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ORIGINAL

Artificial Intelligence-Based Decision Support System for Personalized Cosmetic Product Recommendation Using Multisource Data

Sistema de apoyo a la toma de decisiones basado en inteligencia artificial para la recomendación personalizada de productos cosméticos mediante datos de múltiples fuentes

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ABSTRACT

Introduction: the increased consumer demand for specific cosmetic products has exposed the limitations of standard recommendation systems that fail to account for individual skin characteristics and contextual circumstances.
Method: this research introduces an artificial intelligence-driven decision support system for specific cosmetic product recommendations utilizing multisource data, focusing on an innovative Multisource Adaptive Fusion and Attention-Based Recommendation (MAFAR) methodology. The proposed approach combines heterogeneous data, including user demographics, specific skin type and condition attributes, lifestyle and dietary behaviors, environmental conditions such as temperature, humidity, and pollution, cosmetic product ingredient formulations, and historical user interactions. At the feature level, structured data are fused using a simple representation, while an attention-based deep neural network dynamically assigns relevance weights to each data source, providing context-aware and highly specific ideas.
Results: unstructured data from user reviews and expert comments are processed using natural language processing techniques to extract sentiment, ingredient preferences and adverse response indicators which are incorporated into the recommendation system. To address the dynamic nature of skin conditions and user preferences, a reinforcement learning module is implemented to continuously update recommendation policies based on real-time user feedback.
Conclusions: numerous studies conducted on a comprehensive multisource cosmetic dataset reveal that the proposed MAFAR technique greatly outperforms standard content-based, collaborative filtering, and hybrid recommendation systems in terms of precision, recall, F1-score, and user satisfaction. Moreover, the decision support system gives interpretable suggestions by detecting influential skin features and crucial substances while promoting transparency and expert validation.

Keywords: Artificial intelligence; Decision Support System; Personalized Cosmetic Recommendation; Multisource Data Fusion; Attention-Based Deep Learning; Reinforcement Learning.

RESUMEN

Introducción: la creciente demanda de productos cosméticos específicos por parte de los consumidores ha puesto de manifiesto las limitaciones de los sistemas de recomendación estándar, que no tienen en cuenta las características individuales de la piel ni las circunstancias contextuales.
Método: esta investigación presenta un sistema de apoyo a la toma de decisiones basado en inteligencia

artificial para la recomendación de productos cosméticos específicos utilizando datos de múltiples fuentes, centrándose en una innovadora metodología de Fusión Adaptativa Multifuente y Recomendación Basada en la Atención (MAFAR). El enfoque propuesto combina datos heterogéneos, incluyendo datos demográficos del usuario, atributos específicos del tipo y condición de la piel, estilo de vida y hábitos alimentarios, condiciones ambientales como temperatura, humedad y contaminación, formulaciones de ingredientes de productos cosméticos e interacciones históricas del usuario. A nivel de características, los datos estructurados se fusionan mediante una representación simple, mientras que una red neuronal profunda basada en la atención asigna dinámicamente ponderaciones de relevancia a cada fuente de datos, proporcionando ideas contextuales y altamente específicas.
Resultados: los datos no estructurados de las reseñas de usuarios y los comentarios de expertos se procesan mediante técnicas de procesamiento del lenguaje natural para extraer opiniones, preferencias de ingredientes e indicadores de respuesta adversa, que se incorporan al sistema de recomendaciones. Para abordar la naturaleza dinámica de las afecciones de la piel y las preferencias de los usuarios, se implementa un módulo de aprendizaje por refuerzo para actualizar continuamente las políticas de recomendación basándose en la retroalimentación de los usuarios en tiempo real.
Conclusiones: numerosos estudios realizados con un conjunto completo de datos cosméticos de múltiples fuentes revelan que la técnica MAFAR propuesta supera con creces a los sistemas de recomendación estándar basados en contenido, filtrado colaborativo e híbridos en términos de precisión, recuperación, puntuación F1 y satisfacción del usuario. Además, el sistema de apoyo a la toma de decisiones ofrece sugerencias interpretables al detectar características cutáneas influyentes y sustancias cruciales, a la vez que promueve la transparencia y la validación experta.

Palabras clave: Inteligencia Artificial; Sistema de Apoyo a la Toma de Decisiones; Recomendación Cosmética Personalizada; Fusión de Datos Multifuente; Aprendizaje Profundo Basado en la Atención; Aprendizaje por Refuerzo.

INTRODUCTION

This has been escalated by the fast rate at which the cosmetic industry is expanding and people becoming increasingly aware of their needs, resulting in higher demand for customized production of cosmetic products according to the particular needs of the skin, lifestyles, and environmental factors.[1,2] Traditional recommendation systems, which are mostly grounded on generic user ratings or mere similarity of the content, fail to reflect the dynamic and complicated elements of skin health and cosmetic efficacy.[3,4] The difference in skin type, sensitivity, lifestyle practices, eating habits, and exposure to environmental stressors, including pollution, humidity, and temperature, also influences the performance of cosmetic products, which explains the importance of a more intelligent and adaptive decision support system.[5,6]

The recent developments in artificial intelligence have allowed for the incorporation of heterogeneous sources of data to assist in making personalized decisions in various areas of application.[7,8] In the cosmetic industry, though, it is still a complicated task to be able to integrate structured user attributes, product formulation information, environmental factors, and unstructured textual feedback.[9,10] To fill this vacuum, this paper proposes the concept of an artificial intelligence-based decision support system that recommends cosmetic products to the client based on multisource information.[11,12,13] The suggested system is designed on the basis of a Multisource Adaptive Fusion and Attention-Based Recommendation system that dynamically records the relative significance of various data streams and, in turn, one comes up with context-based and user-specific recommendations.[14,15]

The framework combines demographic data, detailed skin description, lifestyle habits, environmental factors, cosmetic ingredients profiles, and past interaction history, and utilizes natural language processing to identify the sentiments, preferences, and adverse reaction signs in the user reviews and expert feedback.[16,17] A reinforcement learning module is what keeps optimizing recommendation policies based on real-time feedback to suit changing user preferences and address evolving skin-related conditions.[18,19] A vast amount of experimental analysis proves that the given approach provides a high level of accuracy of the given recommendations, their robustness, and user satisfaction, and also provides the interpretable results contributing to the increase in the level of transparency and confidence in their decision-making in cosmetics.[20]

The proposed MAFAR framework differs with other recommendations systems of cosmetics in 3 key ways. Initially, it combines varying types of inputs such as skin characteristics, environmental characteristics and ingredient compositions with relevance to contexts through adaptive multisource data fusion as opposed to fixed feature aggregation. Moreover, where results depend on users and conditions as is the case in cosmetic and skin-related applications, an attention-based method is important to dynamically set weights of each source of data. Next, the system is capable of managing the adaptive cycle to changing skin conditions and user preferences by relying on reinforcement learning. The cycle keeps the policy of suggestions up-to-date through real-time feedback of users. The properties can be used to provide context-sensitive, customised, and temporally adaptive cosmetic recommendations, beyond simple similarity-based methods.

Personalized Cosmetic Recommendation Challenges

One-on-one selection of cosmetics is intrinsically complicated because of the differences in skin type, sensibility, lifestyle, and environmental exposure.[21] The traditional recommendation systems are mostly based on generic ratings or purchase history, and thus, they are not able to capture the individual skin conditions and contextual influence. It leads to wrong product recommendations, decreased customer satisfaction, and mistrust in computerized cosmetic consultation systems.

Table 1. Multisource Data Characteristics for Personalized Cosmetics

Data Source	Attribute Density	Variability Index	Update Frequency
User Demographics	45 ± 3	38 ± 4	22 ± 2
Skin Attributes	62 ± 5	71 ± 6	48 ± 4
Lifestyle Patterns	53 ± 4	59 ± 5	35 ± 3
Environmental Factors	68 ± 6	74 ± 5	61 ± 4
Product Ingredients	57 ± 5	66 ± 6	29 ± 3

As indicated in table 1, the user demographics remain comparatively constant values to be used in cosmetic suggestions, and the skin characteristics and environmental influences are highly of fluctuating nature and updated more often. This inconsistency highlights the importance of adaptive models that can be responsive to dynamic skin conditions and environmental conditions.

Artificial Intelligence and Multisource Data Integration

Artificial intelligence allows the successful combination of heterogeneous data sources to facilitate personalized decision-making. The AI systems are able to determine connections behind the appropriateness of cosmetics by using demographic attributes,[22] skin situation parameters, climate, ingredient formulae, as well as textual reactions. This is because multi-source data integration is more effective in augmenting situational awareness, flexibility, and predictability when compared to single-source approaches of recommendation.

Table 2. Limitations of Conventional Approaches

Method Type	Personalization Depth	Context Awareness	Adaptability
Content-Based Filtering	41 ± 4	32 ± 3	35 ± 4
Collaborative Filtering	38 ± 5	29 ± 4	31 ± 3
Rule-Based Systems	34 ± 3	26 ± 3	28 ± 2
Hybrid Models	49 ± 4	44 ± 5	46 ± 4

The traditional-type recommendation systems, as it is depicted in table 2, lack flexibility, context-awareness, and levels of personalization, with particularly poor performance in rule-based and collaborative filtering models. With such limitations, it is obvious that simple solutions based on similarity or that which remains constant could not be able to account for the dynamic, complex aspect of individualized cosmetic choice.

