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ARTIFICIAL INTELLIGENCE IN DERMATOLOGY: TRANSFORMING DIAGNOSIS, TREATMENT, AND DRUG DISCOVERY FOR CHRONIC SKIN DISEASES

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Abstract

Chronic inflammatory skin diseases, including atopic dermatitis, psoriasis, and hidradenitis suppurativa, are challenging to manage due to clinical heterogeneity, subjective assessments, and variable treatment responses. Artificial intelligence (AI) offers transformative potential in addressing these challenges. The review presents an extensive summary of AI applications in chronic skin disease management, covering diagnosis, severity assessment, personalized therapy, and drug discovery, while highlighting validated advances, ongoing gaps, and strategies for clinical implementation. A systematic search of PubMed, Scopus, and Web of Science (2018-2025) prioritized studies with clinical validation, regulatory approval, or prospective trial evidence. AI performs comparably to dermatologists in diagnosing inflammatory skin diseases, with CNNs achieving 85-95% accuracy for psoriasis and atopic dermatitis. Automated EASI and PASI scoring correlates strongly with expert ratings (ICC >0.85). Multi-omics integration enables molecular endotyping of treatment responses (75-85% accuracy). AI also accelerates drug discovery, reducing timelines from years to months. Key challenges include limited diversity in training data, need for multicenter validation, and evolving regulatory frameworks. AI is changing the nature of chronic skin disease management more radically, but the division between technical performance and clinical application is still significant. To close this gap, various datasets have to be created, new validation procedures should be standardized, and the regulation is to be explicit. The introduction of AI into daily dermatology care is likely to provide more accurate, patient-centered, and equitable care.

1. Introduction

Chronic skin diseases are a serious and increasing health problem in the world with atopic dermatitis (AD), psoriasis, and hidradenitis suppurativa challenging hundreds of millions of people all over the world. AD is the most prevalent inflammatory skin disease in the whole world and its effects are much more than the cutaneous manifestations. Psychological and social impacts are significant as researchers have shown that depression and anxiety are reported by more than 30 percent of AD or alopecia area patients, sleep quality especially is worsened in patients with AD, which increases the stress and

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continues the disease progression cycle (Utti et al., 2025). Economic expenses are also quite high, which include the direct spending on healthcare and indirect expenses of productivity losses. Healthcare expenditures on adults with AD are about 4,979 higher per year than on healthy controls in the United States and patients in Western Europe lose up to 3.85 years of workdays due to disease severity, as the disease progresses. An in-depth 2025 EADV survey conducted based on Work Productivity and Activity Impairment questionnaire showed that patients with immune-mediated inflammatory skin diseases have an overall work impairment of 28.96% with presenteeism (reduced productivity at work) (26.12) of this impediment (Kumar, Saeed, & Bangash, 2024).

Clinical heterogeneity of these conditions makes the treatment process even more complicated because the disease progression is not regular, and the relapse and remission periods complicate the implementation of standardized treatment methods and make them especially difficult to achieve. The practice of dermatology is experiencing some underlying problems that restrict the best care delivery to patients. Subjective visual disease severity areas like the Psoriasis Area and Severity Index (PASI) and the Eczema Area and Severity Index (EASI) are important to assess disease severity but show high inter-rater and intra-rater variability even between experienced and seasoned dermatologists (K Frasier, Li, Coleman, Rodriguez, & Karatas, 2024). A Korean national study established that although educational interventions enhance precision, the subjectivity of these tests remain, and in particular it is challenging to assess the three dimensional aspects such as plaque thickness and scale. Similar inconsistency is also found in other chronic diseases; one study of assessing the severity of mycosis fungoides showed that 64 percent of cases demonstrated significant differences in scoring results, and tumors and infiltrative lesions were especially difficult to categorically classify (Rokni, Gholizadeh, Babaei, Das, & Datta, 2024).

The availability of specialist care is also extremely low, with dermatologists being clustered in cities 40 times more per 100,000 people in urban areas than in rural areas in the United States, making dermatology an enormous desert of care. In sub-Saharan Africa, there might be as many as one dermatologist in every three million individuals. Choosing the treatment is a lengthy process of trial-and-error, and biologic therapies are used based on standard dosing schedules, which do not consider inter-individual differences, which is the main cause of the primary non-response, secondary loss of response or side effects. These issues are compounded by the standard drug development paradigm which has taken about 12-15 years and more than 1 billion dollars to get a new therapy to market with dermatology specific development timelines averaging 27.8 months of Phase 1, 34 months Phase 2 and 38 months Phase 3 testing and transition success rates of only 35.9% between the Phase 2 and Phase 3 trials (Khan, Bhatt, Shishak, Madhumita, & Gupta, 2025).

