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# Developing an artificial intelligence-based decision support system for personalized sunscreen recommendation using the Preference Selection Index method

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**Abstract**

Increasing *ultraviolet* radiation exposure and the low adoption of *sunscreen* among men, compounded by difficulties in selecting products suitable for different skin types, highlight the need for a more objective and personalized recommendation system. This study aims to develop a web-based *Artificial Intelligence Decision Support System* (AI-DSS) using the *Preference Selection Index* (PSI) method to recommend *sunscreen* products according to users' skin types. A *Research and Development* approach with the *Extreme Programming* (XP) model was employed, involving a survey of 249 male students, evaluation of 10 *sunscreen* alternatives using five criteria, and system validation through *Root Mean Square Error* (RMSE). The results indicate that *Active Ingredient Count* (0.598) and *Product Label Claims* (0.536) are the most influential criteria, while Amaterasun UV Sunscreen Serum achieved the highest preference score (0.95). The system achieved an RMSE of 0.0089, demonstrating excellent computational accuracy. This study contributes an objective, accurate, and data-driven AI-based recommendation system to support personalized *sunscreen* selection.

**Keywords:** Artificial intelligence, Decision support system, Preference selection index, Sunscreen, Extreme programming.

**Abstrak**

Paparan radiasi *ultraviolet* dan rendahnya penggunaan *sunscreen* pada laki-laki, yang diperparah oleh kesulitan memilih produk sesuai tipe kulit, menunjukkan perlunya sistem rekomendasi yang lebih objektif dan personal. Penelitian ini bertujuan mengembangkan *Artificial Intelligence Decision Support System* (AI-DSS) berbasis *web* menggunakan metode *Preference Selection Index* (PSI) untuk merekomendasikan produk *sunscreen* berdasarkan karakteristik tipe kulit pengguna. Penelitian menggunakan pendekatan *Research and Development* dengan model *Extreme Programming* (XP), melibatkan survei terhadap 249 mahasiswa, evaluasi 10 alternatif *sunscreen* berdasarkan lima kriteria, serta validasi sistem menggunakan *Root Mean Square Error* (RMSE). Hasil penelitian menunjukkan bahwa *Active Ingredient Count* (0.598) dan *Product Label Claims* (0.536) merupakan kriteria paling berpengaruh, sedangkan Amaterasun UV Sunscreen Serum memperoleh nilai preferensi tertinggi (0.95). Nilai RMSE sebesar 0.0089 menunjukkan akurasi sistem yang sangat tinggi. Penelitian ini berkontribusi menyediakan sistem rekomendasi *sunscreen* yang objektif, akurat, dan mendukung pengambilan keputusan berbasis data.

**Kata Kunci:** Kecerdasan buatan, Sistem pendukung keputusan, *Preference selection index*, Tabir surya, *Extreme programming.*

## Introduction

Ultraviolet (UV) radiation, particularly UVA (320–400 nm) and UVB (290–320 nm), is one of the major environmental factors contributing to a wide range of acute and chronic skin disorders (Bernerd et al., 2022). Its adverse effects include erythema (sunburn), hyperpigmentation, increased transepidermal water loss (TEWL), premature skin aging, DNA damage, and an elevated risk of skin cancer (Papaccio et al., 2022). In recent years, sunscreen has become one of the most effective photoprotective measures for minimizing the harmful effects of UV exposure (Ngoc et al., 2019). Consequently, sunscreen is no longer regarded solely as a cosmetic product but has become an essential component of skin health maintenance and the prevention of various skin disorders associated with excessive sun exposure.

Despite the well-established benefits of sunscreen, its use among men remains considerably lower than among women (Hall et al., 2026). This disparity is influenced by several factors, including limited awareness of the importance of photoprotection, the perception that skincare products are primarily intended for women, and difficulties in selecting products that match individual skin characteristics (Tamer et al., 2025). A preliminary survey involving 249 male students from the Information Technology Program at the University of Jember revealed that 75.1% of respondents did not use sunscreen regularly, while 58.6% reported difficulties in choosing products that suited their skin needs. These findings indicate that sunscreen selection remains a significant challenge and requires a more systematic approach to assist users in identifying the most appropriate products.