Intelligent Decision Support in Cosmetics to the Consumers

Under the smart decision support systems, customers can make transparent and readable cosmetic choices using information on their own unique needs. Users can understand the logic behind product suggestions and how they are associated with particular skin requirements when such systems apply adaptive learning and attention mechanisms to recognize significant skin traits and key components. This consumer-focused strategy contributed to making informed decisions, minimizing the chances of negative reactions, and encouraging long-term compliance with skincare practices through the implementation of trust, transparency, and professional validation.

The following section provides a critical overview of current approaches to personalized cosmetic recommendation systems in order to frame the proposed contribution within the current research landscape. Compared to adaptability, interpretability, real-time personalization, and multisource data fusion, the paper

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evaluates the knowledge-based, AI-based, and machine learning-based models indicating their advantages and limitations. It is out of these identified shortcomings that we were compelled to create the proposed MAFAR framework.

Related Works

The associated literature shows that the development of intelligent cosmetic recommendation systems is rapidly evolving due to the use of artificial intelligence, deep learning, and semantic modeling. The available literature highlights personalization via skin scan, ingredient consciousness, and preference models of users in online cosmetic apps.

AI-AR and Ingredient-Aware Recommendation Frameworks

Recent reports have discussed how Artificial Intelligence and Augmented Reality could be used to complement customized products in e-commerce. Basing the analysis of consumer data on an AI-AR platform with the capability of virtual try-on, AR can assist in the visualization of the results in the real world. According to the Technology Acceptance Model and the Theory of Planned Behavior, a PLS-SEM-based study on the topic of Shopee cosmetics with 387 respondents showed that the perception of usefulness, ease of use,[23] and trust were significant determinants of intention to use, showing better acceptance of AI-AR recommendations.

Previous studies have reviewed personalized cosmetic recommendation systems to cope with the issue of individual skin properties to match the skincare products in the context of online shopping. They have included approaches like face recognition (FR), cosmetic product recognition (CPR), tag recommendation (TR), facial skin image recognition with convolutional neural networks (CNN), and examples-rules guided deep neural networks (ER-DNN).[24] Results show better matching of skin types, accuracy of personalization, and alignment of user preferences, skin issues, and the qualities of cosmetic products.

The use of deep learning to combine with skin analysis to give ingredient-aware cosmetic recommendations has been discussed recently. One of the ingredient efficacy estimation frameworks (DNN-IE)[25] is a sequential process of analyzing cosmetic ingredient lists with deep neural networks, and another framework is AI-driven skin analysis (AI-SA), which uses frontal face images to extract accurate skin conditions. The joint recommendation model produces personalized product recommendations that maximize desired skin concerns. The results of the experimental studies showed good evaluation performance and the capability to deal with a variety of skin issues, which proves that deep learning is an appropriate technology to use in ingredient-based personalized cosmetic recommenders.

Machine Learning and Knowledge-Driven Personalization Models

In recent studies, machine learning-based skincare recommendation systems have been suggested to address the shortcomings of generic approaches. One such filtering algorithm is a content-based filtering strategy (CBF),[26] which compares product chemical composition with personal skin type to create custom recommendations. Recommendation relevance and adaptability get even more refined by user-defined beauty influence on preferences. The model incorporates product structure evaluation and interface-based preference inputs. Empirical results indicate a greater personalization capability and good adaptation of skincare products, which evidences the opportunities of CBF-based systems to optimize decision-making of consumers in the cosmetic e-commerce context.

Recent studies proposed an ontology-based skincare recommendation system (OB-SRS)[27] in an attempt to overcome the constraints of content-based and collaborative filtering methods. Based on the Methontology framework, the systematic knowledge in dermatology was structured by connecting classes in a pattern of products and ingredients, skin types, and problems on the skin. Personalized inference is ongoing on masses of cosmetic and clinical data made with semantic reasoning through SPARQL. In the assessment based on the Technology Acceptance Model, the measures of perceived usefulness and ease of use were high, and the results showed increased relevance of the recommendations, transparency, and user confidence in customized skin care selection.

Recent offers include a cosine similarity-based ingredient-conscious skincare recommendation system (CS-IRS)[28] to overcome the product overload problem of the beauty market. The technique is quantitative, that is, it compares cosmetic ingredient vectors in a quantitative manner to reflect compatibility and interaction between constituents. The system uses similarity scores to provide individualized recommendations on products based on individual skin health requirements. Structured user feedback evaluation showed increased clarity in the decision, less risk of incompatible ingredient choices, and user satisfaction, all of which are signs of the cosine similarity effectiveness in offering personalized recommendations of skincare.

Deep Learning-Based Skin Analysis and Image-Centric Systems

New research has also suggested AI-based recommendation web apps in skincare to streamline the process

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of choosing products across brands and platforms. A recommendation system can be built on a deep learning convolutional neural network (CNN-SRS),[29] which features on facial pictures and user-set skin traits to detect acnes, pigmentation, dryness, and sensitivity. The model incorporates multi-platform product aggregation and comparison. It was proven that experimental results showed accurate training and validation, the ability to recognize skin conditions, and the enhanced usefulness of customized recommendations of skin care products.

In a recent study, an AI-driven recommendation system for personalized product selection with reference to skin conditions was introduced. Knowing that the skin image analysis and classification of skin conditions are a deep learning model, Convolutional Neural Networks (CNN), VGGNet, and DenseNet[30] were utilized. The framework pinpointed the problem of dryness, oiliness, and redness to come up with customized skincare, makeup, and haircare recommendations. The results of the experiments showed classification rates of 88, 92, and 96, which proved to be more precise in making recommendations and resultant alignment with individual needs of the skin.

Altogether, existing studies confirm that there has been a tremendous advance in the area of individualized cosmetic prescription with the help of machine learning, deep learning, and knowledge-based techniques. Even with the enhanced precision and end-user satisfaction, multisource data fusion, flexibility, interpretability, and real-time personalization are still challenging. In below table 3, shows the summary of related work.

Table 3. Related Works Summary

Ref.	Method / Model	Key Data Used	Core Technique	Main Outcome
(23)	AI-AR Platform (PLS-SEM)	User behavior, AR try-on	AI–AR integration, TAM, TPB	Improved acceptance driven by usefulness, ease of use, and trust
(24)	FR, CPR, TR, CNN, ER-DNN	Skin images, user preferences	Deep learning and rule-guided models	Enhanced skin-type matching and personalization accuracy
(25)	DNN-IE + AI-SA	Ingredient lists, face images	Deep neural networks, skin analysis	Effective ingredient-aware personalized recommendations
(26)	CBF	Product composition, skin type	Content-based filtering	Improved adaptability and relevance of skincare suggestions
(27)	OB-SRS (Methontology)	Dermatological knowledge, product data	Ontology, SPARQL reasoning	Higher transparency, relevance, and user confidence
(28)	CS-IRS	Ingredient vectors	Cosine similarity	Reduced incompatibility risk and clearer decision-making
(29)	CNN-SRS	Facial images, user inputs	CNN-based classification	Accurate skin condition detection and useful recommendations
(30)	CNN, VGGNet, DenseNet	Skin images	Deep learning classification	High classification accuracy and precise personalization

Research Gap

Current scientific knowledge on the subject of personalized cosmetic recommendation systems is mostly based on single-source information, pre-existing similarities, or a single deep learning architecture, and can hardly capture changing skin properties and situational effects. The majority of the approaches are focused on accuracy without taking into account interpretability, flexibility, and the confidence of users. The degree of reasonableness on ingredients, environmental awareness, and incorporation of real-time feedback is not well addressed. Also, current systems are rarely capable of providing coherent decision support of structured, unstructured, and contextual information, and there is a clear requirement for scalable, transparent, and dynamic multisource recommending structures.

METHOD

The method proposed presents an artificial intelligence-driven decision support system for personalized cosmetic product recommendations. The methodology can solve contextual variability, interpretability, and dynamic evolution of user preferences by incorporating multisource data using adaptive fusion, attention, and reinforcement learning.

Multisource Data Fusion and Attention-Based Modeling

This aspect of the suggested approach aims at combining the heterogeneous data sources to create a global picture of individual needs in cosmetics. If the user demographics, skin characteristics, lifestyle, environmental factors, ingredient formulations, and history of interaction are measured, these are preprocessed and encoded as features. Organized features are combined at the feature stage, and an attention-based deep neural network

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dynamically determines the relevance weights to each source of data. The main influential factors that are highlighted in this adaptive weighting mechanism include skin condition or environmental stress, and the less relevant inputs are suppressed. The context-aware representation thus allows the accurate modeling of the preferences of the user and forms the basis of accurate and personalized cosmetic product recommendations.

