cosmetics

Review

Cosmetology in the Era of Artificial Intelligence

Vasiliki Sofia Grech *, Vasiliki Kefala and Efstathios Rallis

Department of Biomedical Sciences, School of Health and Care Sciences, University of West Attica, Campus 1, 12243 Athens, Greece; valiakef@uniwa.gr (V.K.); erallis@uniwa.gr (E.R.)
* Correspondence: vgkrek@uniwa.gr

Abstract: The integration of artificial intelligence (AI) in cosmetology is transforming the industry in numerous ways, including the introduction of advanced tools such as at-home skin analysis devices that can evaluate skin quality and augmented reality applications that allow users to virtually try on various makeup products. These innovations empower individuals to make well-informed decisions about their cosmetic care and enable cosmetologists to predict treatment outcomes with higher accuracy. In this way, AI enhances patient satisfaction by better aligning expectations with achievable results. A computerized database search was performed to identify articles relevant to this topic. A comprehensive search was applied to the following electronic databases: IEEE Xplore, PubMed, Google Scholar, and Research Gate. This review explores four key areas in the current literature where AI contributes to cosmetic procedures. Firstly, AI democratizes skincare by making products and services more accessible to everyone. Secondly, it bridges the gap between physicians and cosmetic suppliers by enlightening collaboration and innovation. Thirdly, it improves the assessment of cosmetic ingredients by ensuring better safety and efficacy, and lastly, AI provides an ethical alternative to animal testing by replacing the Local Lymph Node Assay (LLNA) and the Guinea Pig Maximization Test (GPMT) with in silico models. While AI offers significant benefits, it also raises concerns about data privacy, informed consent, and the potential for promoting unrealistic beauty standards. Addressing these challenges involves implementing measures such as anonymization and de-identification techniques to protect sensitive data and safeguard informed consent for data collection and processing. This article aims to highlight the responsible and ethical use of AI in cosmetology, emphasizing the importance of accuracy and customization in cosmetic care, which represents a significant advancement in the industry.

Keywords: artificial intelligence; machine learning; cosmetology; custom cosmetics; acne; dermatological diversity; safety; data privacy; ethical AI

check for updates

Citation: Grech, V.S.; Kefala, V.; Rallis, E. Cosmetology in the Era of Artificial Intelligence. *Cosmetics* **2024**, *11*, 135. https://doi.org/10.3390/cosmetics11040135

Academic Editor: Enzo Berardesca

Received: 24 June 2024
Revised: 30 July 2024
Accepted: 6 August 2024
Published: 9 August 2024

1. Introduction

Cosmetology is a unique field focused on otherwise healthy patients, often involving local treatments such as creams for addressing acne, aging, and other skin issues. Although these beauty-related dermatological conditions do not pose a direct threat to physical health, they can significantly impact the quality of life [1]. In recent years, AI and machine learning (ML) techniques have been integrated into esthetics to improve cosmetic outcomes. Nonetheless, there has been limited research on the applications of ML and AI in this field.

The literature review conducted by Vatiwutipong et al. in 2023 [2] is one of the first to compile recent and relevant research on employing AI technologies to address challenging questions in cosmetology [2]. Choosing the right cosmetic product can be challenging for customers due to the vast array of ingredients and product availability. AI's predictive capabilities can align expectations with achievable cosmetic results and resolve unrealistic expectations, allowing patients to make informed decisions [3]. Additionally, AI is increasing access to cosmetologists and personalized cosmetic products for diverse and underrepresented populations through tele-esthetics [4], home-based applications, and personalized skincare, which is an important step in democratizing cosmetology [5].

Moreover, in silico models utilize AI to calculate the sensitizing potential of chemicals contacting the skin. They are less expensive, faster, and not restricted to laboratories compared to in vitro models, which are characteristics that make them more attractive tools for hazard evaluation, particularly in a screening context [6]. Today, in silico models are completely replacing animal testing in the European Union [7]. Our paper aims to highlight the contributions of AI in cosmetology, particularly in bridging the gap between cosmetologists and physicians in managing acne [8]. AI is creating more sophisticated and accessible diagnostic tools, combining machine learning expertise with domain-specific knowledge to address real-world healthcare challenges, offering advanced diagnostic capabilities, personalized product recommendations, and the possibility of remote surveillance by dermatologists. Additionally, this paper underlines the importance of personal data safety in the cosmetic industry, highlights the safety of custom cosmetic products, and addresses the limited representation of dermatological diversity in cosmetology through AI.

2. AI in Cosmetic Outcome Prediction: Aligning Expectations with Achievable Results

AI in cosmetology has advanced significantly, offering predictive capabilities that enrich patient satisfaction by aligning expectations with achievable results. This technology allows patients to make informed decisions about cosmetic procedures by providing a tangible preview of expected outcomes. Accurate outcome prediction is crucial as it helps cosmetologists and patients focus on feasible and satisfactory plans. Unlike medically compulsory procedures, cosmetic treatments offer various options influenced by patients' preferences and financial considerations. By effectively forecasting responses, practitioners can associate patient expectations with achievable results, thereby enhancing overall satisfaction and trust in the process [2,3].

Customer satisfaction is a critical factor in the cosmetic industry as it influences product purchases. Recent studies have broadened and explored AI's potential in emotion recognition and utilized it for personalized cosmetic advice. More specifically, Kim et al. [9] developed Convolutional Neural Network (CNN) models for analyzing electroencephalography (EEG) data to objectively measure consumers' emotions during the application of cosmetic creams. The aim was to understand consumers' emotions using EEG as they applied four different creams with various textures. The EEG data, categorized based on the subject's preference score as "like (positive)" or "dislike (negative)", was analyzed using frequency bands—alpha, beta, low gamma, and high gamma. These data were then organized into a matrix that incorporates both frequency and spatial information, and seven CNN-based models were developed and evaluated, achieving a 75.4% accuracy rate in predicting user satisfaction. This approach provides valuable insights into user preferences, aiding cosmetologists and patients in making informed decisions about cosmetic products. This is the first study to apply a CNN-based deep learning method using EEG data to evaluate preferences for cosmetic creams, highlighting an under-researched area in AI applications within cosmetology [9]. However, this is not the first study to develop deep learning techniques by using EEG, since a year ago, EEG and galvanic skin response (GSR) data have been employed to measure emotional responses to different emollients and lip balms during consumer experiences [10]. This research could be expanded to include not only the texture of a product but also other sensory aspects, such as smell, and provide an even more comprehensive understanding of consumer preferences.

Cosmetic makeup is a global practice that enhances beauty and expresses emotions, continuously adapting to cultural and societal trends. Despite the wide array of publications detailing cosmetic techniques, the application of makeup has traditionally been a multidisciplinary process. In 2007, Tong et al. [11] were among the first to introduce a method for simulating virtual make-up applications. This method involved using a computer-based technique called "cosmetic transfer", which utilized the ratio of "before" and "after" makeup images to replicate makeup effects on a target face. The process computed these effects on a pixel-by-pixel basis from three aligned images sharing the same 2D geometry. While the approach was successful in achieving realistic cosmetic transfers, it was acknowledged that the results were not flawless [11]. Since then, more sophisticated AI-based algorithms have been developed to assess facial features for makeup applications. By addressing the complexity introduced by factors such as face shape, eye color, skin tone, etc., an automatic system was developed by Flament et al. [12] to provide "blind" expertise advice. Before makeup application, an AI-based automatic descriptor performs a comprehensive analysis of 23 facial traits, hairs included, from customers' selfies as an aid for make-up practices. This system was validated by a panel of 12 makeup experts and included a diverse group of participants, demonstrating its ability to offer accurate, personalized cosmetic advice across a wide demographic range [12].

In the realm of skincare, Shi et al. [13] developed an AI tool called SkincareMirror, which predicts a user's appearance after long-term use of skincare products. This tool is particularly beneficial for customers as it provides a visual forecast of the anticipated results using a combination of product function labels, user images, and efficacy ratings. SkincareMirror has proven especially useful for individuals with varying levels of skincare knowledge, helping them make quicker and more informed decisions by visualizing the potential long-term effects. The tool's effectiveness is evidenced by increased satisfaction and efficiency among users, especially men with less skincare expertise, compared to traditional shopping methods [13].

Advancements in AI and deep learning models hold significant promise for the cosmetic industry, as seen in Figure 1. These technologies assist dermatologists and patients in selecting suitable treatment options, potentially leading to the development of sophisticated simulation tools. These tools could simulate multiple cosmetic procedures simultaneously and consider a broader range of patient characteristics and preferences. As research progresses, these innovations are expected to transform cosmetic practices, ensuring that patients receive treatments that meet their expectations and enhance their overall experience [2].