Selecting an appropriate sunscreen is inherently a multi-criteria decision-making problem because each product differs in terms of SPF value, UVA protection level (PA), active ingredient composition, texture, and product label claims (McDonald et al., 2022). These characteristics must be matched with the user's skin type to maximize photoprotection while minimizing the risks of irritation, acne, or excessive skin dryness. Given the wide variety of sunscreen products currently available on the market, users often encounter difficulties in objectively comparing available alternatives (Maldonado López et al., 2025). Therefore, a decision support system capable of simultaneously evaluating multiple criteria is required to generate sunscreen recommendations that are more accurate, objective, and tailored to individual user needs.

Several researchers have developed recommendation systems for sunscreen and other skincare products using Multi-Criteria Decision-Making (MCDM) approaches. Alisha Firdaus et al. (2024) applied the *Simple Additive Weighting* (SAW) method to recommend sunscreen products based on multiple evaluation criteria; however, the method relies heavily on subjectively assigned criterion weights. Similarly, Sofian and Aprilianta (2025) employed the *Technique for Order Preference by Similarity to Ideal*

*Solution* (TOPSIS), which demonstrated effective ranking performance but involved relatively complex computations when handling both qualitative and quantitative data. In contrast, the *Preference Selection Index* (PSI) method automatically determines criterion importance without requiring predefined weights, resulting in a simpler, more objective, and more consistent evaluation process for ranking alternatives.

Based on these challenges, this study aims to develop a web-based decision support system for personalized sunscreen recommendation according to users' skin types using the *Preference Selection Index* (PSI) method. The system was developed using the *Extreme Programming* (XP) approach to produce adaptive, maintainable, and user-oriented software through an iterative development process. This study is expected to provide a more objective decision-making tool for selecting appropriate sunscreen products while increasing public awareness, particularly among men, of the importance of sunscreen as an essential component of skin health protection. In addition to its practical contribution for end users, this study is also expected to broaden the application of the PSI method in decision support systems within the healthcare and skincare domains.

## Method

This study employed a *research and development* (R&D) approach to develop a web-based decision support system for recommending sunscreen products using the *Preference Selection Index* (PSI) method (Richey & Klein, 2014). The system was developed using the *Extreme Programming* (XP) methodology because of its ability to accommodate evolving user requirements through an iterative and feedback-oriented development process. The research procedure consisted of data collection, preparation of alternatives and evaluation criteria, data preprocessing, PSI-based computation, web-based system development, and recommendation validation. These stages were conducted sequentially to ensure that the data, computational process, and resulting system maintained a high level of consistency and accuracy in generating sunscreen recommendations based on users' skin types. Figure 1 illustrates the overall workflow of the proposed sunscreen recommendation system using the PSI method and the *Extreme Programming* (XP) development approach.

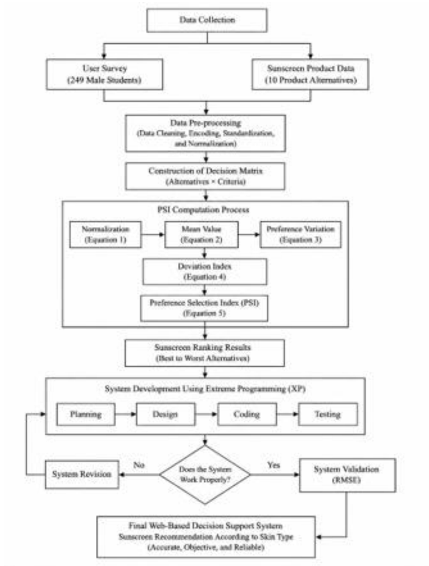


Figure 1. Research workflow of the proposed sunscreen recommendation system

Source: Developed by the authors (2026).