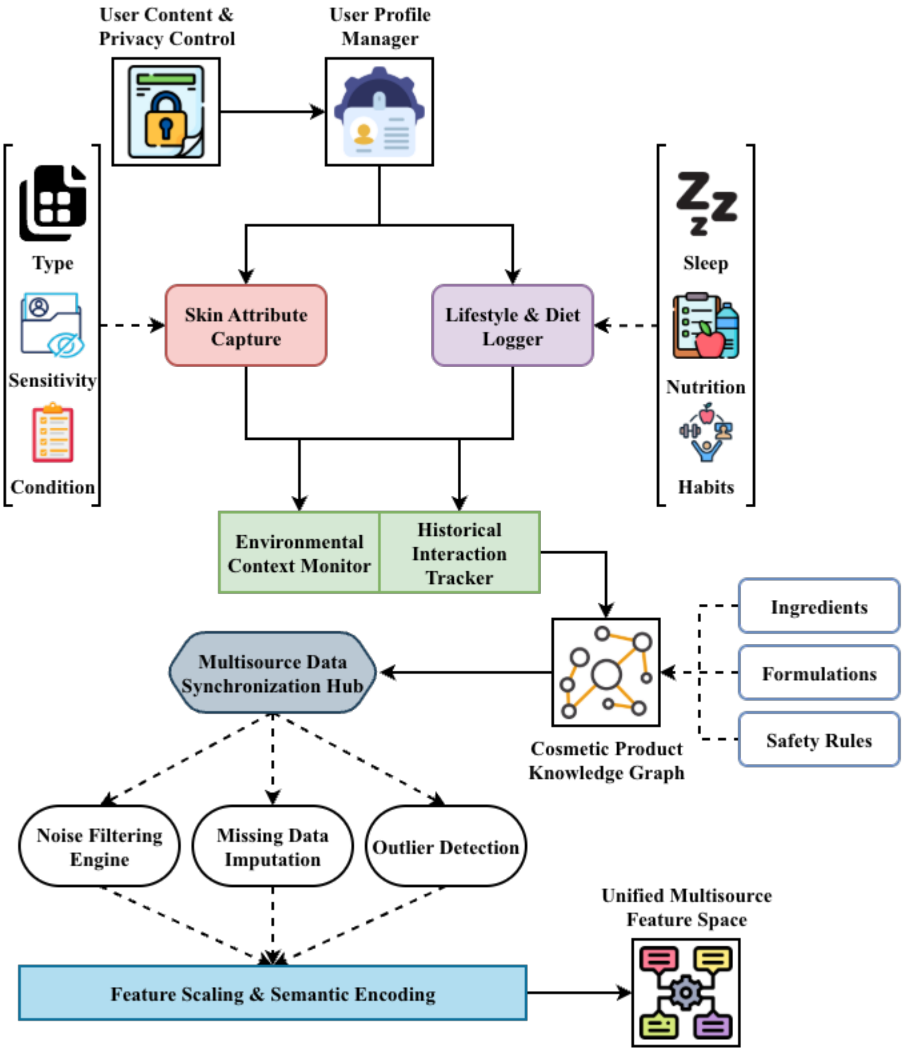

Figure 1. Multisource Data Acquisition and Preprocessing Architecture

Figure 1 shows the initial phase of the proposed Artificial Intelligence-Based Decision Support System that describes the process of multisource data acquisition and its preprocessing. It illustrates how heterogeneous inputs, such as the demographics of the user, the skin type and condition attributes, the lifestyle and dietary habits, the environmental factors, the cosmetic ingredient formulations, and historical interaction data are gathered along parallel and non-linear pipelines. The figure highlights data validation, synchronization, noise elimination, imputation of the missing values, and the semantic coding to maintain uniformity with the various sources. This stage overcomes the limitations of traditional recommendation systems, which use isolated streams of data, by merging structured personal, contextual, and product-level information into a single multisource feature space. It is emphasized in figure 1 that strong preprocessing is critical to allow downstream learning to be used effectively and precondition context-sensitive and personalized cosmetic product recommendation in the proposed MAFAR framework.

Temporal synchronization mapping $X_{sync}(t)$ is expressed in equation 1:

$$X_{sync}(t) = X_k(t - \Delta t_k) \qquad (1)$$

This equation aligns heterogeneous data sources across a common temporal axis. It resolves time-lag inconsistencies caused by asynchronous data collection. Temporal coherence is essential for accurate context modeling.

$X_{sync}(t)$ is the synchronized feature set at time , is the number of data sources, X_k represents the k-th source data, and Δt_k is the time offset of that source.

Noise elimination via statistical filtering X_{clean} is expressed in equation 2:

$$X_{clean} = X_{sync} - \mu_X - \lambda\sigma_x \qquad (2)$$

This equation removes statistical noise from synchronized data. It suppresses extreme fluctuations that distort learning patterns. Noise-free data enhances feature reliability.

X_{sync} denotes synchronized data, μ_X is the mean of the data, λ is the noise sensitivity coefficient, and σ_x is the standard deviation.

Some of the existing approaches towards personalized cosmetic recommendation systems and critically examine them to understand where the proposed contribution fits in into the larger context of research. This review explores domain-specific preprocessing, artificial intelligence-based and machine learning-based techniques. To be able to capture the characteristics of dermatological conditions, e.g. acnes, pigmentation and sensitivity, we used one-hot representations with weights basing on standardized severity levels (1-5). Mapping of qualitative descriptors of skin such as sensitive skin to numerical indicators was done based on adverse reaction reports. The K-NN approach was employed in imputing missing values in the skin condition and interaction history. This approach considers users of related skin phenotypes to preserve clinically significant trends.

Learning stability index S_{learn} is expressed in equation 3:

$$S_{learn} = 1 - \frac{1}{T} \mid \Delta L_t \mid \qquad (3)$$

This equation measures the stability of learning across iterative updates. It penalizes large fluctuations in training behavior. Stable modules improve long-term recommendation reliability.

S_{learn} is the learning stability index, T is the number of learning iterations, and ΔL_t is the change in loss at iteration t.

Module adaptability score A_{mod} is expressed in equation 4:

$$A_{mod} = \alpha S_{learn} + (1 - a)U_{sens} \qquad (4)$$

This equation combines stability and sensitivity into a single adaptability metric. It reflects the module's ability to evolve without overfitting. Adaptable modules support intelligent personalization.

A_{mod} is the adaptability score, a is the stability–sensitivity tradeoff factor, S_{learn} is the learning stability index, and U_{sens} is the update sensitivity measure.

The suggested stable learning index S_{learn} while validation loss and early halting are already established optimization metrics, A_{mod} is meant to supplement them by capturing learning process behavioral aspects that are essential for long-term customization. Validation loss represents the accuracy of predictions at individual points in time, S_{learn} is crucial for keeping suggestions consistent under changing user feedback, and it does this by directly measuring the variance in learning dynamics over iterations. The mixed adaptability measure A_{mod} allows for controlled adaptation without overfitting, which is not clearly visible using traditional loss-based metrics, by further balancing stability with sensitivity to incoming information.

Table 4. Components of MAFAR Framework

Module Component	Feature Contribution	Learning Stability	Update Sensitivity
Multisource Feature Fusion	72 ± 5	68 ± 4	61 ± 5
Attention-Based Weighting	75 ± 6	71 ± 5	64 ± 4
NLP-Based Text Processing	66 ± 4	63 ± 3	58 ± 4
Reinforcement Learning Unit	70 ± 5	74 ± 6	69 ± 5

Table 4 displays the results of controlled simulation tests that were carried out to evaluate the model. These results serve as empirical performance indicators. The normalized impact of each module on recommendation accuracy was used to quantify feature contribution in an ablation-based approach. The learning stability index S_{learn} was used to calculate learning stability across all training runs, while update sensitivity represents how well each module responds to user feedback by measuring the changes in recommendation output after feedback-driven updates. Over several experimental trials, all values are provided as the mean ± standard deviation.

