SIMPLIFICATION OF USER PREFERENCE RULES FOR PERSONALIZED MAKEUP RECOMMENDATION IN AN AUTOMATIC VIRTUAL MAKEUP SYSTEM

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ABSTRACT

This study introduces a method for simplifying user preference rules in a virtual makeup system while maintaining user satisfaction with the generated results. Preference rules extracted using interactive evolutionary computation and fuzzy inference often contain redundant antecedent conditions, which reduce interpretability. To address this issue, we propose a rule-simplification method based on cosmetic feature importance, defined by their frequency of appearance across generations. The performance of the proposed approach is evaluated in experiments involving 16 participants, comparing user satisfaction with preference rules generated from rule sets containing 3, 5, 7, and 10 conditions. The results suggest that users' makeup preferences can be represented with fewer conditions without a significant decrease in satisfaction. These findings indicate that the proposed method preserves the essential characteristics of user preferences and is particularly effective in simplifying complex "dislike" preference rules.

Keywords: Interactive evolutionary computation, winner-based paired comparison method, genetic algorithm, preference rule simplification, virtual makeup.

1 INTRODUCTION

Recent years have witnessed increased use of online shopping and online counseling across a wide range of age groups, attributable to the widespread adoption of smartphones and impact of the COVID-19 pandemic. This has accelerated digital transformation in the cosmetic domain, including the deployment of virtual makeup systems that bridge the gap between digital representations and real products (Yupelmi et al., 2023). Such systems have been shown to reduce consumer anxiety during product trials and to enhance user engagement and brand trust (Micheletto et al., 2025).

Despite these advantages, most existing virtual makeup systems require users to manually select and combine individual cosmetic items, which are time-intensive and require considerable cognitive effort. To overcome this limitation, automatic makeup generation methods that

consider facial features and personal attributes have been proposed (Nguyen & Liu, 2017). However, these approaches provide limited support for explicitly representing and explaining user preferences in a human-interpretable form.

Interactive evolutionary computation (IEC) has been applied to virtual makeup systems to interactively acquire user preferences (Takenouchi et al., 2023). To mitigate user fatigue caused by repeated evaluations, paired-comparison methods have been introduced in IEC and shown to be effective for preference extraction (Takagi & Pallez, 2009). Winner-based paired comparison (WPC) represents a practical implementation of paired comparison in IEC-based virtual makeup systems. Building on this framework, Takenouchi et al. (2025) proposed a preference-rule-generation mechanism based on fuzzy inference. Preference rules make it possible to identify the cosmetic features associated with each user's evaluations and provide reasons for personalized recommendations. However, redundant antecedent conditions make it difficult to identify which features primarily affect each recommendation.

To address these limitations, this paper introduces a method for simplifying preference rules generated in an IEC-based makeup support system using the WPC method. Shorter rules enable users and system designers to identify influential cosmetic features more easily and understand recommendation results with fewer conditions. Unlike methods that explain prediction results after model construction, the proposed method directly simplifies preference rules obtained through IEC based on antecedent occurrence frequency. Its contribution is an interpretable Kansei-based framework that reduces redundant conditions while maintaining subjective satisfaction. The proposed method was evaluated through a user study with 16 participants to examine whether reducing the number of antecedent conditions affects user satisfaction.

2 PROPOSED SYSTEM

2.1 System overview

Figure 1 schematically illustrates the proposed IEC-based virtual makeup system using the WPC method. Makeup patterns evolve through user evaluations using a genetic algorithm (GA), and "like" and "dislike" preference rules are extracted from individuals with high and low fitness values. For example, a simplified preference rule with three antecedent conditions can be expressed as follows: if the foundation is dark, the lipstick is dark, and the eyeshadow is light, then the user evaluates the makeup as "like."

This study focuses on the rule-simplification module, which improves interpretability by reducing redundant antecedent conditions based on feature frequency. Minor refinements to makeup transparency thresholds are introduced to enhance visual realism.