The research data consisted of two primary components: survey data and sunscreen product data. The survey involved 249 male students from the Information Technology Program at the University of Jember to collect information regarding sunscreen usage behavior, skin type categories, and the challenges encountered when selecting appropriate sunscreen products. Skin type classification adopted in this study comprised normal, oily, and dry skin, following the dermatological standards proposed by Mahto (2006) and the *Transepidermal Water Loss* (TEWL)-based skin physiology model developed by Luebberding et al. (2013). Subsequently, the dataset was constructed using ten sunscreen product alternatives collected from active ingredient repositories, dermocosmetic product information, and publicly available regulatory documentation. Each alternative was evaluated using five criteria: *SPF Rating*, *PA Grade*, *Active Ingredient Count*, *Texture Suitability*, and *Product Label Claims*. These criteria were selected because they represent the key factors influencing both the effectiveness of skin protection and user comfort during sunscreen application. Before the computational process, all data underwent preprocessing, including data cleaning, standardization of qualitative attributes into a five-point Likert scale based on cosmetic sensory evaluation guidelines (Marque et al., 2022), normalization of numerical attributes as benefit-type criteria according to the PSI procedure, and encoding of categorical variables, such as converting PA ratings from PA+ = 1 to PA++++ = 4 following UVA protection standards. These preprocessing procedures ensured that the dataset was standardized, comparable, and ready for the decision-making process.

The *Preference Selection Index* (PSI) method was employed to generate an objective ranking of sunscreen alternatives without requiring predefined criterion weights (Obeidat et al., 2025). The computation began with the construction of a decision matrix, $X = [x_{ij}]$, where each alternative $A_i$represents a sunscreen product and each criterion $C_j$represents an evaluation attribute. The decision matrix was subsequently normalized using the following equation:

$$n_{ij} = \frac{x_{ij}}{\max(x_j)} \qquad (1)$$

Next, the mean normalized value for each criterion was calculated as follows:

$$N_j = \frac{1}{m}\sum_{i=1}^{m} n_{ij} \qquad (2)$$

The resulting mean values were then used to determine the *Preference Variation*:

$$\phi_j = 1 - N_j \qquad (3)$$

Subsequently, the *Deviation Index* for each criterion was calculated using:

$$D_j = \frac{PV_j}{\sum PV_j} \qquad (4)$$

A higher deviation index indicates that a criterion possesses greater discriminatory power in distinguishing the quality of the evaluated alternatives. Finally, the *Preference Selection Index* for each alternative was calculated using the following equation:

$$PSI_i = \sum_{j=1}^{n} N_{ij}\, \phi_j \qquad (5)$$

The alternative with the highest PSI value was identified as the most suitable recommendation because it exhibited the highest overall level of conformity across all evaluation criteria.

System development followed the *Extreme Programming* (XP) methodology, which consists of four major phases: *planning*, *design*, *coding*, and *testing*. During the *planning* phase, system requirements were identified based on the survey findings and the functional requirements of the recommendation system. The *design* phase focused on database architecture, user interface design, and the integration workflow of the PSI method into the application. During the *coding* phase, all web-based system functionalities were implemented, enabling users to select their skin type and automatically obtain sunscreen recommendations. Finally, the *testing* phase was conducted to verify that every system feature functioned as intended and that the PSI computation implemented within the application consistently matched the manual calculation results.

To evaluate the system's computational accuracy, the PSI scores generated by the application were compared with those obtained through manual calculations using the *Root Mean Square Error* (RMSE) metric. RMSE was calculated based on the differences between the preference values produced by the system and those obtained manually across all sunscreen alternatives. A lower RMSE value indicates a higher level of agreement between the automated and manual computations. Therefore, the developed system can be considered capable of generating accurate, objective, and reliable sunscreen recommendations to assist users in selecting products that best match their skin characteristics.

## Results and Discussion

### Active ingredients and product claims dominate sunscreen preference ranking

The *Preference Selection Index* (PSI) method provides an evaluation framework capable of distinguishing the quality of each sunscreen alternative based on the combination of five key evaluation criteria. The computational procedure was performed sequentially, beginning with the identification of evaluation criteria, followed by data normalization, calculation of the *preference variation* and *deviation index*, and finally the determination of the preference value for each alternative. This approach enables all products to be evaluated using a uniform assessment framework without requiring subjective criterion weighting from decision-makers. The computational results indicate that each criterion contributes differently to the ranking process, resulting in varying preference values across the evaluated alternatives. These findings demonstrate that the PSI method effectively identifies the most influential factors in determining sunscreen recommendations based on the characteristics of each product.