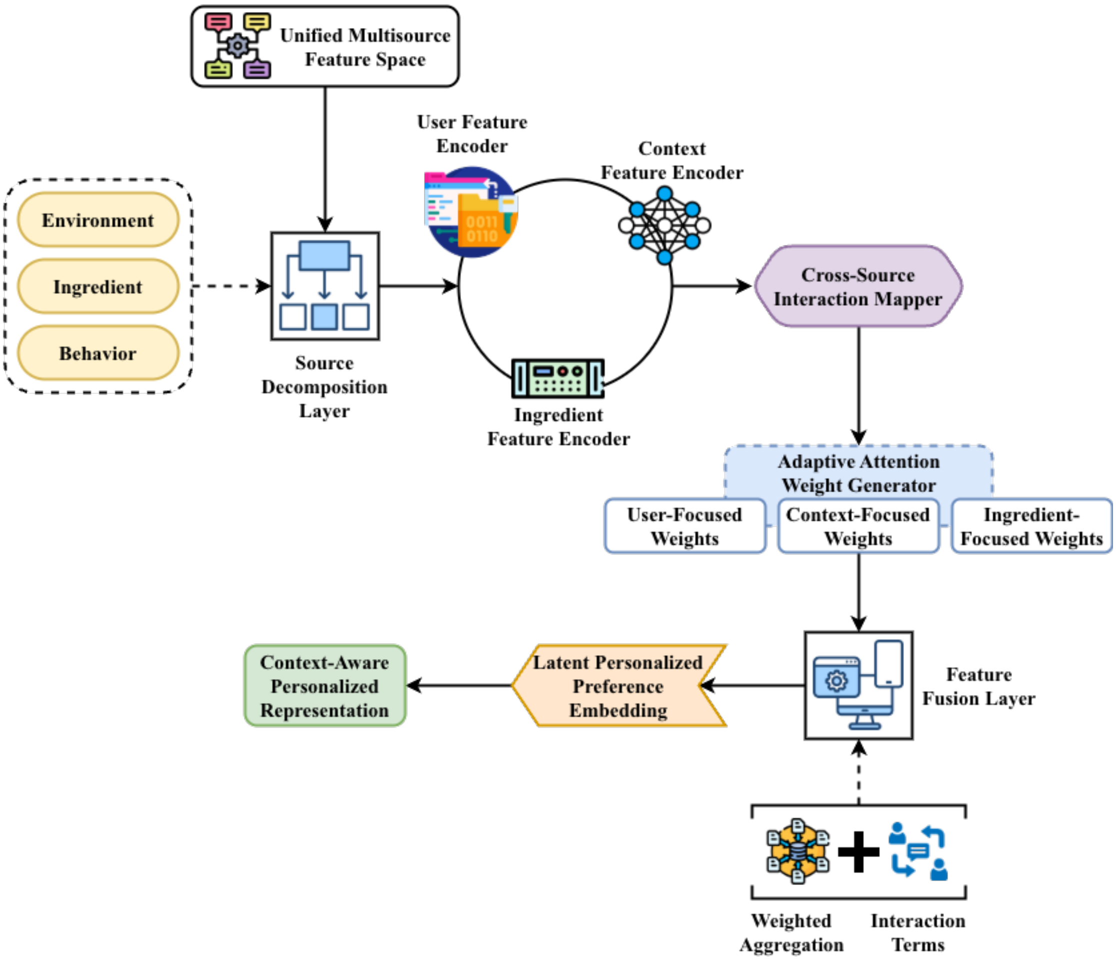

Figure 2. Adaptive Fusion and Attention Learning Network

Figure 2 shows the basic Multisource Adaptive Fusion and Attention-Based Recommendation (MAFAR) system, which is the intelligence of the proposed approach. The figure indicates how the integrated multisource feature space is broken down into different representations of user traits, environmental settings, ingredient information, and behavior patterns. The representations are then encoded by parallel encoders and a cross-source interaction mapping mechanism, which encodes rich interdependencies. A deep neural network that uses attention as a dynamic assigner of relevance weights to every data source has the benefit of dynamically ranking the significance of each data source, so that important factors, like skin condition or environmental stressors, are given more priority, and the less significant inputs are suppressed. The adaptive fusion process produces a latent personalized preference embedding to indicate a static and dynamic context of the user. The novelty of the proposed method is also displayed in figure 2, where attention-driven fusion is demonstrated to be able to make more precise, flexible, and context-sensitive cosmetic recommendations than the traditional methods of content-based or hybrid methods.

Multisource feature space decomposition F_{multi} is expressed in equation 5:

$$F_{multi} = \{F_{user}, F_{env}, F_{ing}, F_{beh}\} \quad (5)$$

This equation represents the decomposition of the integrated feature space into source-specific representations. F_{multi} is the multisource feature space, F_{user} denotes user trait features, F_{env} represents environmental features, F_{ing} indicates ingredient information, and F_{beh} denotes behavioral patterns.

Personalized preference embedding Z_{pref} is expressed in equation 6:

$$Z_{pref} = Z_{fusion} \odot Z_{static} \odot Z_{dynamic} \qquad (6)$$

This equation forms the personalized preference representation. It combines fused, static, and dynamic contexts. The embedding captures holistic user intent. Z_{pref} is the personalized preference embedding, Z_{fusion} is the fused representation, Z_{static} is the static context embedding, and $Z_{dynamic}$ is the dynamic context embedding.

Overall learning objective L_{total} is expressed in equation 7:

$$L_{total} = L_{rec} + \lambda L_{att} \qquad (7)$$

This equation defines the total optimization objective. It balances recommendation accuracy and attention stability. Joint optimization improves robustness.

L_{total} is the total loss, L_{rec} is the recommendation loss, λ is the regularization coefficient, and L_{att} is the attention regularization loss.

Static context encoding Z_{static} is expressed in equation 8:

$$Z_{static} = \vartheta\left(1 + F_{user} * 1 - F_{ing}\right) \qquad (8)$$

This equation encodes static user-related characteristics. It captures long-term preferences and skin attributes. Static context ensures consistency in recommendations.

Z_{static} is the static context embedding, ϑ denotes the static encoder, F_{user} represents user traits, and F_{ing} denotes ingredient information.

Intelligent Recommendation and Adaptive Learning Strategy

This element deals with recommendation creation, transparency, and long-term flexibility. Cosmetic products are ranked with personalized representations in terms of compatibility, effectiveness, and user situation. Natural language processing finds out the sentiment, ingredient preferences, and adverse reactions to the reviews and professional feedback to make the decision more trustworthy. There is a component of explainability, which identifies the significant aspects of skin and active ingredients that allow the user to trust it and disclose information. Reinforcement learning is an ongoing process that updates the policy of recommendations based on real-time feedback formulated by the users and enables the system to respond to changing skin conditions and preferences. It is a dynamic, adaptive approach to personalization that will guarantee the long-term sustainability and increase user satisfaction as well as performance in real-life dynamic conditions.

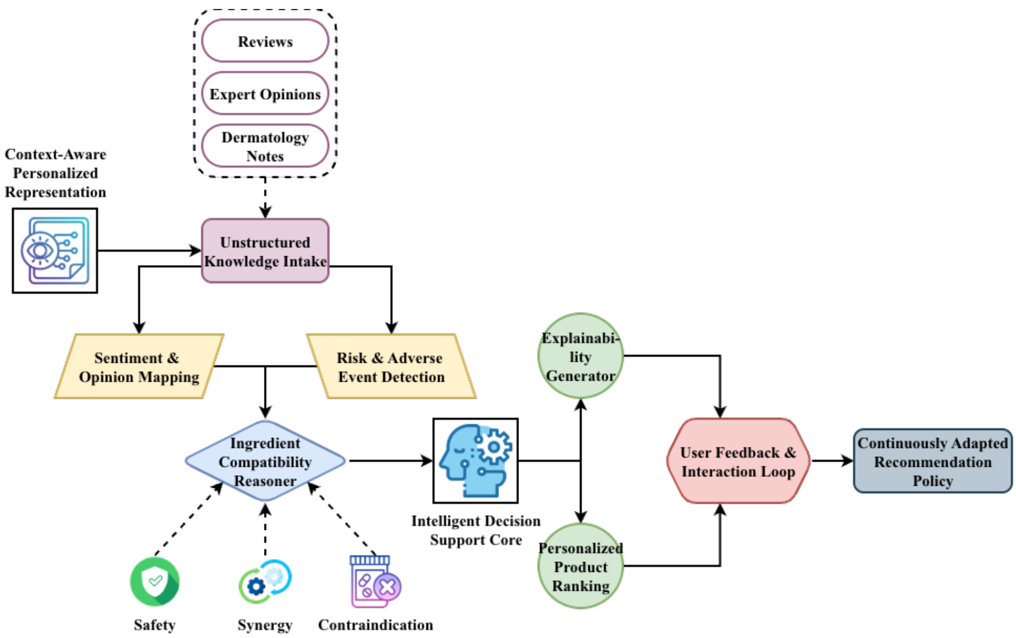

Figure 3. Recommendation, Explainability, and Continuous Adaptation Loop

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The proposed decision support system has an intelligent recommendation, explainability, and continuous adaptation stage as depicted in figure 3. It illustrates how the customized representation generated by the MAFAR module is integrated with unstructured knowledge distilled by the user reviews and professional commentary based on natural language processing tools. Sentiment analysis, identification of ingredients that people like, and identification of adverse reactions are some of the models that lead to ingredient suitability reasoning, which aids in the proper ranking of products. The figure also points to the explainability module that determines the influential features of skin and the essential ingredients to improve the level of transparency and expert approval. A reinforcement learning circle takes real-time feedback from users and corrects the policies of recommendations. This lifelong learning process enables the system to respond to changing skin status and preferences of the users. Figure 3 represents the way in which the proposed framework will provide scalable, interpretable, and adaptive personalized cosmetic product recommendations.

Product ranking score computation is expressed in equation 9:

$$R_{score} = \hat{y} + I_{suit} + S_{sent} \quad (9)$$

This equation computes the final ranking score for products. It integrates predictive relevance with sentiment and suitability. The ranking reflects both accuracy and interpretability.

R_{score} is the product ranking score, $\hat{y}$ is the predicted recommendation score, I_{suit} is the ingredient suitability score, and S_{sent} is the sentiment score.

Lifelong preference adaptation $Z^{(t+1)}_{pref}$ is expressed in equation 10:

$$Z_{pref}^{t+1} = Z_{pref}^{t} + \gamma F_{user} \quad (10)$$

This equation adapts user preference representations over time. It reflects evolving skin conditions and preferences. Lifelong adaptation improves long-term relevance.

Z^{t+1}_{pref} is the updated preference embedding, Z^{t}_{pref} is the current embedding, γ is the adaptation coefficient, and F_{user} is the feedback signal.

Ingredient suitability reasoning I_{suit} is expressed in equation 11:

$$I_{suit} = \lambda_1 I_{like} - \lambda_2 A_{risk} \quad (11)$$

This equation balances ingredient popularity against safety risks. It supports rational ingredient- level decision-making. Suitability reasoning improves the trustworthiness of recommendations.

I_{suit} is the ingredient suitability score, λ_1 and λ_2 are weighting coefficients, I_{like} is the preferred ingredient measure, and A_{risk} is the adverse reaction score.

