Artificial Intelligence in Personalized Skincare and Cosmetics: A Systematic Literature Review

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April 5, 2025

I Introduction

Artificial intelligence (AI) is significantly impacting numerous industries, such as healthcare, finance, and personalized consumer products. The cosmetics and beauty industry is also following this path, with AI-powered technology playing a significant role in product suggestions, virtual fitting, and dermatological evaluations. Computational methodologies, particularly deep learning frameworks, and computer vision are utilized by AI systems to provide recommendations on a personalized basis, depending on skin type, season, and personal preference [1], [2].

Customizing cosmetic recommendations is required, given that conventional methods fail to address individual dermatological customer needs. The latest developments in machine learning have allowed skin-type categorization to be performed automatically via convolutional neural networks. Convolutional Neural Networks (CNNs) [3], augmented reality (AR) [4], virtual try-on applications, and machine learning algorithms that recommend users suitable skincare products [5] improve the user experience by providing more precise, evidence-based recommendations and reducing product incompatibilities.

Despite the fact that some issues remain, all of this is still significant. AI-based recommendation systems often face the problem of bias from limited and static training data and data collections. Furthermore, the problem of data privacy is also applicable, as these systems are using users' uploaded facial images and users' skin data. Finally, the effectiveness of AI-based recommendations, based on independent variables such as light conditions, image quality, and surroundings, which make variabilities in results [6], [7].

Rationale for the Research Question: The increasing application of AI in cosmetic personalization raises important questions about whether it is effective, reliable, and unbiased. AI-powered cosmetic recommendation Information systems rely on the convergence of diverse sources of information, like skin type analysis, behavior, and environmental parameters, i.e., climatic and environmental conditions [8]. Whereas artificial intelligence models have managed to improve recommendation accuracy, studies show that data accuracy, fairness of models, and responsiveness to evolving behaviors remain challenges [9]. In addition, customer trust in AI-enhanced beauty products is also dependent on the transparency and explanation of the Algorithms, as customers should possess an understanding of the rationale behind the recommendations they receive.

Given these considerations, this systematic review addresses the following research question:

"How do artificial intelligence techniques, including deep learning, computer vision, and augmented reality, enhance personalized skincare and cosmetic product recommendations?"

The primary aim of the present research is to discuss current artificial intelligence techniques used for cosmetic product recommender systems, their advantages and drawbacks, and identify key research gaps. By synthesizing the most recent literature, this review seeks to deliver a comprehensive overview of how artificial intelligence can facilitate personalized beauty guidance and consider challenges and ethical considerations of data-driven methods.

II Method

A. Search strategy

The review used the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to document the literature search and article selection process. As per the research question, the IEEE Xplore database is a significant one through which was chosen to retrieve literature. The choice of this database is justified by the fact that IEEE Xplore provides coverage of the newest technology developments that are very specific to the interests of this review, such as artificial intelligence, machine learning, and computational applications. The academic reviews appraised the suitability of IEEE Xplore for systematic reviews, with high precision, recall, and reproducibility—required features for systematic literature review. IEEE Xplore supports Boolean search queries, enhanced filtering, and organized indexing; therefore, it is a perfect choice to obtain pertinent AI-based research on personalized cosmetic formulation. It covers engineering, computational intelligence, and applied sciences; therefore, it offers a high level of assurance in obtaining quality studies related to AI-powered product personalization.

Keywords selected to focus on the research scope include:

- Artificial Intelligence, Machine Learning, Deep Learning, Neural Networks, AI: Ensuring the inclusion of AI-related research.
- Cosmetic formulation, beauty products, makeup, skincare, personal care: Narrowing the scope to the beauty industry.
- Application, technique, technology, method, approach: Including studies discussing AI-driven approaches in cosmetic product personalization.

The final Boolean search query was structured as follows:

(”Artificial Intelligence” OR ”Machine Learning” OR ”Deep Learning” OR ”Neural Networks” OR ”AI”) AND (cosmetic OR makeup OR ”beauty products” OR skincare OR ”personal care”) AND (application* OR technique* OR technolog* OR method* OR approach*)*

All Metadata search was performed to retrieve the most relevant articles, yielding an initial result of 553 articles.