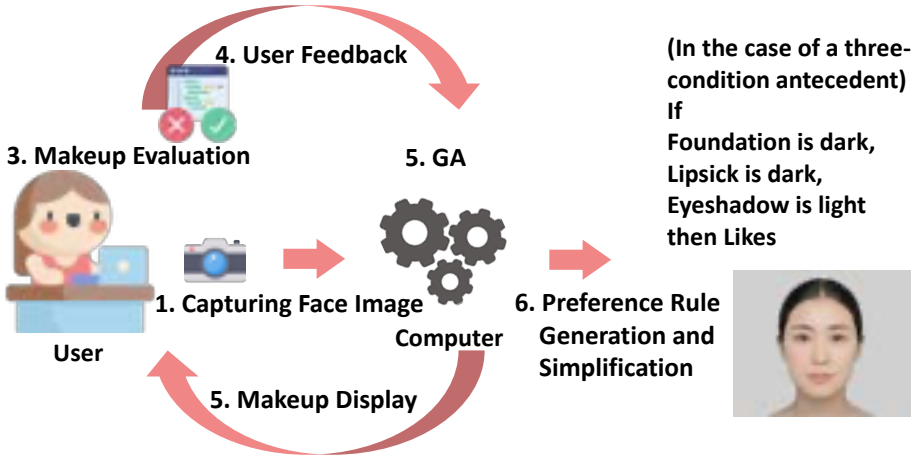


Figure 1. Overview of a Virtual Makeup System Incorporating Preference Rule Generation and Simplification Using IEC and WPC

2.2 Gene coding of makeup parts

Figure 2 illustrates the makeup configuration and its encoding scheme. The colors and opacity levels of six makeup parts—foundation, lips (lipstick), eyeshadow, cheeks (blush), eyebrows, and eyeliner—are encoded in a 28-bit gene string, resulting in a large combinatorial search space. Figure 3 illustrates the individual makeup parts used in the proposed system.