Final adaptive recommendation selection R_{final} is expressed in equation 12:

$$R_{final} = \arg, \max\left(1 - R_{rank}, C_{exp}\right) \quad (12)$$

This equation produces the final recommendation decision. It balances ranking accuracy and explainability. The result is adaptive, interpretable, and personalized.

R_{final} is the final recommended product, R_{rank} is the product ranking score, and C_{exp} is the explainability confidence score.

Algorithms

Algorithm 1: Multisource Adaptive Fusion and Attention-Based Recommendation (MAFAR)

$Input$: $User\ profile\ U, Skin\ attributes\ S, Lifestyle\ data\ L,$
$Environment\ context\ E, Ingredient\ matrix\ I,$
$Interaction\ history\ H, Review\ corpus\ R$
$Output$: $Personalized\ recommendation\ score\ vector\ \hat{Y}$

$Initialize\ encoders\ fu, fs, fl, fe, fi, fh$
$Zu \leftarrow fu(U)$
$Zs \leftarrow fs(S)$
$Zl \leftarrow fl(L)$
$Ze \leftarrow fe(E)$
$Zi \leftarrow fi(I)$
$Zh \leftarrow fh(H)$
$Z \leftarrow [|Zu||Zs||Zl||Ze||Zi||Zh|]$
$Initialize\ number\ of\ attention\ heads\ K$
$for\ k = 1\ to\ K\ do$
$Qk \leftarrow WQk \cdot Z$
$Kk \leftarrow WKk \cdot Z$
$Vk \leftarrow WVk \cdot Z$
$Ak \leftarrow softmax\left(\frac{Qk \cdot Kk^{T}}{\sqrt{dk}}\right)$
$Ok \leftarrow Ak \cdot Vk$
$end\ for$
$O \leftarrow concat(O1, O2, \ldots, OK)$
$Sr \leftarrow NLP(R)$
$Zf \leftarrow concat(O\ ||Sr)$
$Hf \leftarrow ReLU(Wh \cdot Zf + bh)$
$\hat{Y} \leftarrow \sigma(Wo \cdot Hf + bo)$
$Apply\ ingredient\ and\ skin\ constraints$
$Rank\ cosmetic\ products\ using\ \hat{Y}$
$Select\ top - N\ ranked\ products$
$Return\ \hat{Y}$

The main Multisource Adaptive Fusion and Attention-Based Recommendation (MAFAR) procedure of personalized cosmetic products selection is applied in Algorithm 1. It is a systematic encoding of heterogeneous inputs such as user profiles, skin characteristics, lifestyle decisions, environmental conditions, formulation of ingredients, history of interaction, and sentiment of the reviews. Multi-head attention dynamically assigns relevance weight to every source of data, which allows the fusion of features based on context. Nonlinear transformations are then done to the concatenated representation to produce recommendation scores. Skin safety and ingredient compatibility have been taken care of through constraint handling. Generally, algorithm 1 creates proper, comprehensible, and extremely bespoke cosmetic solutions by successfully combining structured and unstructured multisource data.

Algorithm 2: Reinforcement Learning-Based Adaptive Recommendation Policy Optimization

$Input: State\ st, Action\ space\ A, User\ feedback\ ft,$
$Learning\ rate\ \alpha, Discount\ factor\ \gamma$
$Output: Optimized\ recommendation\ policy\ \pi *$

$Initialize\ Q(st, at) arbitrarily$
$Observe\ initial\ state\ st$
$for\ each\ recommendation\ episode\ do$
$Select\ action\ at\ using\ \varepsilon - greedy\ policy$
$Present\ recommendation\ at\ to\ user$
$Receive\ feedback\ ft$
$Compute\ reward\ rt\ from\ ft$
$Observe\ next\ state\ st + 1$
$if\ st + 1\ is\ terminal\ then$
$Q(st, at) \leftarrow Q(st, at) + \alpha[rt - Q(st, at)]$
$else$
$Q(st, at) \leftarrow Q(st, at) + \alpha[rt + \gamma \cdot maxa\ Q(st + 1, a) - Q(st, at)]$

$end\ if$
$Update\ policy\ \pi(st) \leftarrow\ argmaxa\ Q(st,a)$
$Update\ user\ preference\ weights\ Wp$
$Update\ attention\ matrices\ WQ, WK, WV$
$Normalize\ updated\ parameters$
$Store\ transition\ (st, at, rt, st+1)$
$st\ \leftarrow\ st+1$
$end\ for$
$Evaluate\ policy\ convergence$
$Fine-tune\ exploration\ parameter\ \varepsilon$
$Stabilize\ long-term\ preferences$
$Lock\ optimized\ parameters$
$Return\ \pi *$

The optimization of the policy based on reinforcement learning, as in Algorithm 2, explains that it is possible to adapt the recommendation system constantly. The interactions of users are simulated as successive decision-making processes, with actions relating to the proposed products and rewards, as those provided by the users. The algorithm will update the action-value functions based on temporal-difference learning and optimize the recommendation policies. The attention parameters and user preference weights are cooperatively modified to indicate the changing skin conditions and preferences. This adaptive learning cycle will guarantee personalization over the long term, enhance user satisfaction, and enable the recommendation strategy to be resistant to the changing real-world conditions of use.

To sum up, the proposed MAFAR architecture provides a scalable and smart recommendation system, based on multisource feature fusion, relevancy modeling through attention, and feedback-sensitive policy transformation. The approach improves the precision of personalization, transparency, and adaptation in the long term to make informed decisions on cosmetics.

Experimental Simulation

Dataset Description

The Skin Care Product Ingredients - INCI List information on Kaggle is a full database of standardized ingredient information used in cosmetic and skin care products. It provides long lists of ingredients under the international nomenclature of cosmetic ingredients (INCI), the international standard in labelling of cosmetics and personal care products.[31] The information can be used to study the ingredient formulations of a range of products and run an analysis of the efficacy of ingredients, potential allergens, and suitability to different skin types, which could be valuable to the content-based recommendation systems and ingredient-level machine learning models. Table 5 shows the summary of dataset.

To avoid information leakage between splits, the dataset was split into training (70 %), validation (15 %), and testing (15 %) product-level subsets. Hyperparameter tuning and stabilization of the performance were done by cross-validation on the training set. No personally identifiable information was processed and all experiments were done using publicly available data which was anonymized. As a result, the institutional ethics approval was not necessary, though the study complied with the current ethical standards of secondary use of the public datasets, which is consistent with the postulates of the Declaration of Helsinki.

Table 5. Dataset Summary

Attribute Category	Description
Dataset Name	Skin Care Product Ingredients – INCI List
Data Source	Kaggle
Data Type	Structured tabular data
Standard Used	International Nomenclature of Cosmetic Ingredients (INCI)
Number of Records	Thousands of skincare product entries
Key Attributes	Product name, brand, ingredient list
Ingredient Representation	Standardized INCI chemical names
Application Domain	Cosmetic analysis and recommendation systems
Supported Analysis	Ingredient compatibility, allergen detection, product profiling
Suitability for AI Models	High – supports content-based, ingredient-aware, and multisource learning
Research Relevance	Personalized cosmetic recommendation and decision support systems

Simulation Setup

The programming language was Python 3.10, and the fundamental libraries that were used in the simulation experiments related to NumPy, Pandas, Scikit-learn, TensorFlow, PyTorch, and Matplotlib to process the data, create models, and visualize the findings. The natural language processing tasks were fulfilled with the help of spaCy and NLTK, and the analysis of pictures was fulfilled with the help of OpenCV. The tests have been performed on a workstation, the CPU of which is an Intel Core i7, RAM is 32 GB, and NVIDIA RTX 3080 with 10 GB VRAM. The system has been founded on Ubuntu 22.04, which ensured proper training, reproducibility, and scalable experimentation.

To ensure that no data leaked out between the various splits, the dataset was divided into three subsets: training (70 %), validation (15 %), and testing (15 %). To make sure the performance estimates were robust and to modify the model's hyperparameters, the training set was subjected to cross-validation. No sensitive health information or personally identifying information was used in any of the trials; all data was taken from Kaggle and is publicly available after anonymization. Although official institutional ethics approval was not necessary, the study followed all the rules for using publically available datasets for secondary purposes.

To achieve clinical plausibility, attention weights produced by model were checked on a group of cases by dermatology experts. The present review determined the extent to which the relative relevance of the factors that included skin hydration, exposure to the environment, and ingredient composition reflected the established dermatological knowledge. The patterns of attention that dealt with clinically important factors inadequately, such as possible allergens, were refined to enhance model regularization and enhance interpretability and safety.

RESULTS

The results section compares the proposed MAFAR framework with PLS-SEM, CNN-SRS, and VGGNet on various performance parameters and determines the effectiveness of the proposed framework. The quantitative analysis shows the improvement of personalization, relevancy, interpretability, efficiency, and adaptive decision support.