Table 1. Benefit criteria used in sunscreen evaluation

| Criterion | Description | Type | Scale/Unit |
|---|---|---|---|
| SPF Rating | UVB protection strength | Benefit | SPF 15–50+ |
| PA Grade | UVA protection level | Benefit | PA+–PA++++ (Ordinal 1–4) |
| Texture Suitability | Compatibility with skin type (Normal, Oily, Dry) | Benefit | Likert Scale (1–5) |
| Product Label Claims | Claims such as non-comedogenic, oil control, hydrating | Benefit | Ordinal Scale (1–5) |
| Active Ingredient Count | Number of UV filters (Organic/Inorganic) | Benefit | 1–6 Ingredients |

Source: Authors' analysis (2026).

Table 1 shows that all evaluation parameters were classified as benefit-type criteria, indicating that higher values represent better product quality. These five criteria were selected because they capture the primary aspects influencing both the effectiveness of ultraviolet protection and user comfort across different skin types. *SPF Rating* and *PA Grade* represent the levels of UVB and UVA protection, whereas *Texture Suitability*, *Product Label Claims*, and *Active Ingredient Count* reflect product characteristics that influence compatibility with users' skin needs. Classifying all evaluation attributes as benefit criteria provides a consistent basis for the normalization process and ensures that all sunscreen alternatives can be compared objectively during the subsequent computational stages.

Following the normalization process, each criterion was analyzed using the *preference variation* and *deviation index* to determine its relative contribution to distinguishing the quality of sunscreen alternatives. A higher *deviation index* indicates greater discriminatory power, meaning that the corresponding criterion exerts a stronger influence on the final ranking. Conversely, lower values indicate that most alternatives exhibit relatively similar characteristics for that criterion, thereby reducing its contribution to the evaluation process. The complete results of the *mean normalized value*, *preference variation*, and *deviation index* calculations are presented in Table 2.

Table 2. Active ingredient count produces the highest deviation index

| **Criterion** | **Mean Normalized Value** | **Preference (PV)** | **Variation** | **Deviation Index** |
|---|---|---|---|---|
| SPF Rating | 0.93 | 0.07 | | 0.144 |
| PA Grade | 0.85 | 0.15 | | 0.309 |
| Texture Suitability | 0.82 | 0.18 | | 0.371 |
| Product Label Claims | 0.74 | 0.26 | | 0.536 |
| Active Ingredient Count | 0.71 | 0.29 | | 0.598 |

Source: Authors' calculation using the PSI method (2026).

Figure 2 presents a visual comparison of the *deviation index* values for all evaluation criteria, highlighting their relative contributions to the sunscreen recommendation process.

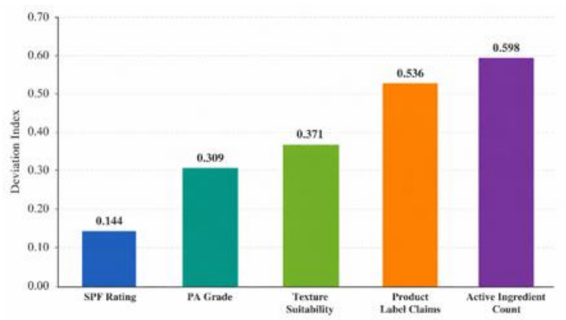


Figure 2. Deviation index distribution of sunscreen evaluation criteria

Source: Authors' calculation using the PSI method (2026).

As illustrated in Figure 2, *Active Ingredient Count* achieved the highest *deviation index* (0.598), followed by *Product Label Claims* (0.536), whereas *SPF Rating* recorded the lowest value (0.144). The visualization clearly demonstrates that the two highest-ranking criteria possess substantially greater discriminatory power than the remaining three criteria in differentiating the quality of sunscreen alternatives. Moreover, the noticeable decline between *Product Label Claims* and *Texture Suitability* indicates that formulation-related characteristics exert a stronger influence on the evaluation process than conventional protection indicators such as SPF and PA ratings. Therefore, Figure 3 reinforces the findings presented in Table 2 by demonstrating that the number of active ingredients and product label claims are the dominant factors driving variations in preference values generated by the PSI method.