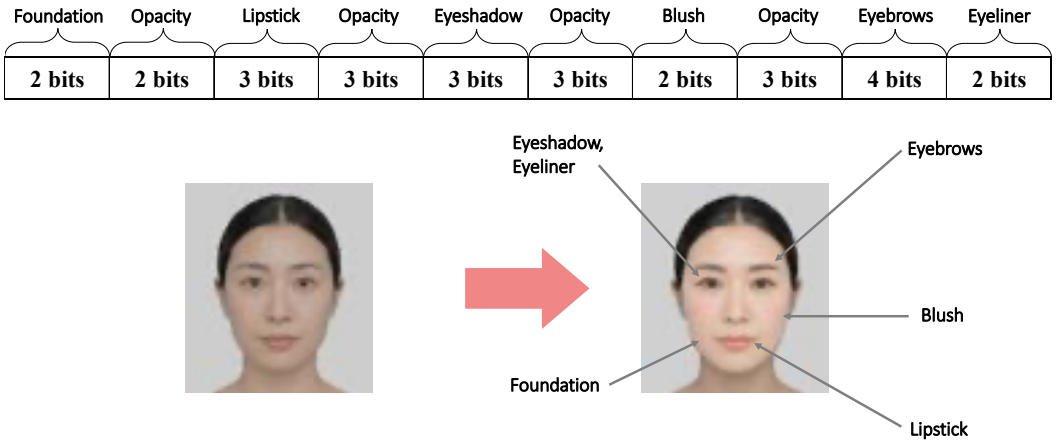


Figure 2. Makeup Configuration

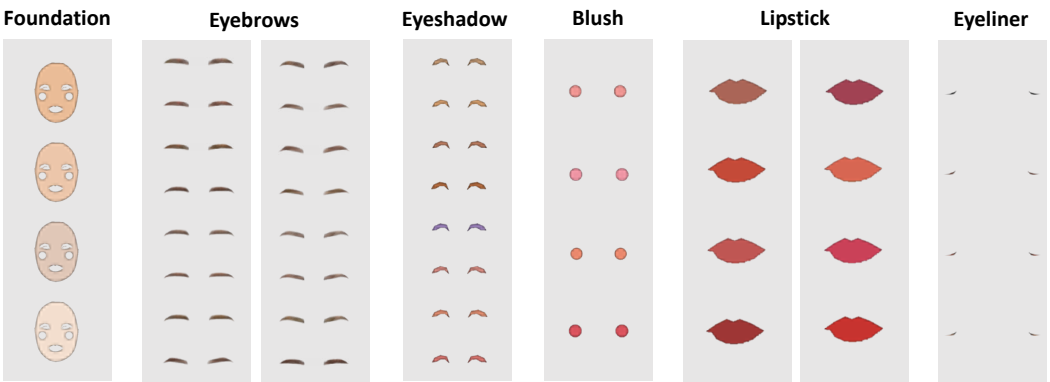


Figure 3. Makeup parts

2.3 Individual evaluation using WPC

Figure 4 illustrates the evaluation protocol within the WPC method. In WPC, individuals are evaluated through paired comparisons: two individuals are presented to the user, and evaluation scores are iteratively updated based on the comparison results to obtain a relative ranking.

All individuals are initially assigned an evaluation score of 1. In each comparison, the user selects the preferred individual, and the winner's score is updated according to predefined rules, while the other individual is replaced. This process is repeated until all individuals have been evaluated.

Table 1 summarizes the score-update rules, including cases where the user selects "both like" or "both dislike." These rules adjust evaluation scores according to relative preference consistency, following previous studies (Takenouchi et al., 2025).

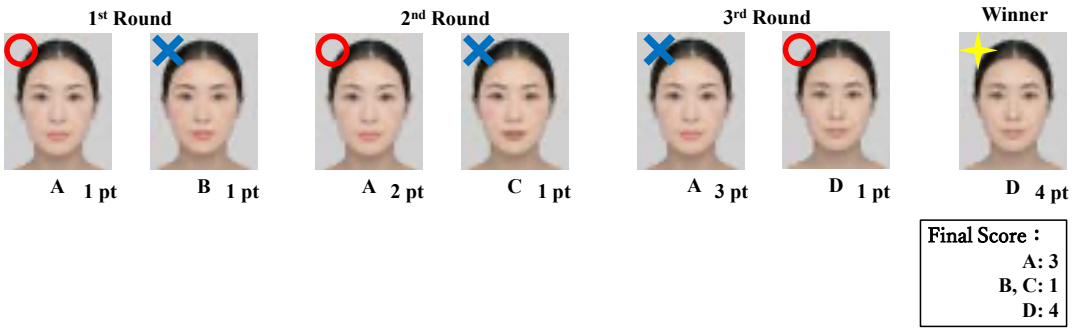


Figure 4. Individual evaluation method

Table 1. Changes in evaluation scores when "both like" or "both dislike" is selected

		Both like	**Both dislike**
Evaluation scores of presented makeup patterns	Match	Scores of both patterns +1	Scores of both patterns -1
	Mismatch	Lower score →Higher score	Higher score →Lower score

2.4 Fuzzy rule structure

The fuzzy rules used in this study adopt a general structure consisting of antecedent and consequent parts. The antecedent assigns binary labels to each feature, and the consequent takes binary evaluation labels. The number of antecedent features is set as $M = 10$. The rules are defined as

$$R_i = (R_i^1, R_i^2, \ldots, R_i^M, O_i) \quad (1)$$

where R_i^j denotes the antecedent label of the j-th feature in the i-th fuzzy rule, and O_i represents the consequent label of the corresponding rule.

2.5 Membership function design

Following previous studies (Takenouchi et al., 2025), two-label membership functions are defined for all makeup parts and their opacity, with minor modifications to reflect makeup design

characteristics. For foundation, eyebrow, and eyeliner, dark/bright labels are used, whereas subtle/vivid labels are assigned to lipstick, eyeshadow, and blush. The opacity of selected makeup parts is represented by light and heavy labels. Figure 5 shows the lipstick membership function as a representative example. The consequent membership functions consist of “dislike” and “like” labels.