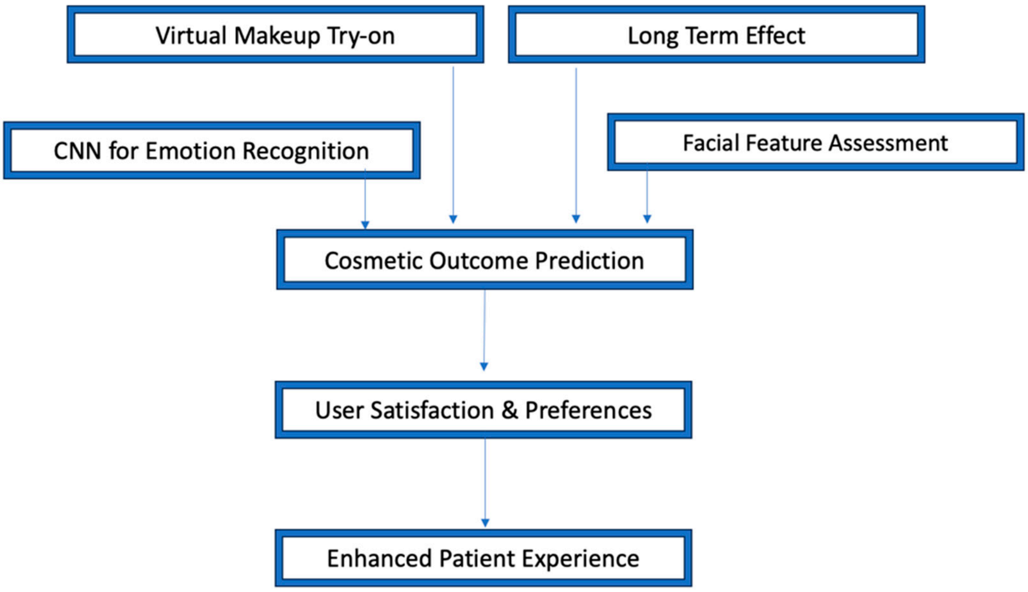

Figure 1. AI methods used for cosmetic outcome prediction in cosmetology.

3. The Role of AI in Democratizing Skincare: Transforming Accessibility and Personalization

AI democratizes cosmetology by making esthetic care more accessible, affordable, and convenient. Technologies like tele-esthetics enable remote consultations by analyzing skin conditions through photographs, benefiting individuals in remote or underserved areas. This reduces the costs associated with traditional in-person visits, making expert advice more affordable and accessible. The convenience of receiving personalized skincare recommendations from home saves time and effort, particularly for those with busy schedules or mobility issues. Additionally, the scalability and decreasing cost of AI tools ensure that high-quality care is available to a broader population. These technologies also provide safe and effective remote services for basic esthetic concerns and facilitate appropriate referrals for more complex cases, thereby enhancing inclusivity and equity in access to cosmetic and skincare services [4].

Furthermore, AI is transforming skincare by expanding accessibility and improving the assessment of dermocosmetic ingredients across diverse populations. A fully remote study showcased an AI-based classification system that analyzed selfie images from a varied and representative group of 1041 US women of different ages and ancestries, including East Asian, Non-Hispanic Euro-American, African American, and Hispanic Euro-American, covering all Fitzpatrick phototypes. This study, which did not provide specific instructions for taking selfies, demonstrated that the AI system could accurately and clinically assess seven facial signs. The results, cross-verified by evaluations from 50 diverse US dermatologists, highlighted the system's precision, although it noted areas for improvement in skin tone analysis, particularly for pigmentary spots and in the younger, older, and darkest phototype groups. To enhance accuracy, new datasets from numerous countries have been obtained, and the automatic grading system has been upgraded. The study emphasized the importance of using well-distributed datasets across all demographics to ensure fair representation and reduce bias, as demographic factors can significantly affect biometric algorithms. This approach enables more inclusive and personalized skincare recommendations, thereby democratizing access to advanced skincare assessments and enhancing equity in skincare practices [14].

Despite advancements in AI, its application to the skin of color (SOC) faces significant limitations due to underrepresentation in datasets. Current AI programs often rely on the Fitzpatrick Skin Phototype (FST I-VI) scale to classify skin tones, but this scale is flawed for SOC classification. A 2024 review [15] found that only 30% of AI programs in dermatology reported data related to the SOC, highlighting the extent of this issue. The FST scale, originally designed to determine the risk of burning during phototherapy among Caucasians, is an unreliable indicator of skin pigmentation for diverse populations. Studies have shown that the FST does not effectively represent the Black community, often exaggerating the prevalence of type IV skin among them. This can lead to inadequate cancer risk assessments and a lack of accuracy in evaluating the SOC. Consequently, AI programs may perform poorly in identifying lesions in the SOC, and biases in algorithms can disproportionately impact individuals with darker skin [15].

An alternative classification tool, the Monk Scale [16], developed by Harvard Professor of Sociology Dr. Elias Monk, offers a more inclusive categorization by dividing individuals into 10 different skin type categories based on skin color and ethnic background. This scale aims to capture a broader spectrum of human skin pigmentation, providing a more accurate representation of diverse skin tones. Google has partnered with Dr. Monk to enhance the diversity of images displayed across its products, including image searches. Similarly, Facebook/Meta's Casual Conversations data suggest using the Monk Scale alongside the Fitzpatrick Skin Phototype (FST) scale to improve skin tone representation in AI algorithms, promoting fairness and diversity while minimizing bias. Adopting comprehensive scales like the Monk Scale can expand the categorization of skin tones and demonstrate a commitment to inclusive representation across industries. Addressing these challenges by utilizing well-distributed datasets and inclusive classification tools is crucial for overcoming bias and ensuring equitable and accurate dermatologic and cosmetic care [15].

In summary, AI technologies are revolutionizing skincare by making it more accessible and personalized, particularly for diverse populations. Table 1 below provides an overview of how AI democratizes skincare. These advancements highlight the importance of individuality in skincare, empowering people to make informed decisions about their hair and skin through home-based applications and personalized products. Companies are utilizing AI through skincare quizzes that gather data on demographics, skin characteristics, and esthetic preferences, which machine learning algorithms then analyze to recommend suitable cosmetic products tailored to individual needs. Virtual try-ons further enhance this experience, allowing users to experiment with makeup styles from the comfort of their homes. Additionally, free applications and devices offer online skin analyses and personalized recommendations, using high-definition cameras and portable tools for objective assessments. By catering to the unique needs of diverse populations, AI is promoting greater accessibility and inclusivity in skincare, ensuring that everyone can benefit from customized and effective treatments [5].

Table 1. A summary of how AI democratizes skincare.

Key Area	Description
Remote Consultations	AI technologies enable remote skin consultations through photograph analysis.
Cost Reduction	AI lowers costs by facilitating remote consultations and assessments.
Convenience and Personalization	Provides personalized skincare recommendations accessible from home.
Scalability and Accessibility	Ensures high-quality skincare services are available to a broader population.
Diverse Population Representation	Improves skincare assessments' accuracy across diverse populations.
Enhanced User Engagement	Uses tools like virtual try-ons and personalized product recommendations.
Addressing Skin of Color (SOC) Limitations	Adopts inclusive classification tools to reduce bias in skincare assessments.
Objective Assessments	Uses high-definition cameras and portable tools for objective skin assessments.

4. AI Is Bridging the Gap between Physicians and Cosmetologists

Collaboration between dermatologists and cosmetologists plays a crucial role in managing and treating acne, a chronic multifactorial inflammatory disease of the pilosebaceous follicle that significantly impacts patients' quality of life. Acne affects over 85% of adolescents and often continues into adulthood, with an increasing incidence of adult acne being characterized by periodic flare-ups [1]. Cosmetologists often serve as the first point of contact for patients, offering preventive care through personalized skincare treatments and educating them on proper skincare routines. Depending on the severity of the acne, dermatologists and cosmetologists work together to select appropriate treatments, with dermatologists addressing inflammatory effects and cosmetologists helping to maintain clear skin. This teamwork enhances long-term treatment efficacy and patient satisfaction [8].

Understanding the unique characteristics of each type of acne is crucial for effective diagnosis and tailored treatment approaches. Cosmetologists must have adequate skills, and dermatologists should oversee the treatment of medical skin conditions [17]. The integration of AI has significantly advanced the diagnosis and treatment of acne by focusing on the unique characteristics of various acne types. Table 2 shows AI software applications for acne diagnosis. AI tools, such as CNN-based methods, have become essential in this field, offering advanced diagnostic capabilities. For instance, Shen et al. [18] introduced a CNN-based approach in 2018 that could automatically identify seven types of acne lesions (nodules, pustules, cysts, papules, blackheads, whiteheads, and normal skin) with an accuracy of 81%. This method utilized a binary classifier to distinguish skin areas from non-skin areas and a seven-class system for detailed acne classification by leveraging pre-trained models like VGG16 for feature extraction [18].

In 2019, Junayed et al. [19] developed AcneNet, a deep residual neural network that categorizes five types of acne lesions, namely closed comedo, open comedo, cystic, pustular, and keloidalis, achieving over 94% accuracy. This model employs convolutional layers, pooling layers, fully connected layers, and activation functions to enhance its classification capabilities [19]. In 2022, Kim et al. [20] introduced a method for detecting and counting facial acne lesions, offering a reliable means of classifying acne lesions into inflammatory and non-inflammatory categories, and it was validated on a dataset of 20,699 manually labeled lesions. This system also proved to be valuable for teledermatology by visually highlighting acne lesions on the screen, thereby assisting dermatologists in remote consultations [20].