Filters applied to refine the search results:

- Publication years: 2020-2025 – Ensuring that only recent and relevant studies were included, reducing the results to 403 articles.

B. Data preparation

In the present study, no reference management tool was used because the obtained results were concise and could fit into a query.

C. Screening

A citation screening was conducted by reviewing the titles and abstracts of the returned articles. This process filtered out studies that specifically focused on AI usage in personalized cosmetics, resulting in a dataset of 110 papers. Due to the fact that IEEE

Xplore sometimes does not provide full-text access to all sources, an additional online search was conducted to identify full-text versions of the shortlisted papers. This step further filtered out those articles with available full texts for the final selection. For this purpose, ResearchGate and Reddit were used to search for full-text articles. Papers unavailable online were obtained directly from the authors via email. After full-text retrieval, 11 papers were retained for further analysis. To ensure the relevance and quality of the final set of studies, both inclusion and exclusion criteria were applied during the screening process.

Inclusion Criteria::

- Studies published between 2020 and 2025.
- Articles written in English.
- Studies focused on artificial intelligence (AI), machine learning (ML), deep learning, or computer vision.
- Research directly applying AI methods for skincare, makeup, or personalized cosmetic product recommendation.
- Peer-reviewed conference papers or journal articles indexed in IEEE Xplore.
- Studies presenting experimental results, prototype systems, or implemented applications.

Exclusion Criteria::

- Articles outside the beauty or cosmetics domain (e.g., general health applications).
- Theoretical or conceptual papers with no implementation or evaluation.
- Duplicate records or papers without accessible full texts.
- Studies that mention AI but do not focus on personalized recommendation or classification for skincare/cosmetics.
- Reviews, editorials, or white papers not presenting original research.

These criteria helped filter down the initial dataset to studies that directly addressed the use of AI for personalized beauty recommendations. Only papers that described specific models, datasets, or user studies relevant to personalization in cosmetics were retained for analysis. The overall selection process is illustrated in the PRISMA flow diagram (see Fig. 1).