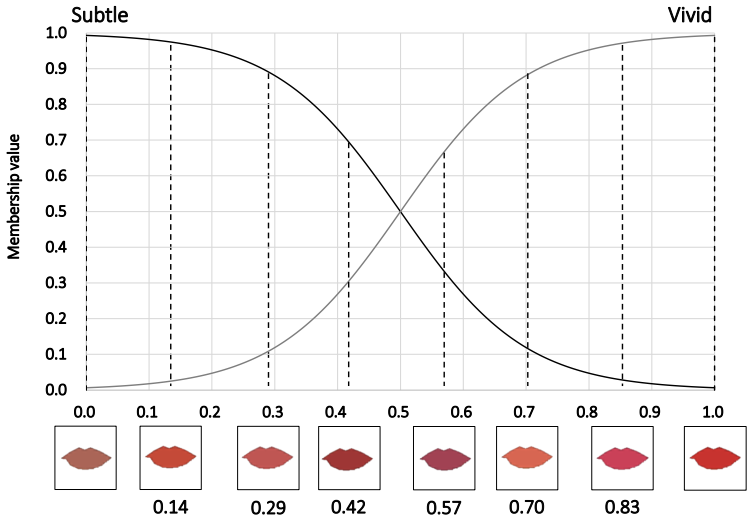


Figure 5. Lipstick membership function

2.6 Preference rule generation and organization

User preferences are represented as a set of fuzzy rules based on membership functions defined for the color and opacity of each makeup part. Each preference rule consists of ten antecedent items: six related to makeup colors and four related to opacity levels, with membership values assigned based on user evaluations.

To investigate the minimum number of antecedent conditions required to adequately represent user satisfaction, multiple rule sets with different numbers of antecedent conditions are constructed and evaluated. This allows us to examine whether reducing the number of conditions affects user satisfaction with the generated preference rules.

In each generation of the IEC process, “like” and “dislike” rules are generated from highly rated and poorly rated makeup patterns, respectively, thereby accumulating preference rules over successive generations.

To reduce redundancy, antecedents are first compared among rules of the same type, i.e., among “like” and “dislike” rules. When three or more of five selected antecedent items (excluding foundation and opacity) share identical membership values, the rules are considered identical and the older rule is compared.

Foundation-related parameters are excluded from this comparison because foundation color tends to exhibit less variation in user preference compared with other makeup parts, and its influence on distinguishing individual preferences is relatively limited.

Next, antecedents are compared between “like” and “dislike” rules. When all six color-related antecedent items match, the rules are considered contradictory and both are removed to maintain consistency. In this manner, we obtain a compact and consistent set of preference rules that reflect user preferences while eliminating redundant and contradictory information.

2.7 Preference-rule-simplification method

This section outlines the proposed rule-simplification method based on reducing the number of antecedent conditions. The importance of each antecedent condition is defined by its frequency of occurrence in the generated preference rules. Conditions with higher importance are retained as the top K antecedents, where $K = 3, 5, 7, or\ 10.$

Let R be the set of all preference rules and c an antecedent condition. The frequency $f(c)$ is defined as

$$f(c) = \sum_{r \in R} I(c \in r) \tag{2}$$

where $I(c \in r)$ is an indicator function that takes the value 1 if the antecedent label c appears in rule r, and 0 otherwise. Thus, $f(c)$ represents the frequency of occurrence of antecedent label c across all extracted preference rules. The importance weight $w(c)$ is obtained by normalizing $f(c)$:

$$w(c) = \frac{f(c) - \min f(c)}{\max f(c) - \min f(c)} \tag{3}$$

Each preference rule originally contains ten antecedents, from which only the top K conditions ranked by $w(c)$ are retained.

2.8 Evaluation interface

Figure 6 shows the evaluation interface used in this study. The user examines two makeup candidates and adjusts the opacity of each makeup part using sliders. Subsequently, the user selects the preferred makeup or chooses both candidates as “like” or both as “dislike.” Based on this input, the system calculates evaluation scores and automatically presents the next pair of makeup candidates. The user repeats this evaluation process for one generation. After the evaluations for a generation are completed, the system applies a GA to generate the next population of makeup candidates. This process is repeated until the final generation is reached. After completing the evaluations of the final generation, the system simplifies the extracted preference rules and generates the final set of simplified preference rules. Next, the system sequentially presents the preference rules with different numbers of antecedent conditions (3, 5, 7, and 10) to the same user, who evaluates each rule using a five-point rating scale.