Table 2. AI software applications for acne diagnosis.

AI Acne Classification Studies	Applications	Details
"An Automatic Diagnosis Method of Facial Acne Vulgaris Based on Convolutional Neural Network" (Shen et al., 2018) [18]	Classification of seven types of acne lesions	Identifies nodules, pustules, cysts, papules, blackheads, whiteheads, and normal skin with 81% accuracy. Uses VGG16 for feature extraction.
"AcneNet—A Deep CNN Based Classification Approach for Acne Classes" (Junayed et al., 2019) [19]	Categorization of five types of acne lesions	Classifies closed comedo, open comedo, cystic, pustular, and keloidalis acne with over 94% accuracy. Utilizes deep residual neural networks.
"Automated Facial Acne Lesion Detecting and Counting Algorithm for Acne Severity Evaluation and Its Utility in Assisting Dermatologists" (Kim et al., 2022) [20]	Detection and counting of acne lesions	Differentiates between inflammatory and non-inflammatory acne. Useful in tele-dermatology for remote consultations.
"Acne Detection Care System using Deep Learning" (Yadav et al., 2021) [21]	Deep learning-based acne detection and personalized care	Uses ResNet-18 to predict the number, location, and severity of acne lesions, providing personalized care with 90% accuracy.

Accurate assessment of acne severity is essential for patient care and clinical studies, yet traditional methods like global severity grading and lesion counting can be time-consuming and inconsistent. AI algorithms, such as PP-YOLO, have demonstrated clinically valid performance in detecting and counting facial acne lesions, improving the reliability of severity assessments [20]. Recently, Yadav et al. [21] introduced "Acne Care", a system using deep learning techniques and the ResNet-18 architecture for acne detection and personalized care. This system can accurately predict the number, location, and severity of acne lesions, providing a useful tool for both self-assessment by patients and clinical diagnosis by doctors. The ResNet-18 model, known for its depth and skip connections, classifies acne severity into four levels—normal, level 0, level 1, and level 2—with up to 90% accuracy. This research highlights the potential of AI to create sophisticated and accessible diagnostic tools, combining machine learning expertise with domain-specific knowledge to address real-world healthcare challenges in acne management [21].

The declining number of dermatologists in Europe [22] has made it challenging for patients to secure timely appointments, leading to irregular follow-ups and suboptimal treatment outcomes. This shortage exacerbates issues such as the inadequate management of skin conditions, increasing the risk of scarring and residual hyperpigmentation and causing a decline in patients' quality of life. Timely and appropriate management is crucial to prevent long-term complications. AI tools significantly enhance patient outcomes by assisting dermatologists and cosmetologists in various ways. These tools facilitate efficient diagnosis and screening by rapidly analyzing skin conditions like acne and recommending treatment plans, thus accelerating the diagnostic process and allowing dermatologists to focus on more complex cases. AI also supports remote consultations and tele-esthetics by providing accurate assessments through images or videos, ensuring that patients receive timely advice and treatment. The continuous monitoring and follow-up capabilities of AI tools help maintain patient adherence to treatment regimens and allows treatments to be adjusted as necessary. Moreover, AI provides educational support to cosmetologists, enhancing their ability to manage skin conditions and fostering effective collaboration with dermatologists. This integration of AI into dermatological care helps bridge the gap left by the declining number of specialists, ultimately improving patient care and quality of life [8,23].

In conclusion, the integration of AI in dermatology and cosmetology is crucial in bridging the gap left by the declining number of specialists. By providing tools for efficient diagnosis, remote consultations, and personalized treatment plans, AI ensures that patients receive timely and accurate care. This advancement not only enhances collaboration between dermatologists and cosmetologists but also improves patient access to essential skincare services, ultimately leading to better health outcomes and quality of life.

5. Using AI in Ingredient Assessments for Cosmetic Recommendations

Choosing the right cosmetic product can be challenging for customers due to the vast array of ingredients and products available in the industry, ranging from natural to chemical formulations. Common ingredients like glycerin, hyaluronic acid, retinol, and ceramides contribute to the effectiveness of cosmetics, but evaluating all possible combinations is impractical as the cosmetic industry includes an estimated 20,000 to 200,000 ingredients and products [24]. Since the pandemic, there has been an increased interest in health and safety, leading users to scrutinize ingredients themselves before purchasing cosmetics. This trend indicates that an ingredient-based approach can provide more precise and reliable recommendations to today's users [24,25].

To assist in this process, algorithms and ML methods are increasingly being used. Researchers have applied various techniques, such as Natural Language Processing (NLP), content-based filtering, and neural collaborative filtering, to analyze customer reviews, product similarities, and user-related data for personalized recommendations. NLP enables computers to understand human language in a meaningful and useful way by extracting explicit information from customer reviews, and neural collaborative filtering provides personalized cosmetic recommendations based on users' past online behaviors and preferences [26,27]. Additionally, the Ingredient Frequency–Inverse Product Frequency (IF-IPF) method validates cosmetics according to skin type, age, and ingredient composition by analyzing cosmetic review sites and user evaluations to identify ingredients believed to have the best effects [28].

Some researchers have focused not only on analyzing cosmetic components but also on evaluating users' skin conditions to better meet users' demands. AI skin analysis, which includes image processing algorithms and deep learning models like YOLOv4, automatically removes noise, enhances face characteristics, and extracts features for skin condition classification [29]. Additionally, another CNN called U-Net [30], initially designed for biomedical image segmentation and uses three-dimensional data for image classification and object recognition, is now used for skin analysis and evaluation. This model achieves the simultaneous segmentation of wrinkles and pores by analyzing the morphological structures of the skin rather than relying on color-based analysis. When provided with an entire face image from various shooting positions, the U-Net architecture excels at localizing wrinkles and pores, outperforming both conventional image-processing approaches and recent deep-learning methods [31]. The prediction results from these machine-learning approaches can provide suitable product recommendations, offering more precise and reliable cosmetic suggestions tailored to individual skin concerns.

In 2024, Lee et al. [24] proposed a complete cosmetic recommendation system that combines ingredient analysis with AI skin analysis to provide personalized recommendations. Existing systems do not quantitatively analyze their performances using proper evaluation metrics, nor do they consider the order of ingredients in cosmetic analysis. In contrast, Lee et al.'s system features specialized AI models for each skin problem, and instead of providing a direct measure of a product's efficacy, it analyzes the order of ingredients in its composition. By using a deep neural network encoder to analyze sequential ingredient data and a deep neural network for skin analysis, the system offers precise and reliable cosmetic suggestions tailored to individual skin concerns. This advancement is expected to provide more objective results on cosmetic effects by offering a more tailored cosmetic prediction for each user's skin status [24].

6. Advancements of In Silico Models in Cosmetology

Cosmetics are likely the most common reason why patients undergo patch testing. Cosmetics can cause delayed type IV hypersensitivity responses, known as Allergic Contact

Dermatitis (ACD), which occurs within 48–72 hours after exposure and presents with symptoms such as rashes, blisters, and swelling, significantly impacting patients' quality of life. The eyelids, being highly sensitive due to their thin stratum corneum and occlusion when the eyes are open, are particularly vulnerable, often developing dermatitis from substances applied to the scalp, face, or hands, even when these primary sites remain unaffected. Small amounts of allergens transferred from the fingers can trigger eyelid dermatitis without visible signs elsewhere. While many cosmetics are free of common allergens, nonspecific irritation still occurs, leading to conditions like *status cosmeticus*, [32] where every cosmetic or soap applied to the face causes itching, burning, or stinging sensations. The face and hands are most commonly affected, but the neck, anogenital region, and other areas can also be impacted [33]. In a current retrospective analysis of Brazilian patients who underwent patch tests for suspected ACD between 2004 and 2017, cosmetics were identified as the fundamental cause of the condition in 16.5% of the patients, of which 89.7% were women [34].

Predicting the possibility of cosmetic components to trigger skin sensitization is crucial. Before 2004, cosmetics and their ingredients were primarily tested on animals using methods like the Guinea Pig Maximization Test (GPMT), the Bühler test, and the Local Lymph Node Assay (LLNA). However, the European Union's cosmetic directive mandated alternatives to animal tests, resulting in a complete ban on animal testing for cosmetic products and ingredients by 1 October 2004 and a total ban by 11 March 2013, regardless of the availability of alternative methods [35]. Consequently, non-animal test methods or New Approach Methodologies (NAMs) have become the preferred choice for risk documentation and descriptions of skin sensitizers, allowing for the development of a non-animal, Next-Generation Risk Assessment (NGRA) framework [36].

Current in vitro tests include the Human Cell Line Activation Test (h-CLAT), Direct Peptide Reactivity Assay (DPRA), LuSens, Myeloid U937 Skin Sensitization Test (MUSST), and the KeratinoSens method [35]. Despite their advantages, the accuracy and reliability of in vitro methods compared to traditional animal tests remain debated. In vitro tests per se cannot substitute animal and human tests since they emphasize only one Adverse Outcome Pathway (AOP). This limitation has led to the development of mathematical models called in silico models to calculate the sensitizing potential of cosmetic ingredients derived from historical epidemiological data [35].