D. PRISMA Flow Diagram

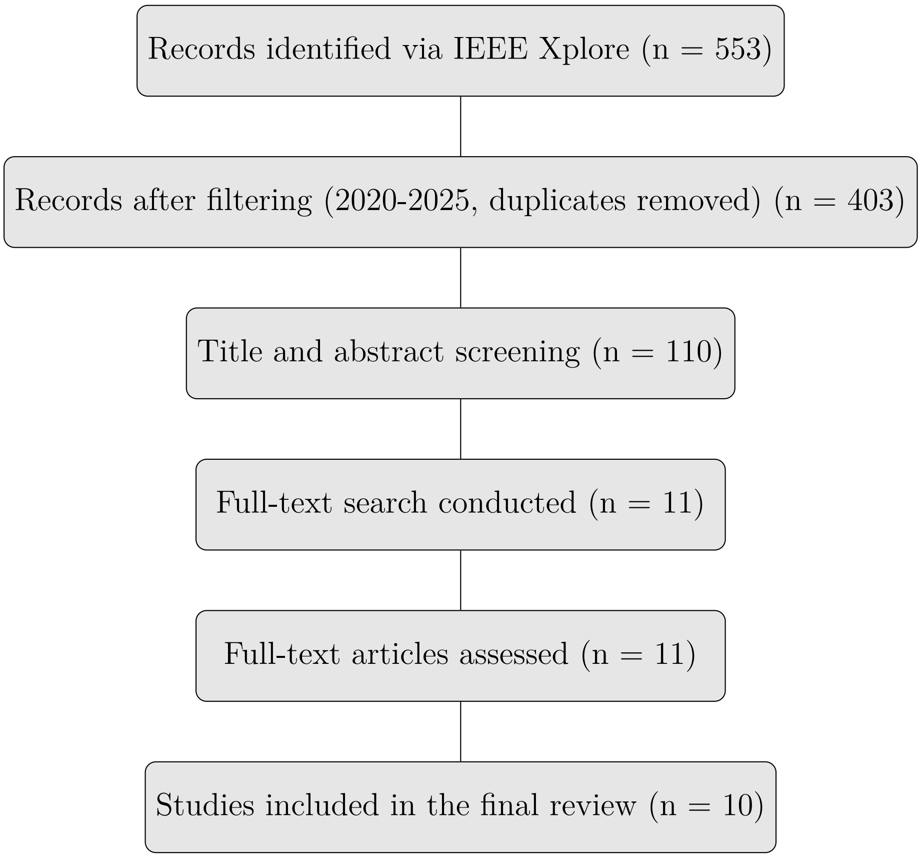

Fig. 1. PRISMA Flowchart for Study Selection

III Results

A. Overview

In this systematic review of AI-powered personalized cosmetics, ten studies were in-part of the total aggregate [1], [2], [3], [4], [5], [6], [7], [8], [9], [10]. These articles collectively employed techniques like convolutional neural networks (CNNs), deep-learning-based recommender systems, content-based filtering approaches, and GAN-powered makeup transfer applications to improve cosmetic product customization. Some were based on skin-type classification (e.g., oily, dry, combination), whereas others handled virtual make-up tests or ingredient-based recommendations.

B. Risk of Bias Assessment

A formal assessment of bias was conducted to explore issues such as participant recruitment, AI model design clarity, sponsors' involvement, and sufficiency of outcome reporting (Table I). Most studies had moderate to high methodological quality; however, certain limitations, such as restricted demographic representation, were identified.

TABLE I
RISK OF BIAS ASSESSMENT FOR INCLUDED STUDIES

Reference	Bias Description
[1]	CNN-based model with preprocessing and augmentation steps; lacks details on dataset size and source. No external validation or demographic diversity reported.
[2]	Model performance details and hyperparameter tuning are insufficiently reported; dataset diversity and bias mitigation strategies are unclear.
[8]	GAN-based virtual makeup simulation tested on 516 Chinese female participants; lacks long-term engagement analysis and demographic variety.
[3]	CNN-based classification for oily, dry, combination, and normal skin types using a self-labeled dataset; dataset size is not reported, and generalizability is limited due to lack of demographic diversity.
[4]	AR-based Virtual Makeover using annotated image datasets. No user study or quantitative evaluation reported; personalization was demonstrated only through visual output.
[9]	Makeup recommendation system tailored to Chinese female users, using BeautyGAN and the SCUT-FBP5500 dataset. While the system reflects local aesthetic standards, it does not disclose user diversity or commercial affiliations, making neutrality of product recommendations unclear.
[5]	Proposes a personalized skincare recommendation engine using YOLOv4 for detecting facial skin issues such as wrinkles, acne, and spots. The system applies image preprocessing and multi-label classification to identify skin conditions and suggest suitable cosmetic products. While the approach is technically sound, the dataset size and diversity are not disclosed, and the impact of real-world factors such as lighting conditions remains unexplored.
[10]	Content-based skincare recommender using 1472 Sephora products and ingredient similarity. While effective, the system lacks demographic diversity and real-world scalability testing.
[6]	CNN-based classifier trained on 1500 Kaggle images (dry, oily, normal). No external validation or real-world deployment discussed. Generalizability remains untested.
[7]	AI-powered foundation shade recommender using a k-means clustering algorithm. The system focuses on inclusivity with 625 foundation shades across 38 brands but lacks large-scale user trials for real-world validation.

C. Benefits of papers

Accurate Skin-Type Classification: Several studies [2], [3] demonstrated strong CNN-based classification performance in identifying oily, dry, or combination skin types, reporting accuracy rates between 85%–92%. Paper [1] also proposed a CNN-based framework with preprocessing and augmentation but did not include dataset size or accuracy metrics. Paper [6] used a CNN trained on 1500 Kaggle images covering oily, dry, normal, and combination skin types, but did not report any quantitative evaluation results. Paper [2] expanded the classification scope with multi-class detection, though hyperparameter settings and model tuning procedures were not described in detail. Overall, while CNNs show promise for automated skin classification, model reliability remains constrained by limited dataset transparency and generalizability.

AR Makeup Simulations: Two articles [4], [8] underscored the value of AR-based or virtual makeup try-ons. The "Virtual Glamour" system [8] employed GANs to map cosmetic styles (e.g., foundation, lipstick) onto user selfies. While prior research [8] referenced a dataset of 516 Chinese women to study facial color change after makeup application, the "Virtual Glamour" system itself was not evaluated on a large user base, and no direct user trial data was reported. Meanwhile, the "Virtual Makeover" [4] integrated personal trait detection (e.g., clothing color, hairstyle) into real-time AR overlays. The system was demonstrated using annotated facial images and tested qualitatively, but no user study or participant-based evaluation was reported.