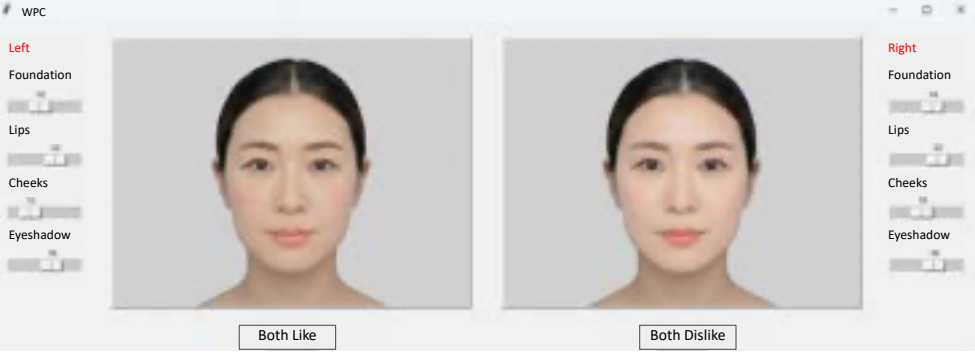


Figure 6. Evaluation interface after facial image capture

3 EVALUATION EXPERIMENT

3.1 Overview

A user study was conducted to evaluate the proposed preference-rule-simplification method using a GA-based makeup design system. This study was approved by the ethics committee of Fukuoka Institute of Technology, and informed consent was obtained from all participants. Preference rules were generated from participants' evaluations and simplified by reducing the number of antecedent conditions. Table 2 summarizes the experimental settings. Sixteen female university students evaluated simplified preference rules containing 3, 5, 7, or 10 antecedents on a five-point scale. This exploratory study used a small sample because each participant repeatedly evaluated makeup patterns over ten IEC generations; therefore, the findings should be regarded as preliminary. The results were analyzed to assess the effect of antecedent reduction on user satisfaction.

Table 2. Experimental settings

Item	Description
Participants	16 female university students
Experimental environment	Same display used for all participants
Population size	10 individuals per generation
Number of generations	10
Gene length	28 bits
Mutation rate	15%
Crossover method	Uniform crossover
Selection method	Roulette selection with elitism
Antecedents (K)	3, 5, 7, 10

3.2 Results of rule generation

Figure 7 shows the number of generated preference rules across all participants. On average, the number of "dislike" rules (9.75) was larger than that of "like" rules (4.50). This suggests that participants have more diverse or clearer criteria for unattractive makeup patterns.