The final stage of the computational process produced the normalized scores and preference values used to establish the final ranking of sunscreen alternatives. Preference values were obtained by aggregating all evaluation criteria following the normalization and *deviation index* calculations, thereby reflecting the overall suitability of each product across the entire set of evaluation parameters. A higher preference value indicates a higher ranking in the recommendation results. These preference values subsequently served as the basis for the web-based decision support system to generate personalized sunscreen recommendations automatically according to users' skin characteristics. The complete normalization results and preference values for all evaluated alternatives are presented in Table 3.

Table 3. Amaterasun UV sunscreen serum achieves the highest preference value

| Alternative | Sunscreen Product | Normalization Result | Preference Value |
|---|---|---|---|
| A1 | Kahf Triple Protection Sunscreen Moisturizer | 0.78 | 0.82 |
| A2 | Somethinc Holyshield! UV Watery Sunscreen Gel | 0.84 | 0.88 |
| A3 | Azarine Hydrasoothe Sunscreen Mist | 0.76 | 0.80 |
| A4 | MS Glow for Men Sunscreen | 0.72 | 0.76 |
| A5 | BLACKOSTA 3 in 1 Bright Sunscreen Moisturizer | 0.81 | 0.85 |
| A6 | ClorisMEN Pro Sunscreen Protection | 0.87 | 0.92 |
| A7 | Gatsby Aesthetic Bright Sunscreen Moisturizer | 0.65 | 0.70 |
| A8 | Biore UV Aqua Rich Watery Essence | 0.85 | 0.89 |
| A9 | Amaterasun UV Sunscreen Serum | 0.89 | 0.95 |
| A10 | Elvicto Sunscreen Expert | 0.70 | 0.74 |

Source: Authors' calculation using the PSI method (2026).

The results presented in Table 3 indicate that *Amaterasun UV Sunscreen Serum* (A9) achieved the highest preference value (0.95), followed by *ClorisMEN Pro Sunscreen Protection* (A6) with 0.92 and *Biore UV Aqua Rich Watery Essence* (A8) with 0.89. In contrast, *Gatsby Aesthetic Bright Sunscreen Moisturizer* (A7) obtained the lowest preference value (0.70), followed by *Elvicto Sunscreen Expert* (A10) with 0.74. These differences demonstrate that the PSI method effectively ranks sunscreen alternatives based on the objective contribution of all evaluated criteria. The dominance of *Active Ingredient Count* and *Product Label Claims* identified in the previous stage is clearly reflected in the final ranking, indicating that these two attributes play a crucial role in differentiating the quality of sunscreen products. The resulting preference values were subsequently integrated into the web-based decision support system to automatically generate personalized sunscreen recommendations, as discussed in the following subsection.

**Web-based AI-DSS successfully automates sunscreen recommendations**

Following the completion of the computational process using the *Preference Selection Index* (PSI) method, the resulting preference values were integrated into a web-based *Artificial Intelligence Decision Support System* (AI-DSS). This integration enables the entire evaluation process to be performed automatically, from receiving user input to generating personalized sunscreen recommendations based on the ranking results. The system was designed so that users are not required to perform manual calculations or understand the mathematical principles underlying the PSI method. All computational processes are executed in the *back-end*, while users interact solely through a simple and intuitive interface. Consequently, the system transforms a previously complex decision-making process into a fast, objective, and easily accessible recommendation service that can be accessed through web-based devices.

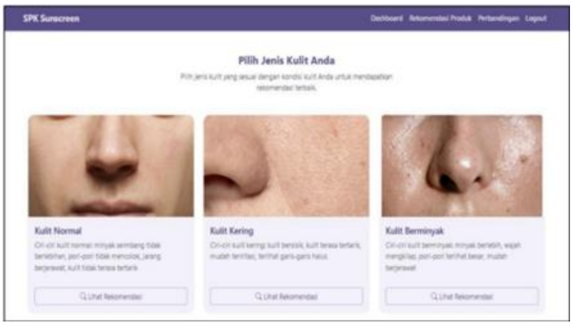


Figure 3. Homepage for skin type selection

Source: Developed by the authors (2026).