Various skin sensitization data, including non-animal and animal data, along with chemical structure information, have been published. The Cosmetic Ingredient Database (CosIng), an online resource created by the European Commission, compiles data and structural alerts to construct predictive models. The quality of data is crucial in developing these models, and creating an in silico model without clean or pure data is challenging. Effective development strategies involve collecting extensive experimental data and understanding biological mechanisms to predict bioactivity and biochemical processes. Currently, diverse simulation approaches such as K-Step Yard Sampling (KY), Decision Trees (DTs), Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), AdaBoost, Logistic Regression (LR), Iterative Least Squares Linear Discriminant (TILSQ), consensus methods, and Bayesian networks are used to develop skin sensitization predictive models [6].

In silico methods also offer significant advantages in the toxicology of cosmetic ingredients via safety assessments, enabling high-throughput screening of extensive chemical libraries without requiring physical experiments. This capability allows for potential candidates to be prioritized before the costly and time-consuming process of molecule synthesis. These approaches utilize existing data more efficiently and support the 3Rs principle (Replacement, Reduction, and Refinement), thereby reducing the reliance on animal testing [37].

Recognizing the complexity of skin sensitization, the Interagency Coordinating Committee on the Validation of Alternative Methods (ICCVAM) under the US Department of Health and Human Services employed a multi-faceted approach that includes machine learning techniques. Specifically, they used LR and SVM to train models on 72 substances and tested these models on an additional 24 substances. The SVM models achieved the highest accuracy, reaching 92%, by integrating data from DPRA, h-CLAT, and read-across, with some models also incorporating KeratinoSens and log P. These machine learning models outperformed traditional methods like the LLNA and individual in vitro methods, highlighting the efficacy of computational approaches in predicting human skin sensitization hazards [38].

Another approach involved developing an ANN for in vitro risk assessment systems. This model uses descriptors like the maximum change in cell-surface thiols (MAC value), CV75 (indicating 75% cell viability), and threshold concentrations for CD54 and CD86 expressions (EC200 and EC150). The ANN model, named "iSENS ver. 1", showed a strong correlation with published LLNA thresholds, suggesting its effectiveness in calculating the skin sensitization potential of chemicals using in vitro data [39].

Additionally, in silico models can be applied to entire cosmetic compounds, and not just individual ingredients. Some commercial or cosmetic products contain sensitizers that do not induce adverse effects when administered in low doses. For example, products that are washed off, such as body lotions or shampoos, have different exposure levels compared to those in direct and prolonged contact with the skin, such as foundations or creams. The disparity in exposure between these groups can be as much as 30 times greater. As a result, qualitative in silico models, which often rely on binary classification, have limited application in the pharmaceutical or cosmeceutical markets. These models typically focus on a single biological pathway and fail to capture the full spectrum of sensitization responses, including weak or moderate effects. They also do not consider variations in product application and exposure levels, such as the difference between leave-on and wash-off products. Therefore, there is a need for more comprehensive and quantitative prediction models. These models provide detailed assessments of the sensitization potency, enabling precise risk evaluations and helping to meet regulatory requirements. Quantitative models improve product safety by identifying safe ingredient levels, aiding in formulation, and protecting consumers from skin reactions. Additionally, they facilitate the comparative analysis of different ingredients, ensuring the development of safer and more effective cosmetic products [6].

In the context of cosmetic ingredient assessments, hundreds of in silico models are available to predict various properties of interest for different endpoints, with some models being offered for free and others requiring a fee. To support this process, the SpheraCosmolife package was developed. This package provides tools to evaluate cosmetic ingredients and predict genotoxicity, mutagenicity, and skin sensitization based on factors such as concentration and product type (e.g., shower gel or lotion). The SpheraCosmolife package facilitates and standardizes the safety assessment of cosmetic products by providing a Margin of Safety (MoS) based on systemic exposure doses. It incorporates models for both exposure and hazard prediction, enhancing the accuracy and reliability of safety evaluations in the cosmetic industry [40].

In 2021, Golden et al. [7] compared eight in silico models against two human datasets, achieving accuracies ranging from 70% to 80%, similar to traditional animal tests like the LLNA. These models were evaluated based on parameters such as coverage, accuracy, sensitivity, and specificity, with additional consideration for optimization features like the probability of accuracy and applicability domain when available. The binary skin sensitization outcomes predicted by each model were compared to the actual sensitization status of the chemicals in the datasets. Interestingly, the models did not consistently mispredict the same compounds, suggesting that a combined approach might improve predictive accuracy. This study highlights the potential of these in silico models as cost-effective tools for predicting skin sensitization [7].

Existing human tests for skin sensitization, including the Human Maximization Test (HMT) and the Human Repeat Insult Patch Test (HRIPT), provide direct results but are hindered by the scarcity of consistent data, ethical concerns, and subjectivity. Conversely, animal tests offer predictive models but are fraught with ethical issues and limitations in accuracy. The increasing adoption of non-animal assays, driven by ethical considerations and technological advancements, has elevated the role of in silico models in supporting preliminary evaluations and complementing experimental data. As seen in Figure 2, the evolution of testing methods is tremendous. Despite these advancements, animal tests, notably GMPT and LLNA, remain mandatory in several countries including Brazil, Canada, Japan, China, and the United States [6].

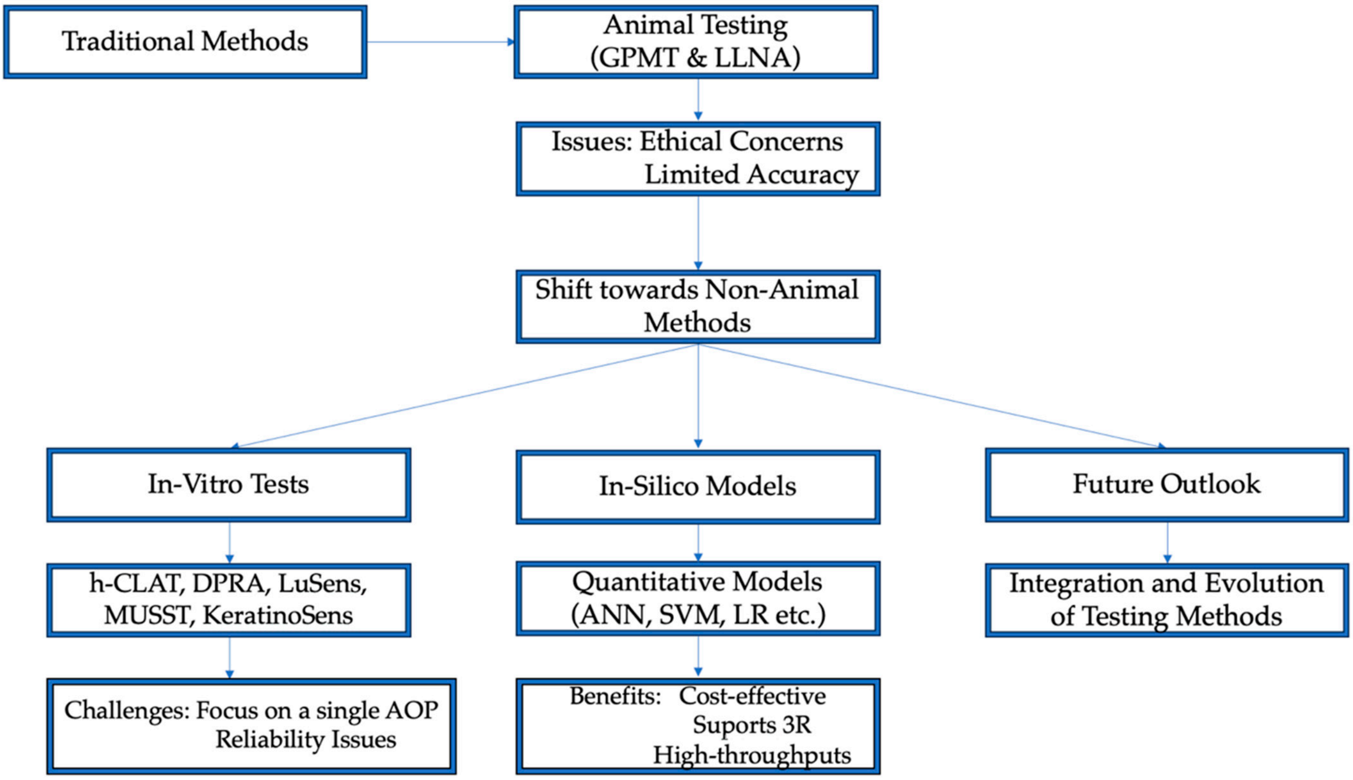

Figure 2. Evolution of testing methods in the cosmetic industry.