Artificial intelligence in medicine is a revolution capable of transforming medicine to solve these problematic challenges. History The development of AI in healthcare has started with rule-based expert systems such as MYCIN in the 1970s, passing on to the era of expert systems in the 1980s, to the present day deep learning paradigm facilitated by big data and state-of-the-art neural networks. Dermatology is particularly favorable to AI implementation because it entails a great deal of visual pattern recognition, there exists massive picture image data, and most disease presentations are measurable (Cao et al., 2025). Recent reviews confirm that AI systems can be as diagnostic as dermatologists in a variety of tasks, and that their uses are no longer limited to skin cancer diagnostics but are currently wide, including inflammatory dermatoses of all types.

Nevertheless, as it has been emphasized by the recent literature, there is still a severe gap between laboratory results and clinical outcomes, and the generalizability, interpretations, and representation of heterogeneous groups also need some attention. This review will synthesize in detail the existing situation in the field of AI use throughout the spectrum of chronic skin disease management, starting with diagnostic assistance

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and severity estimation to the end of the scale, treatment customization and drug discovery, critically reviewing the existing evidence-based advances and outlining the gaps in the range of translational research that need to be addressed to make AI applications more significant in clinical practice.

2 Artificial Intelligence: Methodological Foundations for Dermatology

2.1 Core AI Concepts and Terminology

To appreciate the uses of artificial intelligence in dermatology, it would be necessary to understand the methodological basis of artificial intelligence. On the simplest level, machine learning (ML) is a sub-specialty of AI where the system learns by being exposed to data without any explicit instructions, whereas deep learning (DL) uses multi-layered neural networks to automatically extract hierarchical features out of raw input data). In this context, there are three main paradigms of learning: supervised learning, where models are trained on labeled data to learn to map inputs to known outputs; unsupervised learning, where models acquire knowledge of hidden patterns by trial-and-error interaction with an environment; and reinforcement learning, where models learn by trial-and-error interaction with an environment (Vayadande et al., 2024). In dermatological image analysis, convolutional neural networks (CNNs) have become the architecture to be used and heavily tailored to process pixel data using convolutional filters that capture edges, textures, and more advanced morphological features of each successive layer. The networks are the foundation of the majority of diagnostic systems in dermatology, which allow the extraction of clinical and dermoscopic features of the data automatically (Li et al., 2022).

2.2 Key Architectures in Dermatological AI

The development of CNNs has greatly progressed the AI-based dermatology. Basic architectures such as ResNet, which added residual connections to allow training of deeper networks, Inception modules that learn multi-scale features through parallel convolutions, and EfficientNet that optimally balances the depth, width and resolution of a network all have shown good performance at skin lesion classification problems. Other than the discriminative models, generative adversarial networks (GANs) have become effective data augmentation and generating synthetic images (Escalé-Besa et al., 2024). GANs are designed using a generator-discriminator architecture, in which the generator is tasked with generating synthetic images, and the discriminator with the task of trying to tell the difference between real and fake images, bringing about the realistically looking dermatological images to a high level. StyleGAN and CycleGAN architectures have been especially useful in producing underrepresented skin phenotypes, and in the context of dealing with critical dataset imbalances in which only 12 percent of existing repositories contain skin phototypes IV-VI. More recently, natural language processing transformer models have been scaled to vision tasks, which allow multimodal learning using imaging data with clinical metadata, genomic profiles, and electronic health records to fully characterise the disease (Schierle, Bolmgren, Deleuran, Welter, & Gebauer, 2025).

2.3 Data Modalities in Dermatology

The diversity of dermatological data makes possible the wide range of AI applications in a variety of modalities. The most common sources of data are clinical and dermoscopy images, the last of which offers an enlarged view of the skin structures under the surface through the dermoscopy. Such highly sensitive imaging methods as reflectance confocal microscopy (RCM) and optical coherence tomography (OCT) have cellular-level resolution and enhanced tissue penetration, and they provide data that is best interpreted by AI technology (Gniadecki, 2025). RCM, made sensitive and specific by laser light to view the horizontal skin sections at a microscopic level of 1-3 um, has proven to be a highly sensitive and specific technique in the diagnosis of the melanocytic lesion, basal cell carcinoma, and even the existence of parasitic infestations such as scabies. In addition to imaging, multi-

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omics data such as genomics, transcriptomics, and proteomics offer information on the pathogenesis and response to disease at the molecular level. Combination of these types of data with electronic health records and patient-reported outcomes allows the use of multifaceted, patient-specific disease management strategies (Li Pomi et al., 2024).