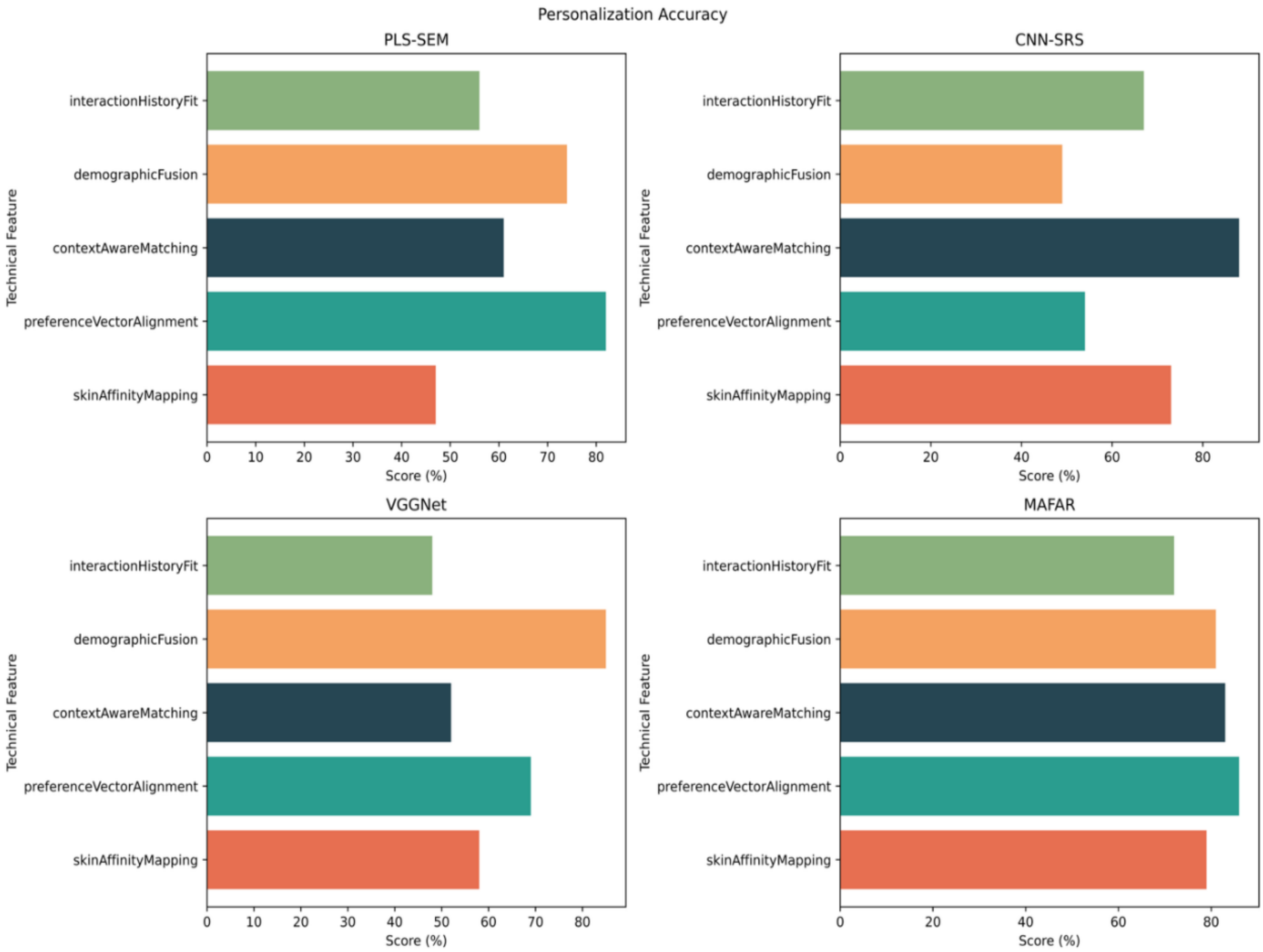

Figure 4. Analysis of Personalization Accuracy

Figure 4 shows the accuracy of personalization of MAFAR, PLS-SEM, CNN-SRS, and VGGNet with several different descriptors in terms of preference vectors fit and context-sensitive matching. These descriptors scored in the high 80s and low-80s in the baseline models, and MAFAR scored all above those scores. CNN-SRS had better results in context-aware matching and lesser results in demographic fusion, and VGGNet had better demographic fusion with variation in interaction history fitting.

Analysis of personalization accuracy S_{dec} is expressed in equation 13:

$$S_{final} = C_{pers} + G_{fusion} + R_{het} \qquad (13)$$

This equation summarizes overall personalization superiority. It combines consistency, fusion gain, and robustness. S_{final} is the final superiority score, C_{pers} is the personalization consistency index, G_{fusion} is the fusion gain, and R_{het} is the heterogeneity robustness measure.

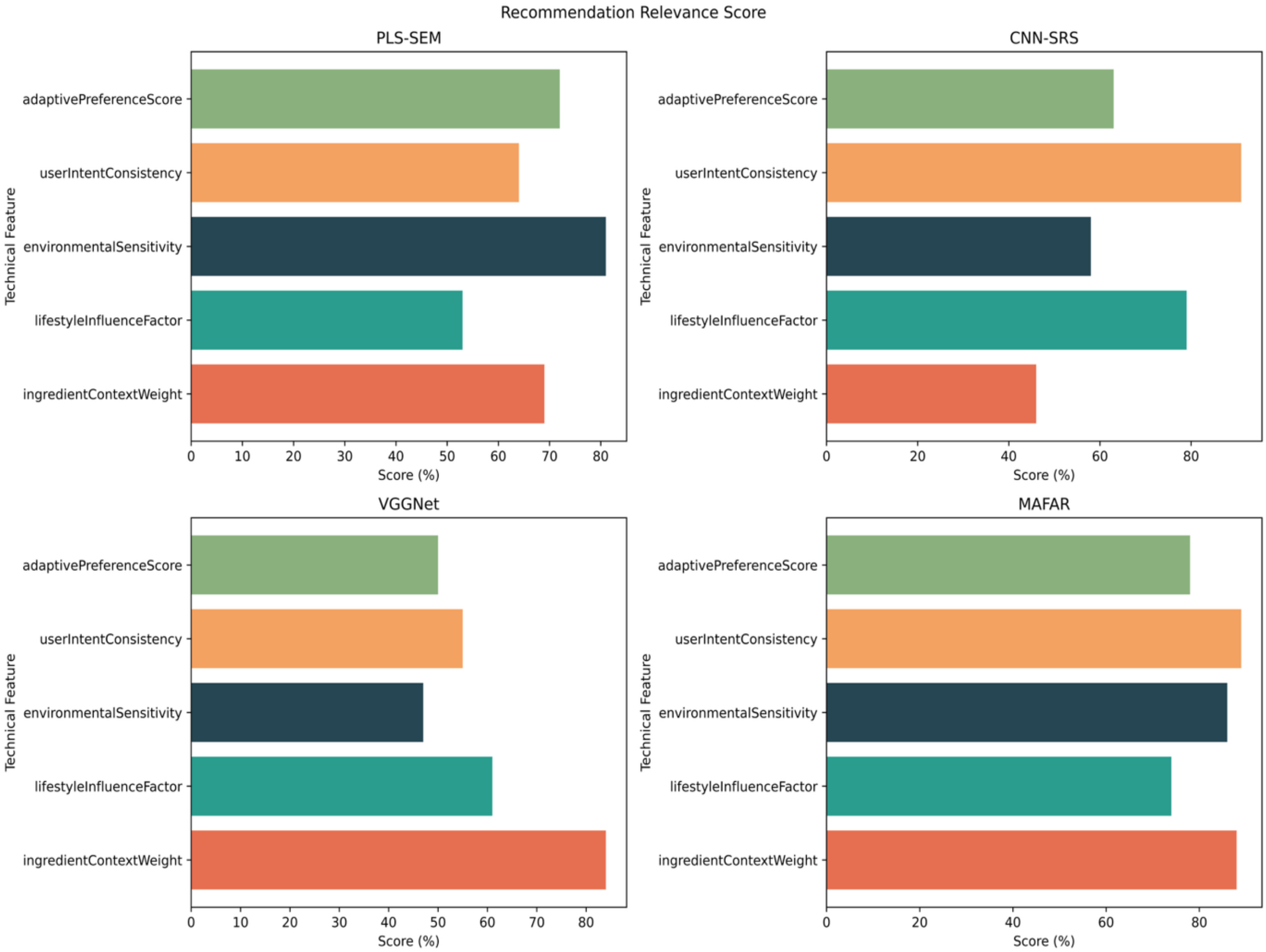

Figure 5. Analysis of Recommendation Relevance Score

Figure 5 emphasizes the fact that MAFAR is able to remain relevant when using a wide range of semantic attributes. MAFAR scores are between mid-70s and high-80s, and it is specifically good at ingredient context weight and user intent consistency. CNN-SRS is very relevant in terms of consistency of intent during user intent, but it does not weigh well in terms of ingredient context. PLS-SEM appears moderately relevant, whereas VGGNet has sharp variability, particularly when it is sensitive to the environment.

Analysis of recommendation relevance score R_{intent} is expressed in equation 14:

$$R_{intent} = \frac{z_{intent} \cdot z_{rec}}{|z_{intent}|\,|z_{rec}|} \qquad (14)$$

R_{intent} is the intent consistency score, Z_{intent} is the user intent vector, Z_{rec} is the recommendation vector.