7. Ethical Considerations and Data Security in AI Applications for Cosmetology

AI and ML technologies have recently become central to the beauty and skincare industries, revolutionizing consumer services by using advanced techniques to analyze skin and hair characteristics. These digital tools offer personalized product recommendations and treatments based on complex data interpretation. However, as AI assumes tasks traditionally performed by humans, it can inherit biases that lead to unjust discrimination. For instance, in cosmetology, ethnicity-related biases often stem from the underrepresentation of certain skin tones, while gender biases may overlook hormonal influences on skin health. Age biases can also contribute to unrealistic expectations regarding youthful appearances. These biases can significantly impact product recommendations and treatment effectiveness. If the training data predominantly feature certain demographics, AI may disproportionately recommend products that are most effective for those groups, leading to inadequate suggestions for individuals with different skin characteristics. This can result in suboptimal treatment outcomes and perpetuate narrow beauty standards, marginalizing those who do not conform to these ideals. Therefore, while AI has the potential to enhance customer experiences with tailored solutions, addressing and correcting these biases is crucial to ensure fair and effective recommendations for all users [41].

The European Union's AI Act, established in 2021 under the title "Laying Down Harmonized Rules On Artificial Intelligence And Amending Certain Union Legislative Acts", serves as a crucial regulatory framework to address the challenges and safeguard fundamental rights in AI applications [42]. This act is essential for ensuring fairness and safety in AI-driven solutions by standardizing the use of AI technologies, promoting transparency, and reducing bias. In the context of AI, fairness involves ethically and equitably treating individuals or groups during the creation and implementation of AI algorithms. Safety pertains to the responsible and dependable use of AI, ensuring that systems operate securely and ethically, thereby protecting users from harm. Data governance involves strategies, policies, and procedures to manage data responsibly, ensuring quality, privacy, and security throughout AI initiatives. These standards are crucial for ensuring that AI algorithms in cosmetology are fair and transparent, offering equal treatment to all individuals, regardless of skin type, ethnicity, or age. Addressing AI bias is both an ethical obligation and a matter of legal and corporate responsibility, essential for maintaining consumer trust as AI systems increasingly influence product recommendations and treatment plans. The AI Act mandates regulatory measures, such as human oversight, accurate training data, and meticulous recordkeeping, to enhance the safety and reliability of AI applications in cosmetology. This comprehensive framework aims to protect consumers' rights and ensure equitable access to beauty and skincare products and services for all users [43].

Non-conformity with global beauty standards presents a significant issue, as traditional cultural ideals have evolved into international norms that prioritize traits such as youthfulness, symmetry, clear skin, slimness, and "Western" features. Biases in AI technologies within the beauty industry can arise from various factors, including algorithmic design, inadequate training, or biased datasets [41]. For instance, the Beauty.AI contest in 2016 revealed a notable bias towards white faces, reflecting broader disparities in representation and fairness [44]. This globalization of beauty standards often disregards cultural diversity, fostering discrimination and promoting unrealistic beauty ideals, which can have health implications. For example, the side effects of whitening cosmetics have been documented, highlighting that cosmetic ingredients can be a serious health concern. Certain ingredients in brightening cosmetics, such as hydroquinone, corticosteroids, and mercury, can cause severe complications, including exogenous ochronosis (also known as "fish odor syndrome"), Allergic Contact Dermatitis (ACD), "steroid addiction syndrome", and acne [6].

Transparency remains a critical challenge in AI systems, which often function as black boxes as they obscure their decision-making processes [45]. Ensuring the reliability of data analysis requires efforts to eliminate performance gaps and to report algorithmic performance across different phenotypic and demographic subgroups. However, many AI service providers are pushing facial analysis technology into conventional use without ensuring the fairness and reliability of these systems [46]. In a study by Buolamwini et al. [47], two commercial facial analysis benchmarks were evaluated concerning phenotypic subgroups. The results show error rates as high as 34.7% for darker-skinned females, making them the most frequently misclassified group, compared to a maximum error rate of 0.8% for lighter-skinned males. These significant disparities, as described in Table 3, highlight the urgent need to develop transparent, fair, and accountable facial analysis algorithms. Today, AI is not only used in cosmetology and medicine but also plays a role in critical decisions like hiring, loan approvals, and even determining the length of prison sentences [47].

Data privacy in AI-driven cosmetology is crucial as the beauty industry often relies on sensitive information such as biometric data and facial analysis. These data, used for personalized beauty product recommendations, typically include background information like location and demographic details (gender and age), skin types and goals, allergies, and behavioral data such as browsing history, transaction records, search keywords, and consumed content [48]. During the 25th International Master Course in Aging Science (IMCAS) in 2024, a digital questionnaire was disseminated to attendees via a QR code scan and Google Forms. Out of 47 doctors from various specialties in cosmetic medicine who responded, nearly half (48.9%) expressed concerns about the data privacy and security implications of AI. This response underlines the necessity for strong protective measures to safeguard personal data in the application of AI technologies [49].

Table 3. Ethical considerations in AI cosmetology.

Ethical Consideration	Description
Bias and Discrimination	AI systems may inherit biases related to ethnicity, gender, and age, leading to unfair treatment and recommendations.
Transparency and Accountability	AI often functions as a "black box", making it difficult to understand its decision-making processes and identify biases.
Data Governance	The responsible management of data is crucial to ensure diversity, quality, and security in AI training and deployment.
Global Beauty Standards and Cultural Sensitivity	AI may perpetuate narrow beauty standards, prioritizing traits like youthfulness and "Western" features and ignoring cultural diversity.
Safety and Health Implications	AI-driven recommendations must consider the safety of cosmetic ingredients and potential health risks to users.
Regulatory and Ethical Oversight	Frameworks like the EU's AI Act emphasize the need for fairness, transparency, and safety, requiring human oversight and accurate data.

Data privacy challenges in AI arise from concerns about protecting personal information, where inadequate measures can lead to breaches, legal issues, and ethical dilemmas. Techniques such as anonymization and de-identification are essential for protecting sensitive data, while secure storage and transmission methods, like encryption, enhance privacy protection. Obtaining informed consent from individuals for data collection and processing is crucial as organizations must clearly communicate the reasons for which the data will be used. Additionally, organizations must ensure that data are used solely for their intended purposes and not repurposed without explicit consent. To address these challenges, organizations should establish robust data governance frameworks and implement stringent quality control processes. Transparency and explainability are vital for building user trust and ensuring accountability. Collaboration with data providers and stakeholders is necessary to facilitate knowledge sharing and address privacy concerns. Adhering to regulatory compliance and incorporating privacy-by-design principles are critical steps in developing ethical and responsible AI systems in cosmetology [50].

8. Future Directions of AI in Cosmetology

The beauty industry is undergoing a profound transformation, particularly within the metaverse, where the alpha generation—children born after 2010—are spearheading change. In the post-COVID-19 era, there has been a marked shift towards non-face-to-face interactions, driving the need for innovative platforms where consumers can test and purchase cosmetics virtually. Thus, the metaverse, combining "meta" (virtual) and "universe" (the universe), offers a rich landscape for these changes. Here, companies can engage in fandom marketing and enhance customer experiences in a way that traditional face-to-face methods cannot, expanding the technological adeptness of the alpha generation to create more personalized and engaging cosmetic experiences [51].

With the advent of Fourth Industrial Revolution technologies, the development of personalized beauty products has become virtually limitless, and the rise of custom cosmetics is a notable trend in the evolving beauty landscape. Consumers now favor cosmetics tailored to their specific needs, a shift that has been accelerated by the COVID-19 pandemic and the increase in mobile shopping. The Republic of Korea has been at the forefront of this trend, implementing a custom cosmetics system that caters to individual preferences through mobile shopping. According to a study by Lee et al. [52], the use of non-face-to-face mobile shopping for customized cosmetics is growing in the contactless era. This trend is closely linked to the increasing awareness of skincare and the recognition of the benefits of customized cosmetics, including the use of interactive apps. However, the burgeoning market for these personalized products also raises concerns about safety, quality control, and the sourcing of raw materials, underscoring the need for stringent safety management practices. As custom cosmetics become more prevalent, ensuring that these products meet high standards for safety and efficacy will be critical to maintaining consumer trust and satisfaction [52].

The safety of custom-made cosmetics is a critical concern, as highlighted in a study by Kim et al. [53]. This study, from the Republic of Korea—the world's eighth-largest cosmetic market—points out safety issues with products made on-site by consumers and sellers. While the hygienic conditions of the environment, instruments, and handlers in customized cosmetic shops were generally good, the study revealed high microbial counts in the final products, indicating possible contamination during production. The key risk factors include semi-solid products, pH values above 10, the transfer of cosmetics to new vessels, and raw materials. Proper heat management during processing is crucial for controlling microbial levels. Although microbial contamination in cosmetics is currently rare, it can compromise product quality and pose health risks, leading to occasional global recalls. The preservation systems of custom-made cosmetics are often not as robust as those of mass-produced items, as these products are created and delivered directly on-site, increasing the risk of contamination during production [53].

Therefore, ensuring the microbiological stability of custom cosmetics requires stringent safety management. In 2021, members of the same scientific team suggested that distributors employ a government-authorized "dispensing chemist of customized cosmetics" for on-site mixing and shop management. According to a law that took effect in 2020 in the Republic of Korea, all substances used for making cosmetics—except forbidden materials, those with limited use, and some designated functional ingredients—are permitted in custom-made products. This approach promises a future where personalized beauty products are both effective and safe, aligning with consumer demands in an evolving market [54].