Figure 3 illustrates the homepage of the proposed system, which serves as the initial point of user interaction. The interface provides three skin type categories—*Normal*, *Dry*, and *Oily*—each accompanied by a brief description of its characteristics to assist users in identifying their skin type independently. After selecting the most appropriate skin type, users simply click the recommendation button, allowing the system to proceed with the evaluation process without requiring any additional input. This design was intended to simplify system usability while minimizing the likelihood of input errors. Furthermore, the visual presentation makes skin type identification more intuitive, enabling users to obtain personalized sunscreen recommendations conveniently without requiring prior knowledge of sunscreen formulations or dermatological concepts.

Once a skin type has been selected, the system automatically retrieves the sunscreen alternatives and their corresponding evaluation criteria stored in the database, including the preference values previously calculated using the PSI method. The system then matches the user's skin characteristics with the stored computational results and generates a ranked list of sunscreen recommendations according to the preference value of each alternative. This entire process is completed automatically within a short period, allowing users to receive recommendation results almost instantly without waiting for lengthy computational procedures. This implementation demonstrates that the PSI algorithm is not only applicable to analytical computations but can also be effectively integrated into a web-based application as the core mechanism for generating personalized sunscreen recommendations.

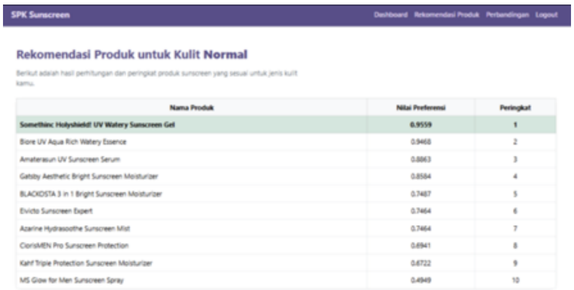


Figure 4. Recommendation results based on psi preference values

Source: Developed by the authors (2026).

Figure 4 presents the recommendation results page, which displays sunscreen products ranked from the highest to the lowest preference value. In addition to the product name, the system provides the corresponding preference value and ranking position for each alternative, enabling users to understand why a particular product occupies a specific position in the recommendation list. Presenting the results in tabular form allows users to compare the quality of multiple alternatives more effectively than receiving only a single product recommendation. By displaying preference values, the system also provides users with a clearer understanding of the relative suitability of each product, thereby enhancing the transparency of the decision-making process. This interface demonstrates that the computational results generated by the PSI method have been successfully translated into user-friendly information through the web-based application.

Before the system could be considered suitable as a decision support tool, a validation process was conducted to verify that the computational results generated by the application were consistent with those obtained through manual PSI calculations. Validation was performed using the *Root Mean Square Error* (RMSE) metric by comparing the preference values generated by the system with those obtained manually across all sunscreen alternatives. This approach was selected because it quantitatively measures the average discrepancy between two sets of numerical values. The smaller the RMSE value, the higher the level of agreement between the system implementation and the theoretical computational model underlying the application.

Table 4. RMSE validation results of the web-based AI-DSS

| Validation Method | Manual Calculation | System Calculation | RMSE |
|---|---|---|---|
| Preference Value Comparison | 8.31 | 8.27 | 0.0089 |

Source: Authors' calculation (2026).

The results presented in Table 4 indicate that the proposed system achieved an RMSE value of 0.0089, demonstrating that the discrepancy between the system-generated results and the manual calculations was negligible. This finding confirms that the web-based implementation of the PSI method successfully reproduced the computational results with a very high level of accuracy. Consequently, the automation process did not compromise the accuracy of the ranking results compared with manual calculations. These findings demonstrate that the developed AI-DSS not only implements the PSI algorithm consistently but also provides accurate, reliable, and practical sunscreen recommendations to support users in selecting products that best match their skin characteristics.