Ingredient-Level Recommendations: Paper [10] introduces a content-based skincare recommender that suggests products based on ingredient similarity and user-defined skin concerns (e.g., acne, dryness). It analyzes 1472 skincare items from Sephora using cosine similarity and a custom IF-IPF method to rank ingredient relevance. In contrast to image-based approaches, this method enables more "scientific" personalization by matching chemical composition to user needs. However, it does not address scalability across larger product ecosystems, nor does it consider ethnic or geographic diversity in skincare preferences.

Foundation Shade Matching: Paper [7] introduced a k-means clustering system to match users with suitable foundation shades from a dataset of 625 options across 38 brands. The system captures real-time skin tone using a webcam and matches it with the closest shade using RGB and CIE Lab values. Although promising as a foundation matching tool, the system does not account for skin undertones and has not been validated through large-scale or multi-ethnic user trials.

D. Limitations of papers

Narrow Demographic Sampling: Several studies [1], [3], [10] relied on demographically limited or unspecified datasets, reducing generalizability across broader populations. For example, [3] focused on a small dataset with oily and dry skin types, without testing on sensitive or mature skin. Paper [10] proposes a content-based recommender but does not report any user-based evaluation. The paper does not mention demographic characteristics, which limits insight into system relevance across different populations. Paper [9] was designed specifically for Chinese consumers, and while culturally targeted, it did not explore applicability across other regions or ethnicities.

Potential Bias in Culturally Targeted Systems: Paper [9] presents a system tailored to Chinese consumers, with localized beauty styles and face analysis. While this cultural targeting can improve user relevance, it raises questions about generalizability to other populations. The study did not explore the potential for bias introduced by regional preferences or limited style diversity.

Data Collection Constraints: Studies [2], [6] relied on user-uploaded facial images, but did not report standards for lighting, pose, or background conditions. These uncontrolled variables may hinder model consistency and real-world performance. Although some authors described basic preprocessing (e.g., image resizing or grayscale conversion), the absence of standardized data pipelines makes replication and evaluation under varied conditions difficult.

Limited Long-Term Validation: While GAN-based and AR systems [4], [8] offered realistic visual outputs, none of the studies assessed long-term user satisfaction, engagement, or consistent use. Paper [7] similarly lacked multi-session evaluations to confirm foundation shade accuracy across lighting or seasonal changes—factors crucial to consumer trust.

IV Discussion

A. General Interpretation of the Results

The results of this systematic literature review underscore the growing importance of artificial intelligence (AI) in personalized skincare and cosmetic recommendations. AI models, such as convolutional neural networks (CNNs), deep learning-based recommendation tion engines, and augmented reality (AR)-based virtual try-on systems, have shown showing promising results in customizing beauty solutions to individual consumers [1], [2], [8].

A number of important advantages cut across the studies reviewed. CNN-based skin-type classification methods achieved high accuracy levels (85%-92%) in distinguishing between oily, dry, and combination skin types [3], [6]. AI-driven virtual makeup trials using AR offered an interactive consumer experience, enhancing user satisfaction and confidence in product selection [4]. Additionally, content-based recommendation systems effectively exploit aged skincare ingredient analysis to suggest best product formulations according to an individual's specific skin issues [10]. The launch of AI-powered foundation shade matching systems has also helped towards inclusivity in the cosmetics sector by catering to the needs of consumers with darker or underrepresented skin tones [7].

Despite these advancements, several challenges remain. Biases in training datasets, limitations in demographic diversity, and inconsistencies in lighting and image quality continue to affect model reliability [6], [9]. Furthermore, although AI systems can successfully match users with suitable products, their long-term efficacy in improving skin health and beauty outcomes remains underexplored [7].

Comparison with Similar Research: Comparing these findings with a similar systematic literature review on AI in cosmetic dermatology [11], notable similarities and differences emerge. Both reviews highlight the efficacy of AI in examining skin conditions, diagnosing cosmetic concerns, and recommending appropriate treatments. The comparable literature review investigate a wider range of AI applications, such as AI-powered diagnosis of skin conditions, treatment planning, and outcome prognostication, while our study aims specifically on AI-driven personalization in cosmetic product recommendations.