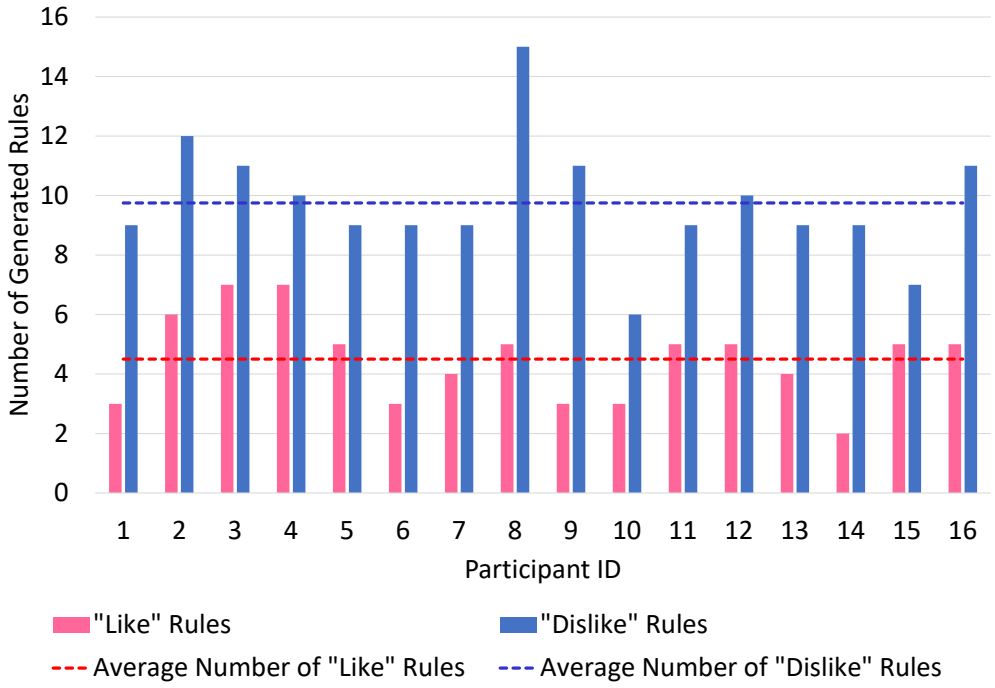


Figure 7. Number of generated preference rules

3.3 Satisfaction levels

Figure 8 illustrates the satisfaction levels for the simplified rules. For “like” and “dislike” rules, the mean scores were 3.08–3.48 and 4.04–4.08, respectively. The Friedman test revealed no significant difference in satisfaction among the four rule sets for either the “like” or “dislike” rules.

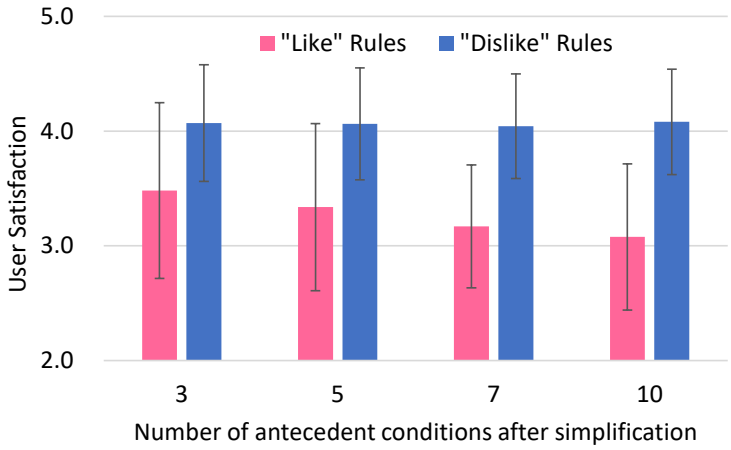


Figure 8. Mean and standard deviation of satisfaction for each preference rule across all participants

4 DISCUSSION

The experimental results showed that the number of generated “dislike” rules was consistently higher than that of “like” rules across all participants, indicating that users have clearer and more diverse criteria for identifying undesirable makeup than for desirable makeup. This suggests that

negative preferences may produce more redundant and complex rule sets than positive preferences.

In terms of user satisfaction, no significant differences were observed among rule sets with different numbers of antecedent conditions for either “like” or “dislike” rules. This indicates that reducing the number of antecedent conditions does not degrade user satisfaction. Moreover, “dislike” rules consistently received higher satisfaction scores than “like” rules, suggesting that simplified rules are more easily accepted when users’ evaluation criteria are explicit.

Simplified rules could provide concise recommendation reasons in virtual makeup, AR, beauty retail, and online consultation services. They may support understanding, personalization, and trust, although these user-centered effects were not directly evaluated.

Overall, these results demonstrate that the proposed simplification method improves the interpretability of preference rules while preserving user preferences, making it suitable for addressing redundancy in conventional preference-rule-generation methods. Thus, this study offers a novel empirical framework that ensures the interpretability of preference rules derived from IEC while retaining only a minimal set of essential information, even when the original rules become overly complex.

5 CONCLUSION

This study established a preference-rule-simplification method for an IEC-based virtual makeup system to improve interpretability. The importance of antecedent conditions was defined using their frequency of occurrence in the preference rules generated during the IEC process, and only high-importance conditions were retained. The results highlighted that users’ preference judgments can be effectively represented using a limited set of cosmetic features. The proposed method was particularly effective in simplifying redundant “dislike” preference rules. From a Kansei Engineering perspective, the method concisely represents subjective preferences using influential cosmetic attributes. However, the occurrence frequency of antecedent conditions does not capture interactions among cosmetic features, and the controlled study with 16 students limits generalizability. Future work will involve larger user studies, comparisons with alternative rule-simplification and explanation methods, including explainable AI approaches, importance measures that consider interactions among cosmetic features, and real-world cosmetic applications.

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