Moreover, bioprinted skin, a momentous advancement in the integration of AI and cosmetology, has been further enhanced through the use of 4D laser-assisted bioprinting and advanced skin culture protocols. These innovations have resulted in bioprinted skin that closely resembles natural human skin, offering a more ethical and precise alternative to animal testing for evaluating cosmetic ingredients [55]. A notable feature of bioprinted skin is its ability to mimic complex human skin characteristics, including sensory-like neurons that can replicate neuroinflammatory responses to harmful stimuli. For example, when capsaicin, a known neurosensitizing agent, was applied within a basic facial moisturizing formulation to these innervated skin models, there was a significant release of neuropeptides and pro-inflammatory cytokines such as substance P, indicating a response similar to what occurs in vivo [56].

This application resulted in a considerable increase in the concentration of CGRP, a neuroinflammatory marker, in the culture medium, demonstrating the model's ability to effectively mimic real skin reactions. This evidence suggests that such bioprinted skin models can be instrumental in screening cosmetic and therapeutic topical formulations for potential inflammatory responses, thereby ensuring product safety. As reliable and reproducible platforms, these Human Skin Equivalents (HSEs) are crucial for confirming the safety of new cosmetic products before they reach consumers. Future enhancements, such as the integration of human-derived neurons, are expected to further improve the accuracy and applicability of these models, reinforcing their importance in the safety assessment of cosmetic and therapeutic products [56].

The integration of robotics in cosmetology has led to significant advancements in various procedures, including laser hair removal and facial esthetic treatments. In laser hair removal, robot-assisted automatic systems have been designed to identify different shapes of treatment areas and ensure uniform laser irradiation across designated skin regions. The use of algorithms and robotics aims to achieve a consistent distribution of laser pulses, thereby minimizing potential side effects. Comparative studies between robot-assisted and physician-directed laser hair removal have shown superior hair removal rates with robotic assistance, highlighting its potential to enhance cosmetic outcomes. Ongoing advancements focus on refining algorithms to optimize performance on curved or slanted skin surfaces, broadening the range of applications for robot-assisted laser hair removal. Research on these systems has demonstrated reliable beam reach and a consistent number of pulses emitted. Additionally, automated scanning devices offer benefits such as shorter pulse durations, precise energy placement, quicker treatment sessions, and reduced operator fatigue [5,57].

Similarly, the use of robotics in cosmetology, particularly in dermatology and plastic surgery for facial esthetic procedures, has brought significant advancements. Robotic systems enhance safety and accuracy by delivering injections with consistent distribution, minimizing human error. These systems operate at a controlled pace, using smaller needles and less pressure, which helps reduce patient discomfort. Moreover, robots standardize procedures by adhering to programmed protocols, ensuring injections are made at specific depths, angles, and locations. This precision helps avoid critical areas of the face, reducing the risk of complications and providing uniform results. Robotic systems can also expedite treatment processes and improve access to these procedures, particularly in remote areas where skilled practitioners may be scarce. These benefits mark significant steps forward in enhancing the safety and efficiency of cosmetic treatments [58].

However, the use of robotics in cosmetology also presents several challenges and risks. The high costs associated with purchasing, maintaining, and repairing robotic systems can make these treatments more expensive for patients. Robots' limited flexibility can restrict their ability to adapt to individual patient needs, leading to less personalized care. The absence of human interaction is another concern, as robots cannot provide the same level of empathy and rapport-building that human practitioners can, which is crucial for patient comfort and trust. Additionally, robots may struggle with making creative adjustments during procedures, potentially impacting the quality of esthetic outcomes. There are also risks of injury from robotic malfunctions or incorrect calibrations, and robots are less capable of effectively assessing and managing patient pain or discomfort. Ethical concerns include issues related to patient data privacy and the broader acceptance of robotic involvement in medical procedures. To address these issues, it is crucial that the use of robotic technology in cosmetology is transparent and patient-centered, ensuring that patients are well-informed about their treatment options and the role of robots in their procedures, allowing them to make decisions that align with their values and preferences [58]. In Table 4 below, key areas of transformation and innovation in AI cosmetology and their potential challenges have been listed, including metaverse integration, custom cosmetics, bioprinted skin, robotic assistance, and ethical and safety considerations.

Table 4. Key areas of transformation and innovation in AI cosmetology.

Category	Description	Potential Challenges
Metaverse Integration	- Virtual testing and purchasing of cosmetics. - Fandom marketing and personalized consumer experiences.	- Ensuring safety and authenticity in virtual environments.
Custom Cosmetics	- Personalized beauty products tailored to individual needs. - Increased demand for custom products via mobile shopping.	- Safety, quality control, and raw material sourcing. - Managing the microbiological stability of on-site mixed products.
Bioprinted Skin	- Ethical and precise alternative to animal testing for cosmetic ingredients. - Mimics human skin, including sensory neurons for accurate testing.	- Technical challenges in replicating complex skin functions and responses. - Cost and scalability of bioprinted skin models.
Robotic Assistance	- Enhances safety and accuracy in procedures like laser hair removal and facial injections. - Standardizes procedures, reducing human error and ensuring consistent results.	- High costs and limited flexibility in adapting to individual needs. - Lack of human interaction and empathy.
Ethical and Safety Considerations	- Patient data privacy and ethical use of AI and robotics. - Necessity for stringent safety management and adherence to regulatory standards.	- Transparency in treatment options and potential risks of robotic involvement in procedures. - Potential for injuries due to malfunctions or incorrect calibrations.

9. Discussion

AI and machine learning (ML) technologies in cosmetology are reshaping the industry, enhancing the personalization, accessibility, and efficiency of beauty products and services. In Figure 3 below, a schematic representation of the key points of the article is illustrated. This transformation is largely driven by specific AI technologies, such as CNNs, NLP, and in silico modeling, with each playing a pivotal role in advancing the field.

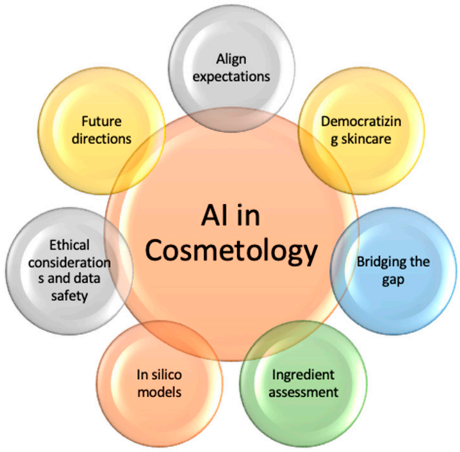

Figure 3. A schematic representation of the key points of this article.

CNNs are a cornerstone in image analysis applications within cosmetology. They have enabled the development of sophisticated diagnostic tools that analyze various skin conditions, such as acne, with remarkable accuracy. For example, CNN-based systems can classify different types of acne lesions (e.g., nodules, cysts, and blackheads) and assess their severity, providing valuable insights that support dermatologists and cosmetologists in treatment planning. This capability is crucial for the early detection and management of skin conditions, significantly improving treatment outcomes [16]. Beyond diagnostics, CNNs are integral to virtual try-on applications, allowing users to visualize the potential results of cosmetic procedures or products before committing to them. This functionality not only helps set realistic expectations but also enhances user engagement and satisfaction, as consumers ca n experiment with different looks in a virtual environment [13].

NLP technologies facilitate the analysis of textual data, such as customer reviews and product descriptions, to extract meaningful insights. In cosmetology, NLP interprets consumer feedback, identifying common concerns and preferences, which is invaluable for refining product recommendations to align closely with user needs [26,27]. NLP also plays a critical role in ingredient analysis, identifying potentially harmful components and suggesting safer alternatives. This capability is particularly relevant in personalized skincare, where understanding the nuanced language of ingredients and consumer feedback can significantly improve product formulation and recommendation accuracy [24]. NLP thus bridges the gap between complex scientific data and consumer-friendly communication, enhancing transparency and trust in cosmetic products.

In silico modeling refers to computational methods used to predict the biological effects of cosmetic ingredients. These models employ machine learning algorithms, such as SVMs and ANNs, to simulate human skin reactions to various compounds, aiding in the assessment of potential allergens and irritants [6]. This method offers a significant advantage over traditional testing, especially in regions where animal testing is restricted or banned [38]. However, in silico models often rely on simplified assumptions and may not fully capture the complex interactions between multiple ingredients in a cosmetic product. As such, they may fall short in predicting the full spectrum of possible skin reactions, especially in products with diverse active components [6]. Despite these challenges, in silico modeling represents a critical tool in the push towards more ethical and efficient cosmetic testing.