A significant distinction lies in the focus on therapeutic suggestions. The [11] exhaustively examines the applications of artificial intelligence within dermatological interventions, particularly in forecasting treatment results, while this research emphasizes the personalization of consumer beauty products through AI technology. Additionally, the dataset utilized encompasses a broader variety of artificial intelligence techniques, such as traditional machine learning methods as support vector machines (SVMs) and decision trees, while this study is primarily concerned with deep learning techniques, CNNs, and AR-based suggestions. The other significant distinction entails the taking into consideration of ethical issues. Whereas reviews recognize the challenges of dataset bias and demographic representation, this study puts more focus on the necessity of training AI models on varied populations to Enhance equity in beauty recommendations. Conversely, the [11] addresses applications of artificial intelligence, for treatment monitoring and regulatory compliance in dermatological interventions. In total, both studies align with the growing participation of AI in the skincare and beauty industry, yet this literature review particularly pinpoints AI's role in contributing to personalized product recommendations; the [11] however gives the broader view with treatment diagnostics and outcomes. Future research needs to synthesize perspectives from both domains to obtain AI-powered solutions assist in both personalizing beauty recommendations and augmenting long-term skincare outcomes.

B. Limitations of the Review Process

The conditions of this systematic review were limited by certain boundaries. Firstly, just English-language journals listed in IEEE Xplore were included, potentially excluding relevant research articles published in other languages or databases. Additionally, the snowball sampling method used in the studies was not applicable, which may have restricted the scope of literature being reviewed. Also, while efforts were made to ensure a comprehensive screening process, the final selection of 10 studies may not capture the full range of AI applications in customized cosmetics.

C. Limitations of the evidence in the review

The study verifies progress in AI-driven cosmetic recommendations, but it is faced with constraints in dataset diversity, methodological clarity and relevance to the real world. Non-heterogeneous datasets hinder generality, whereas data collection inconsistencies affect model reliability. Decreased transparency in optimization and validation reduces replicability. The lack of large-scale user testing subtracts from practicality. Future work needs to expand the dataset, standardize the evaluation procedures and provide extensive validation.

D. Implications of the Results for Practice, Policy, and Future Research

The findings of this review have significant implications for various stakeholders in the beauty and AI industries.

Practice: Beauty retailers and brands can merge AI-driven recommendation systems on digital platforms to provide personalized beauty experiences. AI-driven skin analysis and virtual try-on technologies can help customers make the correct purchasing decisions, reducing product mismatches and returns [4], [8].

Policy: Regulatory bodies should consider establishing standards for AI-based cosmetic recommendation systems to ensure fairness, transparency, and user privacy. Best procedures for real-time facial analysis caution against AI-driven recommendations and data It is necessary to develop protection practices that guarantee consumer trust [7].

Future Research: Several key research directions have emerged from this review:

- Demographic Expansion: Future studies should focus on developing models trained on diverse age groups, ethnicities, and skin tones to improve inclusivity.
- Longitudinal Studies: Research should assess the long-term impact of AI-powered skincare recommendations on skin health and user satisfaction.
- Hybrid Recommender Systems: Combining content-based approaches (ingredient analysis) with collaborative filtering (user reviews) and real-time AR feedback could lead to more robust personalization.

- Standardized Evaluation Metrics: Developing industry-wide benchmarks for assessing the accuracy, fairness, and efficacy of AI-driven beauty solutions will facilitate cross-study comparisons and improve system reliability.

Overall, AI-driven cosmetic recommendation systems are advancing impressively in boosting the customization of beauty products. Such systems entail high-end equipment personalized recommendations using educational methodologies, visual computing, and augmented reality recommendations, thus enhancing customer satisfaction and minimizing gaps in product selection. In spite of these advances, the challenges of guaranteeing fairness, transparency, and long-term performance remain. Training data biases, demographic representativeness, and the lack of standardized measures of assessment remain crucial dimensions that must be resolved. These challenges through improved research techniques, greater regulatory oversight, and continued technological innovations will play a crucial role in defining AI's changing position in the beauty industry.

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