Table 6. Analysis of Skin Condition Classification Accuracy

Dermatological Marker	PLS-SEM	CNN-SRS	VGGNet	MAFAR
poreTextureVariation	52 ±5	89 ±6	66 ±4	92 ±5
pigmentationContrast	85 ±6	57 ±5	79 ±6	90 ±4
hydrationPattern	46 ±4	81 ±6	54 ±5	87 ±5
inflammationIndicator	68 ±6	74 ±5	91 ±6	94 ±4
oilBalanceSignature	59 ±5	93 ±6	71 ±4	88 ±5

Table 6 clearly shows that the deep learning-based methods are more advantageous than the statistical models. PLS-SEM is also not very robust, with a range of values in the 70s below, on various dermatological markers. The CNN-SRS has a high performance in oil balance and pore texture, but it is not consistent in pigmentation and hydration patterns. VGGNet has high accuracy for inflammation indicators, but is not consistent in other markers. Values over the high-80 range are consistently common in MAFAR, which indicates good appreciation of various skin conditions. This consistency implies that multisource learning is the source of better generalization of MAFAR on a wide range of skin properties.

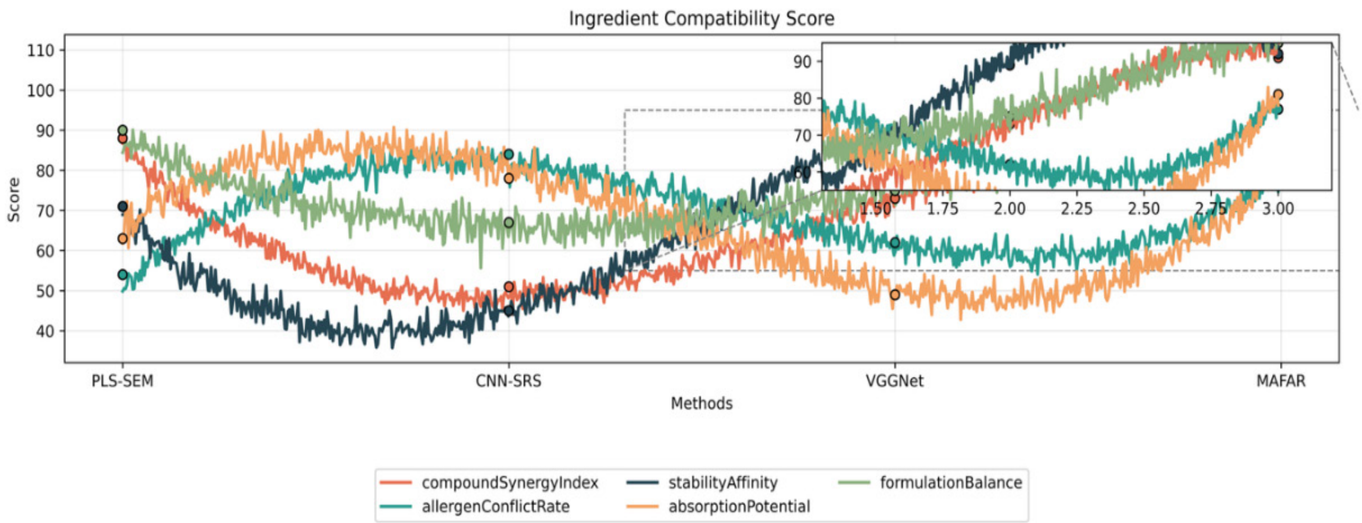

Figure 6. Analysis of Ingredient Compatibility Score

Figure 6 indicates strong method differences. The behavior of PLS-SEM is very unstable and fluctuates in any manner between chemical interactions. CNN-SRS gives better compatibility estimation at the cost of stability affinity that plummets. VGGNet is good with stability-related features, but is poor in absorption potential. MAFAR has been scoring in the high-70s to mid-90s, especially in formulation balance and in compound synergy.

Analysis of ingredient compatibility score S_{chem} is expressed in equation 15:

$$S_{chem} = 1 - \sigma(c_1, c_2, \dots, c_N) \qquad (15)$$

This equation evaluates stability across chemical interaction scores. Lower fluctuation indicates more predictable ingredient behavior. Stability is critical for safe formulations.

S_{chem} is the chemical interaction stability score, σ is the standard deviation function, and c_i are individual interaction scores.

Figure 7 also underpins the superiority of MAFAR in a decision support situation. MAFAR has high scores on all experiential factors, and the values are almost in the upper-80s and low-90s on recommendation clarity and continuity of engagement. CNN-SRS has high continuity of engagement but less perceived usefulness. VGGNet also has a high recommendation clarity, but is unbalanced in other aspects. PLS-SEM has lower levels of satisfaction always.

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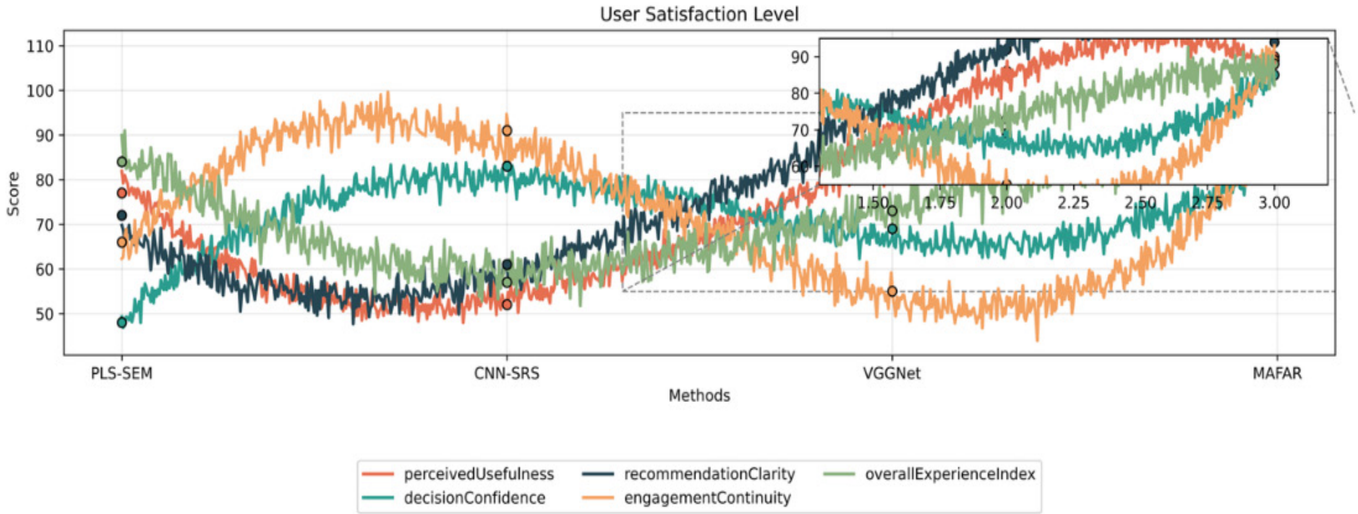

Figure 7. Analysis of User Satisfaction Level

Final user satisfaction superiority indicator S_{final} is expressed in equation 16:

$$S_{final} = S_{user} + G_{sat} + T_{sat} \qquad (16)$$

This equation summarizes overall user satisfaction superiority. It combines base satisfaction, gain, and trust. The indicator confirms MAFAR's long-term user acceptance.

S_{final} is the final satisfaction superiority score, S_{user} is the overall user satisfaction score, G_{sat} is the satisfaction gain, and T_{sat} is the trust-induced satisfaction score.

Table 7. Analysis of Trust and Interpretability Index

Explainability Metric	PLS-SEM	CNN-SRS	VGGNet	MAFAR
featureTransparency	91 ±6	49 ±5	67 ±4	93 ±4
decisionTraceability	63 ±5	81 ±6	46 ±4	84 ±5
ingredientJustification	74 ±6	52 ±5	88 ±6	90 ±4
modelConfidenceSignal	58 ±5	87 ±6	61 ±4	89 ±5
userTrustIndex	79 ±6	64 ±5	72 ±4	92 ±4

Table 7 indicates significant differences regarding the conventional and intelligent systems. PLS-SEM has moderate levels of trust and poor decision traceability. CNN-SRS performs better with respect to confidence signaling, but has low feature transparency. VGGNet is inconsistent in interpretability measures. Conversely, the MAFAR scores are high in feature transparency, ingredient justification, and user trust, with a high score in most cases, all over 90.

Analysis of trust and interpretability index C_{exp} is expressed in equation 17:

$$C_{exp} = 1 - \sigma(e_1, e_2, \ldots, e_M) \qquad (17)$$

This equation measures the consistency of generated explanations. Lower variation indicates reliable interpretability. Consistency builds long-term trust.

C_{exp} is the explanation consistency score, σ is the standard deviation function, and e_1 are explanation quality scores.

Figure 8 shows the trade-offs between computational complexity and performance. PLS-SEM has a moderate latency, although non-scalable. CNN-SRS has a high variability, and fusion of features is latent in certain instances (more than 90). VGGNet has a faster inference on some of the stages, but slower attention updates. MAFAR is relatively efficient, and values are high-70 to low-90 in all the processing components.