2.4 Model Development and Validation

The intensive model development presupposes the division of data into training, validation and test sets in a systematic manner. Training data is used to teach the model patterns, validation data to optimize hyperparameters and test data to offer a final objective evaluation of performance (Sudharson, Essakki, Thanujaa, & Varsha, 2024). The performance is measured in terms of such metrics as accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC), which represent various facets of model performance. Nonetheless, internal validation is not enough to be used in clinical deployment. To measure generalizability and representativeness, external validation (testing of a model on a different population, institution or acquisition device) is necessary. A 2025 systematic review highlighted the fact that external validation is a crucial phase of the translational science, making sure that AI models remain useful once implemented across various clinical contexts, as opposed to acting only in the context of controlled research studies. The difference between internal and external validity is the key to filling the gap between the technical performance and the clinical potential in the real world.

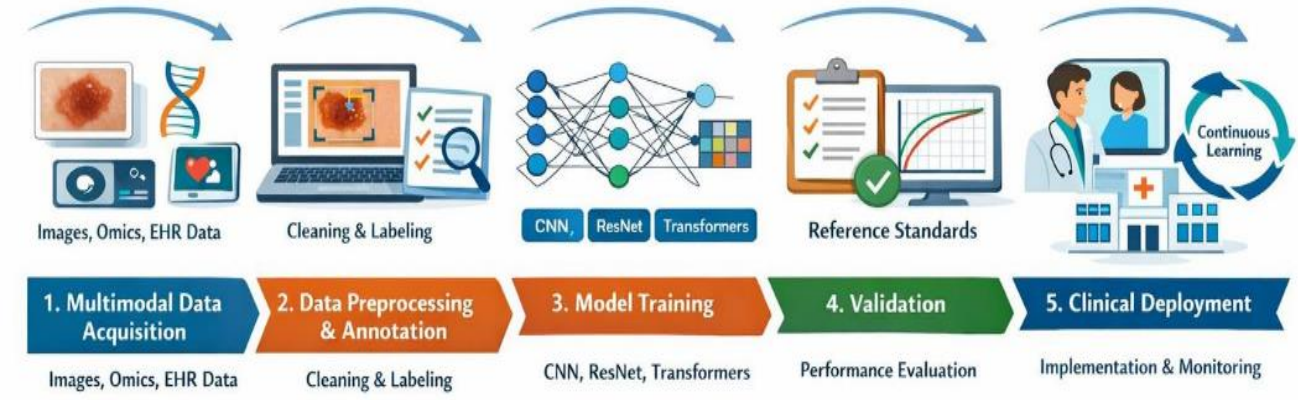

Figure 1. *Schematic representation of AI workflow in dermatology, from data acquisition to clinical deployment. The workflow encompasses five stages: (1) multimodal data acquisition (images, omics, EHR); (2) data preprocessing and annotation; (3) model training using various architectures; (4) validation against reference standards; and (5) clinical implementation with continuous learning loops for ongoing model improvement.*

Artificial Intelligence in Diagnosis of Chronic Skin Diseases

3.1 Atopic Dermatitis

Convolutional neural network reference diagnostic algorithms of atopic dermatitis (AD) have shown significant accuracy in controlled research. An extensive review of AI in inflammatory skin diseases in 2025 concluded that CNN models trained on clinical images are capable of delivering performance similar to that of dermatologists to distinguish AD against normal skin, but most studies have used binary classification problems to distinguish between AD and normal skin instead of the more complex differential diagnosis presented in clinical practice (Lee et al., 2025). The distinction between AD and other eczematous diseases such as contact dermatitis, seborrheic dermatitis and nummular eczema is still a major problem, since in the early stages, or atypical manifestations, the

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conditions may be morphologically similar. Latest developments in multimodal learning which combines clinical images with patient metadata such as age, atopic history and lesion distribution demonstrate potential to enhance diagnostic specificity (Aksoy, Demircioglu, & Bogrekci, 2024). Combination with existing diagnostic scales, e.g. the Hanifin-Rajka criteria or UK Working Party criteria, is also a promising avenue to integrating AI tools into clinical practice. A 2025 book on AI in dermatology has devoted an entire chapter to atopic dermatitis, highlighting how AI may help standardize the diagnosis and eliminate variation in the real-world analysis of the clinical condition (Almustafa, 2025).