While these technologies offer substantial benefits, their application in cosmetology is not without challenges. One significant issue is the inherent bias in AI systems, often due to the underrepresentation of diverse skin tones in training datasets [15]. This bias can result in suboptimal outcomes for individuals with darker skin, as current models may not accurately predict the efficacy or safety of products for these users [47]. The reliance on classification systems like the Fitzpatrick Skin Type (FST) scale exacerbates these issues, as it inadequately represents the diversity of human skin tones. Ethical considerations surrounding data privacy are also critical. AI tools frequently handle sensitive personal and biometric data, raising concerns about transparency and the potential for misuse [50]. The "black box" nature of many AI algorithms—where the decision-making process is not easily understood—compounds these concerns, making it difficult for consumers to trust the technology [45].

Looking forward, the future of cosmetology in the age of AI is poised for continued growth and innovation. The integration of advanced AI technologies will likely lead to more personalized and safer beauty products, as well as more efficient and accessible cosmetic services [54]. Key to this future will be the development of more inclusive AI models that can accurately serve diverse populations, ensuring that all consumers benefit from these advancements. As the industry evolves, there will be a greater emphasis on balancing technological innovation with ethical considerations, particularly regarding data privacy and bias mitigation [14]. The ongoing collaboration between dermatologists, cosmetologists, and AI developers will be crucial in refining these technologies and enhancing their applicability in real-world settings [8].

10. Conclusions

In conclusion, the future of cosmetology in the era of AI holds great promise, offering new levels of personalization, efficiency, and inclusivity. Embracing these technologies will be essential for redefining the cosmetology landscape and improving the overall quality of life for individuals worldwide.

Author Contributions: Conceptualization, V.S.G., V.K. and E.R.; methodology, V.S.G. and E.R.; software, V.S.G.; validation, V.K. and E.R.; formal analysis, V.S.G., V.K. and E.R.; investigation, V.S.G.; resources, V.S.G.; data curation, V.S.G.; writing—original draft preparation, V.S.G.; writing—review and editing, V.S.G. and E.R. visualization, V.S.G.; supervision, V.K.; project administration, V.K.; funding acquisition, V.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new data were created or analyzed in this study.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Dreno, B.; Bordet, C.; Seite, S.; Taieb, C.; Registre Acne, D. Acne relapses: Impact on quality of life and productivity. *J. Eur. Acad. Dermatol. Venereol.* **2019**, *33*, 937–943. [CrossRef] [PubMed]
2. Vatiwutipong, P.; Vachmanus, S.; Noraset, T.; Tuarob, S. Artificial Intelligence in Cosmetic Dermatology: A Systematic Literature Review. *IEEE Access* **2023**, *11*, 71407–71425. [CrossRef]
3. Haykal, D.; Garibyan, L.; Flament, F.; Cartier, H. Hybrid cosmetic dermatology: AI generated horizon. *Skin Res. Technol.* **2024**, *30*, e13721. [CrossRef] [PubMed]
4. Tian, B. Tele-aesthetics in South Asia. *J. Cosmet. Dermatol.* **2017**, *16*, 21–25. [CrossRef] [PubMed]
5. Elder, A.; Ring, C.; Heitmiller, K.; Gabriel, Z.; Saedi, N. The role of artificial intelligence in cosmetic dermatology-Current, upcoming, and future trends. *J. Cosmet. Dermatol.* **2021**, *20*, 48–52. [CrossRef] [PubMed]
6. Ta, G.H.; Weng, C.F.; Leong, M.K. In silico Prediction of Skin Sensitization: Quo vadis? *Front. Pharmacol.* **2021**, *12*, 655771. [CrossRef]
7. Golden, E.; Macmillan, D.S.; Dameron, G.; Kern, P.; Hartung, T.; Maertens, A. Evaluation of the global performance of eight in silico skin sensitization models using human data. *ALTEX* **2021**, *38*, 33–48. [CrossRef] [PubMed]

8. Adamski, Z.; Gornowicz-Porowska, J.; Sobkowska, D.; Kaszuba, K.; Czajkowski, R. Acne—Therapeutic challenges to the cooperation between a dermatologist and a cosmetologist. *Postepy Dermatol. Alergol.* **2021**, *38*, 21–31. [CrossRef] [PubMed]
9. Kim, J.; Hwang, D.U.; Son, E.J.; Oh, S.H.; Kim, W.; Kim, Y.; Kwon, G. Emotion recognition while applying cosmetic cream using deep learning from EEG data; cross-subject analysis. *PLoS ONE* **2022**, *17*, e0274203. [CrossRef]
10. Balconi, M.; Venturella, I.; Sebastiani, R.; Angioletti, L. Touching to Feel: Brain Activity During In-Store Consumer Experience. *Front. Psychol.* **2021**, *12*, 653011. [CrossRef]
11. Tong, W.-S.; Tang, C.-K.; Brown, M.S.; Xu, Y.-Q. Example-Based Cosmetic Transfer. In Proceedings of the 15th Pacific Conference on Computer Graphics and Applications (PG'07), Maui, HI, USA, 29 October–2 November 2007; pp. 211–218.
12. Flament, F.; Zhang, Y.; Yu, Z.; Jiang, R.; Houghton, J.; Sarda Duthil, L.; Arcin, V.; Daniel, R.; Perrier, J.C.; Niviere, J.; et al. Developing an Artificial Intelligence (A.I)-based descriptor of facial appearance that fits with the assessments of makeup experts. *Skin Res. Technol.* **2021**, *27*, 1081–1091. [CrossRef] [PubMed]
13. Shi, C.; Jiang, Z.; Ma, X.; Luo, Q. A Personalized Visual Aid for Selections of Appearance Building Products with Long-term Effects. In Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems, New Orleans, LA, USA, 29 April–5 May 2022; p. 74. [CrossRef]
14. Flament, F.; Jiang, R.; Houghton, J.; Zhang, Y.; Kroely, C.; Jablonski, N.G.; Jean, A.; Clarke, J.; Steeg, J.; Sehgal, C.; et al. Accuracy and clinical relevance of an automated, algorithm-based analysis of facial signs from selfie images of women in the United States of various ages, ancestries and phototypes: A cross-sectional observational study. *J. Eur. Acad. Dermatol. Venereol.* **2023**, *37*, 176–183. [CrossRef] [PubMed]
15. Fliorent, R.; Fardman, B.; Podwojniak, A.; Javaid, K.; Tan, I.J.; Ghani, H.; Truong, T.M.; Rao, B.; Heath, C. Artificial intelligence in dermatology: Advancements and challenges in skin of color. *Int. J. Dermatol.* **2024**, *63*, 455–461. [CrossRef]
16. Google. Developing the Monk Skin Tone Scale: Skin Tone Research. Available online: https://skintone.google/the-scale (accessed on 1 June 2024).
17. Brzozowska, J.M.; Gotlib, J. The Importance of Remote Counseling in Cosmetology and Cosmetic Dermatology. *Pol. Merkur. Lek.* **2023**, *51*, 74–87. [CrossRef] [PubMed]
18. Shen, X.; Zhang, J.; Yan, C.; Zhou, H. An Automatic Diagnosis Method of Facial Acne Vulgaris Based on Convolutional Neural Network. *Sci. Rep.* **2018**, *8*, 5839. [CrossRef] [PubMed]
19. Junayed, M.S.; Jeny, A.; Atik, S.; Neehal, N.; Karim, A.; Azam, S.; Shanmugam, B. AcneNet—A Deep CNN Based Classification Approach for Acne Classes. In Proceedings of the 2019 12th International Conference on Information & Communication Technology and System (ICTS), Surabaya, Indonesia, 18 July 2019; pp. 203–208. [CrossRef]
20. Kim, D.H.; Sun, S.; Cho, S.I.; Kong, H.J.; Lee, J.W.; Lee, J.H.; Suh, D.H. Automated Facial Acne Lesion Detecting and Counting Algorithm for Acne Severity Evaluation and Its Utility in Assisting Dermatologists. *Am. J. Clin. Dermatol.* **2023**, *24*, 649–659. [CrossRef] [PubMed]
21. Yadav, R.; Jain, A.; Sharma, S. Acne Detection Care System using Deep Learning. In Proceedings of the 2024 11th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), Noida, India, 14–15 March 2024; pp. 1–5. [CrossRef]
22. Halpern, S. Teledermatology in Europe. In Proceedings of the 8th World Congress of Teledermatology, Skin Imaging and AI in Skin Diseases 2020, Virtual, 5–6 November 2020. Available online: https://telemedskin.com/the-dermatology-ecosystem-in-europe-differs-from-one-country-to-another/ (accessed on 1 July 2024).
23. Seite, S.; Khammari, A.; Benzaquen, M.; Moyal, D.; Dreno, B. Development and accuracy of an artificial intelligence algorithm for acne grading from smartphone photographs. *Exp. Dermatol.* **2019**, *28*, 1252–1257. [CrossRef]
24. Lee, J.; Yoon, H.; Kim, S.; Lee, C.; Lee, J.; Yoo, S. Deep learning-based skin care product recommendation: A focus on cosmetic ingredient analysis and facial skin conditions. *J. Cosmet. Dermatol.* **2024**, *23*, 2066–2077. [CrossRef] [PubMed]
25. Olivia, S. Post-Pandemic Beauty: The Growing Role of Ingredients. 2022. Available online: https://www.teknoscienze.com/Contents/Riviste/Sfogliatore/HPC4_2022/46/ (accessed on 10 June 2024).
26. Rubasri, S.; Hemavathi, S.; Jayasakthi, K.; Latha, K.; Gopinath, N. Cosmetic Product Selection Using Machine Learning. In Proceedings of the 2022 International Conference on Communication, Computing and Internet of Things (IC3IoT), Chennai, India, 10–11 March 2022; pp. 1–6. [CrossRef]
27. He, X.; Liao, L.; Zhang, H.; Nie, L.; Hu, X.; Chua, T.-S. Neural Collaborative Filtering. In Proceedings of the 26th International Conference on World Wide Web, Perth, Australia, 3–7 April 2017; pp. 173–182. [CrossRef]
28. Nakajima, Y.; Honma, H.; Aoshima, H.; Akiba, T.; Masuyama, S. Recommender System Based on User Evaluations and Cosmetic Ingredients. In Proceedings of the 2019 4th International Conference on Information Technology (InCIT), Bangkok, Thailand, 24–25 October 2019; pp. 22–27. [CrossRef]
29. Li, H.H.; Liao, Y.H.; Huang, Y.N.; Cheng, P.J. Based on machine learning for personalized skin care products recommendation engine. In Proceedings of the 2020 International Symposium on Computer, Consumer and Control (IS3C), Taichung City, Taiwan, 13–16 November 2020; pp. 460–462. [CrossRef]
30. Ronneberger, O.; Fischer, P.; Brox, T. U-net: Convolutional networks for biomedical image segmentation. In *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5–9, 2015, Proceedings, Part III*; Springer: Cham, Sweitzerland, 2015; pp. 234–241.

