit. Future research should integrate psycho-aesthetic factors and class imbalance handling or hybrid models to improve minority class discrimination and enhance personalization.

Figure 2 presents the top 15 input features ranked by *Mean Decrease Gini* from the Random Forest models for *silhouette* and *color_group*, revealing different governing factors for each attribute and reflecting the multidimensional nature of personalized fashion recommendation. For *silhouette*, body morphology features dominate. *body_shape_X* and *body_shape_H* are the most influential variables, indicating that body shape is the primary determinant of silhouette selection. Variables related to body size and proportion, including *BMI, weight, shoulder, leg_length*, and *height*, also contribute substantially. This aligns with garment design theory, where silhouette is largely determined by body structure and anthropometric proportions. Demographic (*age*) and consumption related (*fashion_spending*) variables also appear among the important features, suggesting that silhouette choice is influenced not only by body geometry but also by life stage and fashion investment. In contrast, preference variables such as *desire_youthful*, *desire_confident*, and *desire_elegant* contribute less, indicating that silhouette functions mainly as a structural attribute rather than a perceptual one. For *color_group*, contextual and preference variables are more prominent. *season_Winter* is the most influential feature, highlighting the role of seasonality in color selection. *season_Spring* and anthropometric variables (*BMI, weight, age, height*) also contribute, suggesting that color choice depends on both usage context and visual perception of body proportions. Preference variables including *desire_attention, desire_youthful, desire_elegant*, and *desire_comfort*, together with usage context variables (*occ_party, occ_daily*), further demonstrate the subjective and expressive nature of color decisions. Comparatively, silhouette is primarily determined by body morphology, whereas color_group is more strongly influenced by contextual factors and personal preferences. This explains the higher predictive accuracy observed for silhouette. These findings suggest that silhouette recommendation should prioritize accurate anthropometric data, while *color_group* recommendation should emphasize seasonal information, usage context, and users' expressive intentions. Future research may integrate explainability methods and additional psycho aesthetic variables to improve the modeling of color preference and enhance personalization.



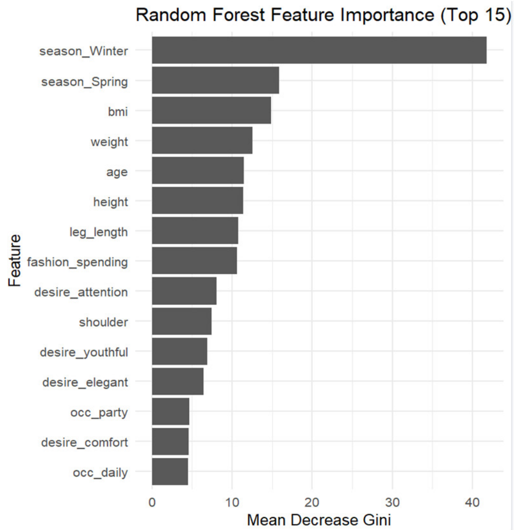
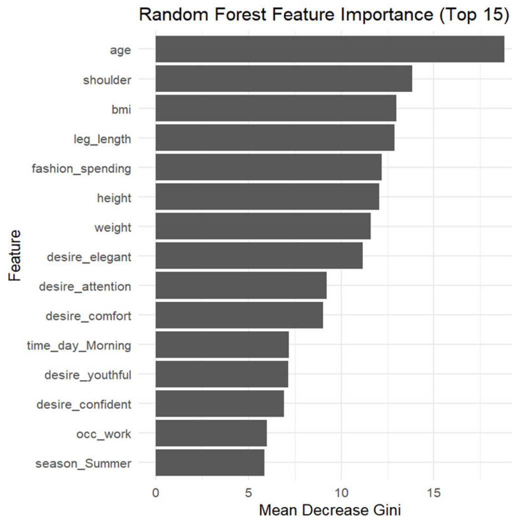


Figure 2. Input feature importance for silhouette and color_group on the test set using RF models



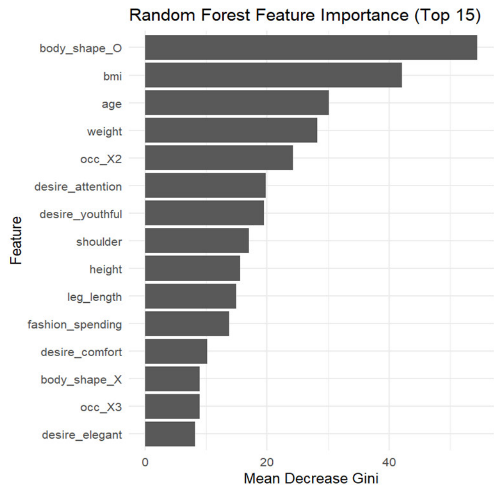


Figure 3. Input feature importance for fabric_type and fit_type on the test set using RF models