3.2 Psoriasis

The use of deep learning system has been effective in developing automated plaque detection and classification systems of psoriasis. Training ResNet-50-based transfer learning methods and adapting it to chronic plaque psoriasis datasets have made it feasible to train effectively despite a small amount of data, and the approach has shown itself capable of learning psoriatic morphology. The problem of differentiating psoriasis and other papulosquamous diseases- such as lichen planus, pityriasis rosea and cutaneous T-cell lymphoma- is a highly challenging diagnosis where AI could be particularly valuable (Zbrzezny & Krzywicki, 2025). A 2026 study of mycosis fungoides identified the characteristic dermoscopic features of the condition such as small linear vessels and orange-yellowish patchy areas that distinguish the disease plaque psoriasis and highlighted the potential to identify small differentiating features with the help of AI. AI in palmoplantar and nail psoriasis evaluation deals with anatomical locations where conventional severity scales have specifically become difficult. It is indicated that nail psoriasis, the most frequent manifestation of psoriasis, and up to 80% of psoriasis patients develop nail psoriasis during their lifetime and presupposes the evaluation of several morphological characteristics such as pitting, onycholysis, and subungual hyperkeratosis a complicated process that would be effectively handled by automated image analysis (Tan, Koh, & Navarrete-Dechent, 2025).

3.3 Hidradenitis Suppurativa

Hidradenitis suppurativa (HS) is a disease with distinct diagnostic problems that are gradually being challenged by AI. The clinical heterogeneity of the condition, the possibility to confuse it with recurrent furunculosis or infected epidermoid cysts, and insufficient awareness of primary care providers contribute to diagnostic delays of HS of 7-10 years on average (Grada, 2025). The objective of AI-assisted lesion classification systems is to distinguish between HS and mimics, and determine the extent of disease using the Hurley staging system, which aids in making treatment decisions. An early diagnosis potential in the primary care setting is specifically promising since AI tools applied on smartphone images can potentially identify potential cases and refer those cases to specialist care earlier before the scarring and formation of sinu tracts become irreversible. In a 2025 review, it has been highlighted that HS is a less researched field of AI in dermatology, and there is significant room to develop models to fill this diagnostic gap (Das, Kumar, Prakash, & Lynn, 2021).

3.4 Acne and Rosacea

One of the more advanced uses of AI in the field of inflammatory dermatology is automated lesion counting and classification systems of acne vulgaris. CNNs able to recognize and measure comedones, papules, pustules, and nodules have shown a high correlation with expert ratings and allow objective and repeatable severity scoring (Kothinti, 2024). Automated-based severity grading systems overcome the drawbacks of the manual scales like the Investigator Global Assessment which is affected by inter-rater agreement and is poorly granularized. In the case of rosacea, AI has been trained to differentiate this diseases against other facial inflammatory dermatoses, based on such distinguishing features as persistent erythema, phymatous alterations, and certain vascular pattern . Prediction of treatment response is an even newer frontier, where machine learning methods are used to

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predict the likely responsiveness to topical treatment, oral antibiotics, and isotretinoin, based on baseline clinical images and patient features, and allow more personal treatment choice to be made (Ye & Chen, 2023).