31. Yoon, H.; Kim, S.; Lee, J.; Yoo, S. Deep-Learning-Based Morphological Feature Segmentation for Facial Skin Image Analysis. *Diagnostics* **2023**, *13*, 1894. [CrossRef]
32. Fisher, A.A. "Status cosmeticus": A cosmetic intolerance syndrome. *Cutis* **1990**, *46*, 109–110.
33. Zirwas, M.J. Contact Dermatitis to Cosmetics. *Clin. Rev. Allergy Immunol.* **2019**, *56*, 119–128. [CrossRef]
34. Hafner, M.F.S.; Rodrigues, A.C.; Lazzarini, R. Allergic contact dermatitis to cosmetics: Retrospective analysis of a population subjected to patch tests between 2004 and 2017. *An. Bras. Dermatol.* **2020**, *95*, 696–701. [CrossRef] [PubMed]
35. Kalicinska, J.; Wisniowska, B.; Polak, S.; Spiewak, R. Artificial Intelligence That Predicts Sensitizing Potential of Cosmetic Ingredients with Accuracy Comparable to Animal and In Vitro Tests-How Does the Infotechnomics Compare to Other "Omics" in the Cosmetics Safety Assessment? *Int. J. Mol. Sci.* **2023**, *24*, 6801. [CrossRef]
36. Gilmour, N.; Kern, P.S.; Alepee, N.; Boisleve, F.; Bury, D.; Clouet, E.; Hirota, M.; Hoffmann, S.; Kuhnl, J.; Lalko, J.F.; et al. Development of a next generation risk assessment framework for the evaluation of skin sensitisation of cosmetic ingredients. *Regul. Toxicol. Pharmacol.* **2020**, *116*, 104721. [CrossRef]
37. Gellatly, N.; Sewell, F. Regulatory acceptance of in silico approaches for the safety assessment of cosmetic-related substances. *Comput. Toxicol.* **2019**, *11*, 82–89. [CrossRef]
38. Strickland, J.; Zang, Q.; Paris, M.; Lehmann, D.M.; Allen, D.; Choksi, N.; Matheson, J.; Jacobs, A.; Casey, W.; Kleinstreuer, N. Multivariate models for prediction of human skin sensitization hazard. *J. Appl. Toxicol.* **2017**, *37*, 347–360. [CrossRef]
39. Hirota, M.; Kouzuki, H.; Ashikaga, T.; Sono, S.; Tsujita, K.; Sasa, H.; Aiba, S. Artificial neural network analysis of data from multiple in vitro assays for prediction of skin sensitization potency of chemicals. *Toxicol. In Vitro* **2013**, *27*, 1233–1246. [CrossRef] [PubMed]
40. Selvestrel, G. SpheraCosmolife: A new tool for the risk assessment of cosmetic products. *ALTEX* **2021**, *38*, 565–579. [CrossRef] [PubMed]
41. Georgievskaya, A.; Tlyachev, T.; Danko, D.; Chekanov, K.; Corstjens, H. How artificial intelligence adopts human biases: The case of cosmetic skincare industry. *AI Ethics* **2023**. [CrossRef]
42. EuropeanCommission. Regulation of the European Parliament and of the Council. Laying Down Harmonized Rules on Artificial Intelligence (Artificial Intelligence Act) and Amending Certain Union Legislative Acts. 2021. Available online: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52021PC0206 (accessed on 1 June 2024).
43. Kenig, N.; Monton Echeverria, J.; Muntaner Vives, A. Human Beauty according to Artificial Intelligence. *Plast. Reconstr. Surg. Glob. Open* **2023**, *11*, e5153. [CrossRef]
44. TheGuardian. A Beauty Contest Was Judged by AI and the Robots Didn't Like Dark Skin. 2016. Available online: https://www.theguardian.com/technology/2016/sep/08/artificial-intelligence-beauty-contest-doesnt-like-black-people (accessed on 1 June 2024).
45. Grzybowski, A.; Jin, K.; Wu, H. Challenges of artificial intelligence in medicine and dermatology. *Clin. Dermatol.* **2024**, *42*, 210–215. [CrossRef] [PubMed]
46. Khalil, A.; Ahmed, S.G.; Khattak, A.M.; Al-Qirim, N. Investigating Bias in Facial Analysis Systems: A Systematic Review. *IEEE Access* **2020**, *8*, 130751–130761. [CrossRef]
47. Buolamwini, J.; Gebru, T. Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification. In Proceedings of the 1st Conference on Fairness, Accountability and Transparency, New York, NY, USA, 23–24 February 2018.
48. Revieve. Personalization and Data Privacy Balance in the Beauty Industry. 2021. Available online: https://www.revieve.com/resources/personalization-data-privacy-balance-in-beauty (accessed on 1 June 2024).
49. Haykal, D.; Ascher, B.; Cartier, H.; Gold, M. Exploring the landscape of AI adoption in cosmetic medicine and surgery: Insights from the 25th IMCAS Congress (International Master Course in Aging Science). *J. Cosmet. Dermatol.* **2024**, *23*, 2673–2675. [CrossRef] [PubMed]
50. Authors, A.; Luz, G.; Olaoye, G. Data Quality and Data Privacy Challenges in AI Applications. Available online: https://www.researchgate.net/publication/378904709_Data_quality_and_data_privacy_challenges_in_AI_applications (accessed on 1 June 2024).
51. Lee, J.; Kwon, K.H. Future value and direction of cosmetics in the era of metaverse. *J. Cosmet. Dermatol.* **2022**, *21*, 4176–4183. [CrossRef] [PubMed]
52. Lee, J.; Kwon, K.H. Recognition and the development potential of mobile shopping of customized cosmetic on untact coronavirus disease 2019 period: Focused on 40's to 60's women in Seoul, Republic of Korea. *J. Cosmet. Dermatol.* **2021**, *20*, 1975–1991. [CrossRef] [PubMed]
53. Kim, H.W.; Seok, Y.; Cho, T.; Rhee, M. Risk factors influencing contamination of customized cosmetics made on-the-spot: Evidence from the national pilot project for public health. *Sci. Rep.* **2020**, *10*, 1561. [CrossRef] [PubMed]
54. Kim, H.W.; Seok, Y.S.; Lee, H.G.; Song, M.K.; Rhee, M.S. Consumers' lack of understanding of customized cosmetics made on the spot and implications for regulations and controls. *Regul. Toxicol. Pharmacol.* **2021**, *124*, 104979. [CrossRef] [PubMed]
55. Cadau, S.; Rival, D.; Andre-Frei, V.; Chavan, M.M.; Fayol, D.; Salducci, M.; Brisson, B.; Guillemot, F. New bioprinted skin, cosmetic in vitro model. *J. Cosmet. Sci.* **2017**, *68*, 85–90. [PubMed]
56. Freer, M.; Darling, N.; Goncalves, K.; Mills, K.J.; Przyborski, S. Development of a mammalian neurosensory full-thickness skin equivalent and its application to screen sensitizing stimuli. *Bioeng. Transl. Med.* **2023**, *8*, e10484. [CrossRef]

57. Pai, V.V.; Pai, R.B. Artificial intelligence in dermatology and healthcare: An overview. *Indian J. Dermatol. Venereol. Leprol.* **2021**, *87*, 457–467. [CrossRef]
58. Kapoor, K.M.; Kapoor, A.; Bertossi, D. Role of Robotics in Neuromodulator and Filler Injections of Face. *Indian J. Plast. Surg.* **2023**, *56*, 470–473. [CrossRef] [PubMed]