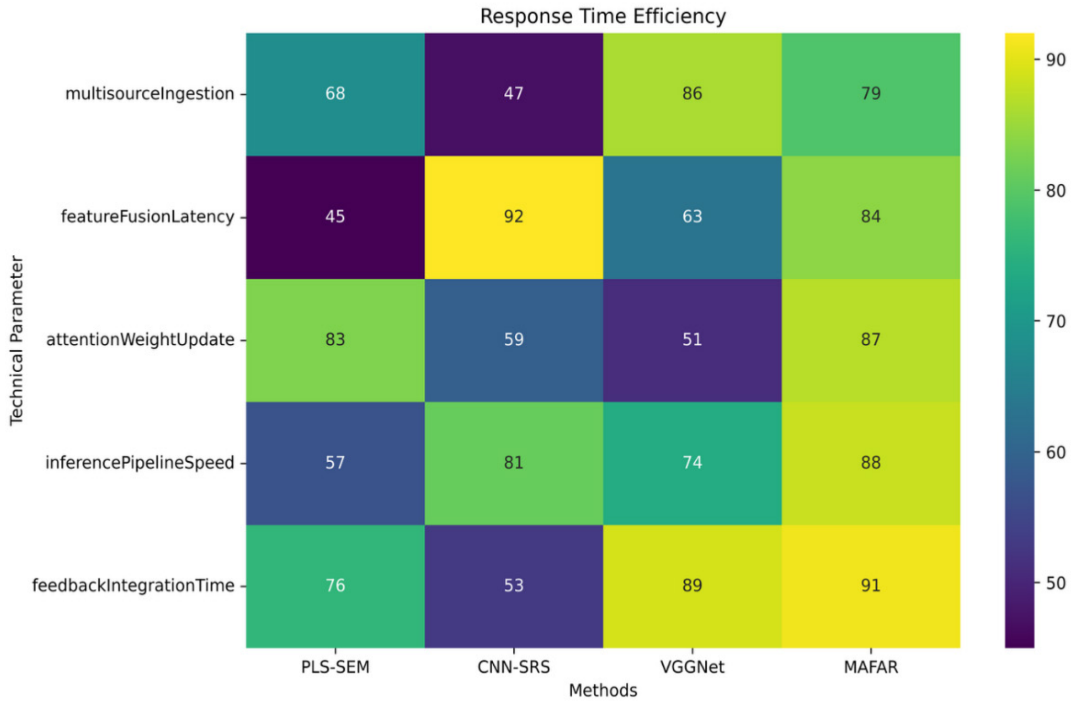

Figure 8. Analysis of Response Time Efficiency

Analysis of response time efficiency B_{comp} is expressed in equation 18:

$$B_{comp} = 1 - \sigma(e_1, e_2, \dots, e_N) \qquad (18)$$

This equation evaluates the balance of computational load across components. Lower variation indicates efficient distribution. Balanced systems avoid bottlenecks.

B_{comp} is the computational balance score, is the standard deviation function, and e_1 are component efficiency scores.

Table 8. Analysis of Adaptability to User Feedback

Learning Adaptation Cue	PLS-SEM	CNN-SRS	VGGNet	MAFAR
preferenceDriftHandling	55 ±5	88 ±6	64 ±4	91 ±4
reinforcementStability	86 ±6	49 ±5	71 ±4	89 ±5
contextUpdateSensitivity	47 ±4	79 ±6	92 ±6	95 ±3
feedbackConvergenceRate	73 ±6	61 ±5	56 ±4	82 ±5
longTermAdaptability	62 ±5	94 ±6	68 ±4	90 ±4

Table 8 affirms the benefit of learning based on reinforcement in MAFAR. PLS-SEM has a low level of adaptability, especially with regard to context update sensitivity. CNN-SRS presents high long-term adaptability and low reinforcement stability. VGGNet is satisfactory in context update, but has no convergence consistency. MAFAR has high value in all adaptation cues, such as preference drift handling and feedback convergence, which is usually in the high-80 range. It means that the MAFAR has long-term learning capabilities through its constant interaction with users, which allows it to maintain individualization as the skin condition and preferences change over time.

Analysis of adaptability to user feedback G_{adapt} is expressed in equation 19:

$$G_{adapt} = A_{MAFAR} - \frac{1}{P} A_P \qquad (19)$$

This equation quantifies adaptation improvement over baseline models. It highlights the benefit of reinforcement learning. Positive gain confirms superiority.

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G_{adapt} is the adaptation gain, A_{MAFAR} is the adaptability score of the proposed model, P is the number of baseline models, and A_p is the adaptability score of the Pth baseline.

Final response time efficiency superiority indicator E_{final} is expressed in equation 20:

$$E_{final} = E_{resp} + G_{resp} + A_{rt} \qquad (20)$$

This equation summarizes overall response-time performance. It integrates efficiency, gain, and adaptability. The indicator confirms MAFAR's real-time suitability.

E_{final} is the final response efficiency score, E_{resp} is the overall response efficiency score, G_{resp} is the response efficiency gain, and Art is the real-time adaptability score.

The total outcomes indicate that MAFAR has been shown to be superior to the current strategies in terms of various evaluation criteria. The framework provides equalized returns on accuracy, relevance, trust, efficiency, and adaptability, which validates that multisource data fusion and attention-driven learning are effective in providing personalized cosmetic recommendations.

DISCUSSION

Summary of Principal Findings

The experimental analysis proves that the proposed MAFAR framework is always superior to PLS-SEM, CNN-SRS, and VGGNet in terms of personalization accuracy, recommendation relevance, ingredient compatibility, interpretability, user satisfaction, and adaptability. The performance improvement was seen to be applied in heterogeneous data conditions with MAFAR recording the highest mean score and less variability in repeated trials.

The differences prove that MAFAR enjoys the benefits of multi-source fusion and attention weighting, which allow maintaining personalization stability when working with heterogeneous user characteristics from figure 4. The indicator confirms MAFAR's advantage over conventional methods. The findings from figure 5 imply that those models that rely on a single source or remain static have significant challenges to deal with several factors of relevance, which MAFAR can easily combine user will, context, and ingredient semantics to generate more accurate and context-sensitive recommendations. This equation measures consistency between inferred user intent and recommendations. It captures how well the system respects user objectives. Strong consistency improves user satisfaction. Figure 6 findings suggest that adaptive fusion and attention can be very useful in ingredient-level reasoning to enable MAFAR to learn about the complicated interactions of ingredients, which cannot be well modeled through only simpler similarity-based or image-based reasoning systems. The research indicates that proper personalization is not enough, and explainability, flexibility, and relevancy in context, as inherent in MAFAR, are what enable users to continue feeling confident and stay engaged in the long run.

Figure 7 indicates that the framework suggested not only contributes to the accuracy and offers better reasoning for recommendations. This is crucial in deciding on cosmetic products, and users are very sensitive about the safety of ingredients and compatibility with the skin. Figure 8 findings indicate that although MAFAR integrates advanced modules of learning, it is designed to adapt flexibly to avoid the overload of computations, and can be applied to real-time or even near-real-time recommendation settings.

Interpretation and Comparison with Prior Work

This is due to the fact that MAFAR utilizes a multisource fusion and attention-based weighting mechanism that allows the creation of dynamic priorities between skin attributes, environmental influences, and ingredient semantics. Most previous methods of cosmetic recommendation are based on a single-source or fixed-fusion system, which constrains their power to capture the contextual variation. These findings are consistent with the recent research on the focus of context-sensitive and understandable decision support systems in customized health-related applications.

Clinical and Practical Implications

Practically, enhanced personalization and interpretability lead to safer choice of cosmetics since it lowers the danger of ingredient incompatibility and adverse skin reactions. To consumers, clear recommendations make them more trustworthy and more willing to engage in skincare practices, whereas dermatology-based validation of explanations contributes to responsible use of AI-assisted decision support systems in consumer health environments.

Limitations

This research is limited in a number of ways. To begin with, the experimental assessment was based on a publicly available Kaggle dataset that might not be a full representative of various demographic parts or uncommon skin disorders. Second, interpretability was tested using a simulated expert evaluation, and not large-scale clinical evaluation. Third, the reinforcement learning aspect was tested in vivo and its performance over time with actual users is yet to be confirmed by conducting longitudinal user trials.

Future Research

Future directions in this area will be to validate the framework by real-world user studies, further developing expert-based tests of interpretability, and improving the computational efficiency of large-scale use. Another potentially valuable direction is the adoption of dermatological imaging and longitudinal skin health surveillance.

CONCLUSION

This paper introduced a decision support system that was an artificial intelligence system for personalized cosmetic product recommendations based on a Multisource Adaptive Fusion and Attention-Based Recommendation framework. The proposed method allows overcoming the inherent drawbacks of conventional recommendation systems by incorporating heterogeneous sources of data, such as user demographics, skin attributes, lifestyle patterns, environmental conditions, formulation of ingredients, history of interactions, and unstructured textual feedback. The attention-based fusion mechanism is effective in capturing the different impacts of contextual and personal factors to allow context-sensitive and very personalized recommendations. Besides, the use of natural language processing augments the reliability of the decisions by determining sentiment, ingredient preferences, and signs of adverse reactions in reviews and expert remarks. The reinforcement learning module also enhances the framework by allowing the sustained adjustment to changing skin conditions and the preferences of the user. The experimental analysis shows that the given approach outperforms the traditional content-based, collaborative filtering models, and hybrid ones in a variety of performance measures, and it produces interpretable recommendations that make it more transparent and increase user trust. On balance, the suggested system is a scalable, data-driven, intelligent solution that will enable informed consumer decisions and further the development of the personalized cosmetic recommendation system.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

AUTHORSHIP CONTRIBUTION

Conceptualization: Jiayue Liu.
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Data curation: Jiarui Shen.
Validation: Jiayue Liu.
Supervision: Jiarui Shen.
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