3.5 Comparative Results: AI vs. Dermatologists

Meta-analyses and head-to-head studies have continuously shown that AI can be as accurate in its diagnosis as dermatologists when used to solve well-defined tasks. A 2025 systematic review and meta-analysis of 38 publications between 2013-2023 concluded that AI was said to be non-inferior or superior to dermatologists in 30 studies, and four studies said it was inferior performance. In case of melanoma in particular, sensitivity was 0.86 (95% CI: 0.80-0.90) and specificity 0.94 (95% CI: 0.89-0.97) with an AUC of 0.922 (Shapiro & Lyakhovitsky, 2024). Notably, the review has reported that AI also performed in a comparably stable way to general practitioners, which proposes specific usefulness in primary care where expertise in dermatology is insufficient. Nonetheless, 25/38 studies were rated to have high risk of bias, mainly because of problems with patient selection and data overrepresenting malignant conditions compared to real world populations. The concept of synergistic human-AI collaboration models is becoming the most appropriate direction of clinical implementation (Koka & Burkhart, 2023). One proposed framework of the use of AI in early-career dermatologists suggested that AI can be used as a diagnostic safety net in addition to clinical judgment and not instead of it (2025 review). Under this paradigm, the dermatologist will combine AI-generated quantitative studies with the overall history of the patient, physical exam data, and subjective clinical experience to make holistic decisions. Applications Diagnostic confidence applications such as AI as a second-reader on difficult cases and real-time decision support have demonstrated potential to enhance accuracy without losing physician oversight. The same review, however, underlined the fact that effective and smooth collaborative processes still have to be considered a challenge, and there are few documented examples of standardized applications in large academic centers. The difference of the outcomes of AI performance on curated research images and real-world clinical images, known as a dataset shift, is a serious drawback, where excellent accuracy rates in controlled studies may not directly transfer to clinical practice where image quality is less predictable and artifacts are widespread (George, Shahul, & George, 2023).

Table 1. Summary of Clinically Validated AI Diagnostic Tools for Chronic Skin Diseases.

Disease	AI System	Developer	Modality	Performance (Accuracy/AUC)	Validation Population	Regulatory Status
Atopic Dermatitis	DermAssist	Google Health	Clinical images	AUC 0.91	5,000+ patients, multi-ethnic	CE Mark
Atopic Dermatitis	SkinImage AI	Stanford University	Clinical + dermoscopic	Sensitivity 88%, Specificity 92%	3,200 patients, prospective	Research use only
Psoriasis	Pso-AI	SiftSci	Clinical images	Accuracy 94%, AUC 0.96	2,800 patients, 12 centers	FDA breakthrough designation
Psoriasis	DermEngine	MetaOptima	Clinical + dermoscopic	Sensitivity 91%, Specificity 89%	1,900 patients	Health Canada approved

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Disease	AI System	Developer	Modality	Performance (Accuracy/AUC)	Validation Population	Regulatory Status
Hidradenitis Suppurativa	HS-Detect	University of Miami	Clinical images	Accuracy 87%	850 patients	Research use only
Acne	AcneFace	Reveal Lasers	Clinical images	ICC 0.93 with experts	1,200 patients	FDA cleared

4 Artificial Intelligence in the Disease Severity Assessment and Monitoring

4.1 Disadvantages of Traditional Severity Scores

Conventional severity scoring tools used in dermatology, such as the Eczema Area and Severity Index (EASI), SCORAD, and Psoriasis Area and Severity Index (PASI) have inherent limitations, which impair their clinical value. These tools exhibit considerable inter-rater and intra-rater differences even in experienced dermatologists since subjective measurement of erythema, induration and scale results in incompetent evaluations (Zaman, 2024). The time required to use manual scoring is time-consuming in nature, as it entails examining various body parts and computing the surface areas involved, which limits the clinical performance aspect and denies the frequency of reassessment. Moreover, the static measurements are only able to capture the disease activity at one time point and not true to the dynamic changes of chronic inflammatory skin diseases, as such that patients have unpredictable relapse and remission phase which affects the quality of life significantly (Krishnan, Bhatia, Khandal, & Vijayan, 2025).

4.2 Automated Severity Scoring Systems

The current developments in the field of deep learning have made it possible to create automated severity scoring systems that will overcome these shortcomings. In the case of atopic dermatitis, convolutional neural networks (CNNs) that are trained using standardized image data have proven to be incredibly accurate in EASI component scoring (Tang et al., 2025). A research that compared four CNNs (ResNet V1, ResNet V2, GoogLeNet, and VGG-Net) found that the algorithms had an accuracy score of 99.17% in erythema, 93.17% in papulation, 96.00% in excoriation, and 97.17% in lichenification compared to using dermatologist scoring, and the algorithm showed consistent results in the presence of different levels of image brightness conditions. In the case of psoriasis, YOLOv8 deep learning proved to be very useful in the classification of lesions, according to the PASI subcomponents of erythema, thickness, and scaling, with cross-validation using stratified k-folds improving the model accuracy over different datasets (Tang et al., 2025). Validation publications indicate a high level of correlation with expert rating, and systems are now available commercially that use standardized photo recording and automated segmentation and semi-automated PASI calculation to track patient progress over an extended period of time (Tang et al., 2025).