**Objective multi-criteria evaluation improves personalized sunscreen recommendations**

*Sun Protection Factor* (SPF) has long been regarded as the primary indicator of sunscreen quality and is often the first piece of information consumers consider when selecting a product (Zaid et al., 2018). However, the findings of this study suggest that this conventional perspective does not fully reflect overall product quality. The *deviation index* revealed that *SPF Rating* achieved a value of only 0.144, considerably lower than *Active Ingredient Count* (0.598) and *Product Label Claims* (0.536). These results indicate that when sunscreen products are evaluated using a multi-criteria approach, their ability to be differentiated depends more on formulation characteristics than on the UV protection level indicated on the packaging. Calderon Alonso et al. (2026) continued to regard SPF as the dominant indicator for evaluating sunscreen effectiveness, whereas Špaglová et al. (2025) emphasized the importance of combining active ingredients with formulation characteristics to determine product quality. This shift suggests that modern sunscreen evaluation can no longer rely on a single protection indicator but instead requires an approach capable of simultaneously considering multiple product attributes. Therefore, this study demonstrates that product formulation provides a more comprehensive basis for sunscreen evaluation than relying solely on SPF values during the decision-making process.

The dominance of *Active Ingredient Count* in this study not only highlights the importance of the number of active ingredients but also demonstrates that the diversity of ultraviolet filters provides the greatest discriminatory power among all evaluated criteria. The *deviation index* of 0.598 indicates that variations in active ingredient composition provide substantially more informative distinctions than other attributes with relatively homogeneous values. This finding can be explained by the fact that combinations of multiple UV filters generally provide broader protection across both UVA and UVB spectra while enhancing formulation stability during daily use. Unlike Thy et al. (2025), who evaluated sunscreen primarily based on UV protection effectiveness, the present study shows that formulation quality becomes the most influential factor when alternatives are assessed simultaneously. Similarly, Tong et al. (2023) reported that greater diversity in active ingredients is positively associated with improved product performance and user comfort across different skin types. Consequently, these findings demonstrate that the PSI method effectively identifies attributes with the highest discriminatory capability, resulting in more objective recommendations than evaluations based on a single criterion.

Another notable finding is the substantial contribution of *Product Label Claims*, which achieved a *deviation index* of 0.536, exceeding both *Texture Suitability* (0.371) and *PA Grade* (0.309). This result suggests that claims such as *non-comedogenic*, *oil control*, and *hydrating* should no longer be regarded merely as marketing strategies but rather as meaningful indicators capable of differentiating product quality according to users' needs. The broader the functional benefits offered by a product, the greater its ability to accommodate the preferences of different skin types. Suphasomboon and Vassanadumrongdee (2026) reported that product claims significantly influence consumers' perceptions when selecting cosmetic products, whereas Quach et al. (2025) found that non-protection attributes have become increasingly important in purchasing decisions for skincare products. The present study extends these findings by demonstrating that *Product Label Claims* not only influence consumer perceptions but also serve as a technically significant criterion within a PSI-based decision support system. Therefore, functional product attributes that were previously regarded as supplementary features can now be considered essential components in the objective evaluation of sunscreen quality.

Although all alternatives were evaluated using the same five criteria, the ranking results indicate that not every product maintained consistent performance across all evaluation attributes. *Amaterasun UV Sunscreen Serum* (A9) achieved the highest preference value (0.95), followed by *ClorisMEN Pro Sunscreen Protection* (A6) with 0.92, whereas *Gatsby Aesthetic Bright Sunscreen Moisturizer* (A7) obtained only 0.70. These findings indicate that the superiority of a sunscreen product is determined not by excellence in a single criterion but by balanced performance across all evaluated attributes. Putri and Sailah (2022) reported that products with well-balanced formulations generally achieve higher user satisfaction than products excelling in only one characteristic. This argument is further supported by Paradowski et al. (2025), who found that multi-criteria approaches produce more stable recommendations than evaluations based on individual parameters. Therefore, the findings of this study confirm that achieving balance across multiple product attributes is the primary factor determining a sunscreen's ranking when evaluated using the PSI method.