The top 15 input features ranked by Mean Decrease Gini from the Random Forest models for *fabric_type* and *fit_type*, revealing different decision mechanisms while highlighting the roles of anthropometric characteristics, consumption behavior, and individual preferences (Figure 3). For *fabric_type*, age is the most influential variable, indicating its central role in fabric selection. This reflects differences across age groups in comfort perception, trend acceptance, and functional priorities. Body morphology variables such as *shoulder, BMI, leg_length, height*, and *weight* also appear prominently, suggesting that fabric choice is closely related to drape, fit, and the ability to conceal body imperfections. *fashion_spending* also shows notable influence, implying that purchasing power affects access to different fabric categories. Preference variables (*desire_elegant, desire_attention, desire_comfort*) further indicate a balance between aesthetics and comfort, while contextual variables such as *time_day_Morning* and *season_Summer* suggest that temporal and seasonal conditions influence fabric selection. For *fit_type*, anthropometric characteristics dominate. *body_shape_O* and *BMI* are the most influential variables, indicating that body shape and body mass index strongly affect perceived garment fit. Age and weight also contribute, reflecting age-related changes in body form and dressing expectations. The contextual variable *occ_X2* shows noticeable influence, suggesting that fit requirements depend on usage purposes such as work or social activities. Preference variables including *desire_attention* and *desire_youthful* indicate that fit functions not only as a sizing parameter but also as a means of self presentation. Compared with silhouette, fit related features are more dispersed, reflecting the multidimensional and subjective nature of fit. Comparatively, *fabric_type* is influenced by age, body morphology, and spending behavior, whereas *fit_type* depends more on body shape, BMI, and usage context, moderated by self expression preferences. This aligns with earlier evaluation results where *fit_type* showed lower Kappa values than *fabric_type*, indicating greater difficulty in learning perceptually defined boundaries. These findings suggest that fabric recommendation should prioritize age, body morphology, and spending data, while fit recommendation requires detailed body shape information combined with usage context and desired personal image. Future studies may incorporate post wear feedback and advanced explainability methods to better capture the notion of fit and improve personalization in intelligent clothing recommendation systems.

The top 15 features ranked by Mean Decrease Gini for clothing length, showing that garment length is jointly influenced by demographic factors, body morphology, consumption behavior, and individual preferences (Figure 4).

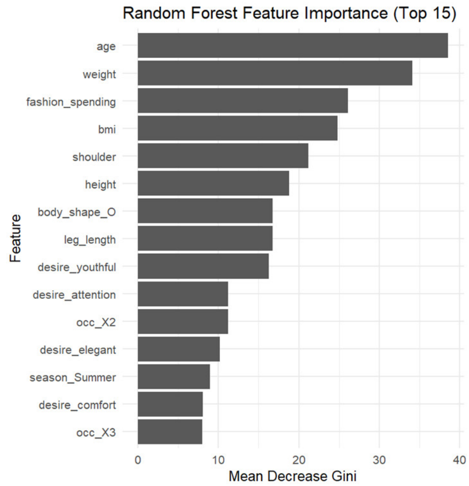


Figure 4. Input feature importance for clothing *length* on the test set using RF model

Age emerges as the most influential variable, highlighting its central role in clothing length preference. This result aligns with practice, as different age groups often exhibit distinct aesthetic norms and acceptance levels regarding garment length. *Weight* and *fashion_spending* follow in importance, indicating that both body characteristics and purchasing power affect length decisions through perceived body proportions and access to diverse styles. Anthropometric variables such as *BMI, shoulder, height, body_shape_O*, and *leg_length* are also prominent, suggesting that clothing length is closely associated with overall body proportions, particularly the relationship between upper body structure and leg length. This observation is consistent with established garment design principles, where length is adjusted to achieve visual balance and improve perceived proportions. Preferenc related variables, including *desire_youthful, desire_attention, desire_elegant*, and *desire_comfort*, further indicate that clothing length functions as a form of self expression rather than merely a sizing parameter. Contextual factors such as *season_Summer* and *occ_X2, occ_X3* also contribute, reflecting the influence of seasonal conditions and occupational environments on clothing choices. Compared with other attributes (*silhouette, color_group, fabric_type*, and *fit_type*), *length* plays an intermediate role between body morphology and aesthetic perception. This is consistent with earlier evaluation results showing moderate to good accuracy but some confusion at boundary classes due to natural overlaps between length categories. These findings suggest that recommendation systems should prioritize accurate age and anthropometric data while incorporating style preferences and usage contexts to improve personalization.

4. CONCLUSIONS

This study successfully developed a women's clothing recommendation system based on a Random Forest model using 20 input features and five output attributes, including *silhouette*, *color_group*, *fabric_type*, *fit_type*, and *length*. Experimental results on the test set indicate that the model achieved moderate to good performance (Accuracy: 0.6339÷0.8125; Balanced Accuracy: 0.6724÷0.8607), with *silhouette* exhibiting the highest predictive accuracy, reflecting the strong relationship between body morphology and overall garment style.

Analysis of the confusion matrices and feature importance revealed that *silhouette* and *length* are primarily driven by anthropometric factors, whereas *color_group*, *fabric_type*, and *fit_type* depend more strongly on usage context and individual preferences. These findings confirm the central role of morphological data in silhouette recommendation while highlighting the necessity of integrating contextual and aesthetic information to enhance personalization. Overall, Random Forest demonstrates clear potential for practical multi-attribute clothing recommendation systems.

5. RESEARCH LIMITATION

The study still has several limitations. Class imbalance, although inherent to the problem, led the model to favor central classes and reduced prediction accuracy for boundary classes, particularly for *fit_type* and *length*. Attributes with strong perceptual subjectivity, such as *color_group* and *fit_type*, achieved only moderate Kappa values, indicating that the current feature set does not fully capture aesthetic factors and individual experiential preferences, and the proposed approach has been validated on a single dataset. In future work, expanding the dataset, incorporating psychological–aesthetic features, and integrating deep learning or hybrid modeling approaches are expected to further improve predictive performance and the level of personalization of the system.

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