One of the principal advantages of the *Preference Selection Index* (PSI) method is its ability to generate objective evaluations without requiring predefined criterion weights from decision-makers. This characteristic is particularly valuable because subjective weighting often introduces inconsistencies, especially as the number of alternatives and evaluation criteria increases. In this study, the *preference variation* and *deviation index* mechanisms identified *Active Ingredient Count* and *Product Label Claims* as the most influential criteria without requiring expert judgment. Unlike Mahmoodian and Zandi (2026), who relied on expert-assigned weights in SAW and AHP methods, the present study demonstrates that the dataset itself can objectively determine the relative importance of each evaluation criterion. This finding is also consistent with Rahma et al. (2019), who concluded that methods without subjective weighting produce more consistent results when applied to data-driven decision support systems. Therefore, the implementation of the PSI method not only improves evaluation objectivity but also enhances the transparency and reliability of the sunscreen recommendation process.

The effectiveness of a decision support system depends not only on the quality of its underlying algorithm but also on its ability to maintain computational accuracy after implementation in a real-world application. This capability is demonstrated by the validation results, which yielded an RMSE value of 0.0089, indicating that the system-generated outputs were almost identical to those obtained through manual calculations. Such a minimal error confirms that the automation process preserved the computational mechanism of the PSI method, ensuring that the generated recommendations remained consistent with the underlying mathematical model. Brauner et al. (2019) explained that implementation errors are among the primary causes of reduced reliability in web-based decision support systems. Conversely, Collier et al. (2018) demonstrated that RMSE is an effective validation metric for assessing the consistency between theoretical models and software implementation. Therefore, the exceptionally low RMSE obtained in this study provides strong evidence that the developed AI-based decision support system accurately implements the PSI method and is suitable for practical decision-making applications.

Although this study demonstrates that *Active Ingredient Count* and *Product Label Claims* are the most influential factors in determining sunscreen recommendations, the proposed model should not yet be considered comprehensive. The current study evaluated only 10 sunscreen alternatives using five evaluation criteria, leaving considerable opportunities for further development through the inclusion of additional attributes such as price, *water resistance*, skin sensitivity, and user comfort. Furthermore, the recommendation mechanism remains *rule-based* and does not yet incorporate individual user preference histories. Wang et al. (2018) demonstrated that incorporating economic attributes can substantially influence the ranking of consumer products, whereas Masciari et al. (2024) emphasized the importance of artificial intelligence-driven personalization in improving the relevance of recommendation systems. Therefore, future research should explore integrating the PSI method with *machine learning* or *recommender system* techniques to develop sunscreen recommendation systems that are not only objective but also adaptive to individual user characteristics and preferences.

**Conclusion**

This study successfully developed a web-based *Artificial Intelligence Decision Support System* (AI-DSS) using the *Preference Selection Index* (PSI) method to generate objective sunscreen recommendations based on users' skin characteristics. The findings revealed that *Active Ingredient Count* and *Product Label Claims* were the two most influential criteria in the ranking process, with *deviation index* values of 0.598 and 0.536, respectively, whereas *SPF Rating* contributed the least, with a value of 0.144. These results demonstrate that sunscreen quality is determined not only by the level of ultraviolet protection but also by product formulation characteristics and functional benefits. Through a multi-criteria evaluation mechanism without subjective weighting, the PSI method produced consistent rankings, with *Amaterasun UV Sunscreen Serum* achieving the highest preference value (0.95). Furthermore, the implementation of the proposed method within the web-based system achieved an RMSE value of 0.0089, indicating that the automated recommendation process maintained high computational accuracy while providing fast, objective, and user-friendly sunscreen recommendations.

This study contributes to the advancement of decision support systems in the skincare domain by demonstrating that a PSI-based multi-criteria approach provides more comprehensive sunscreen recommendations than evaluations relying solely on a single indicator, such as SPF. The integration of the PSI method into the AI-DSS also highlights the potential of artificial intelligence technologies to support more transparent and data-driven decision-making for healthcare and cosmetic products. Nevertheless, this study has several limitations, including the use of only 10 sunscreen alternatives, five evaluation criteria, and the exclusion of additional factors such as price, *water resistance*, skin sensitivity, and individual user preferences. Therefore, future studies are encouraged to expand the number of alternatives and evaluation criteria, incorporate personalized user preference data, and integrate the PSI method with *machine learning* or *recommender system* techniques to develop a more adaptive, accurate, and personalized sunscreen recommendation system.

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