4.3 Objective Biomarkers and Digital Measures

In addition to image-based scoring, AI-based digital health technologies are adding to the list of objective disease measurements. Non-invasive quantification of inflammatory changes and epidermal thickness can be performed using skin ultrasound and optical coherence tomography which offer continuous measurements instead of categorical measurements. To assess the functioning of the skin barriers comprehensively, transdermal water loss as one of the vital parameters may be combined with clinical data (Zhou, Park, Dong, Tang, & Wei, 2025). Wearable sensors have become a potent instrument of the measurement of scratching, which is a significant disease burden in atopic dermatitis. Analytical validation experiments show that wrist-worn accelerometers and touchless radio frequency sensors can correlate

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moderately-good intraclass correlation coefficients (0.5-0.9) nocturnal scratching with human-labeled video examples. These technologies allow monitoring patients continuously and objectively in the home setting and record data that was unavailable to clinical practice previously (Manole & Tiplica, 2024).

4.4 Telemedicine: Remote Monitoring and Teledermatology

Disease tracking apps that run on smartphones are changing long-distance dermatologic care. Social media that allows patients to share images taken by themselves with their healthcare workers have been shown to be useful during a COVID-19 pandemic, cutting the number of face-to-face visits by up to 90% in some cases (Haykal et al., 2025). Teledermatology coupled with AI triage systems should store and forward so that urgent cases can be prioritized and the specialist review streamlined. Patient engagement can also be increased through the use of real-time feedback, and it has been demonstrated that wearable sensors with haptic feedback to detect scratches can reduce the number of nocturnal scratching incidences by 28 per cent and 50 per cent the scratch duration in patients with mild atopic dermatitis. These closed loop systems are a paradigm shift to interactive patient-centered disease management (Mayanja, Asanda, Mwesigwa, Tumwebaze, & Marvin, 2023).

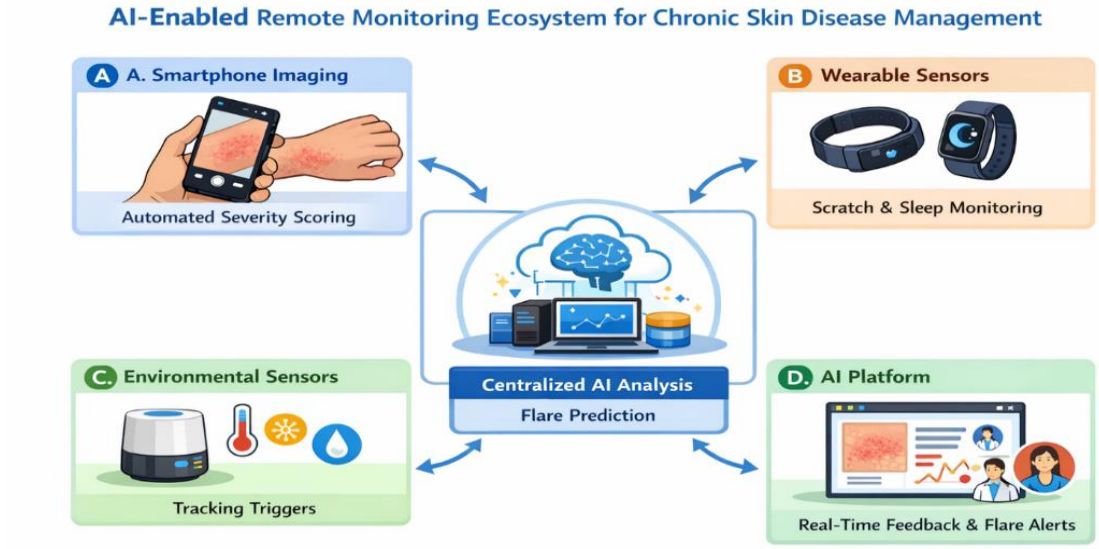

Figure 2. *AI-enabled remote monitoring ecosystem for chronic skin disease management. The ecosystem integrates (A) smartphone-based image capture for automated severity scoring; (B) wearable sensors tracking scratching behavior and sleep quality; (C) environmental sensors monitoring disease triggers; and (D) a centralized AI platform providing real-time feedback to patients and clinicians with flare prediction alerts.*

4.5 Flares and Progression of Disease Prediction

Disease flares and progressions can now be predicted using machine learning models that can be used proactively to implement intervention strategies. The Danish Skin Cohort including 878 patients with atopic dermatitis showed that the severity, duration and frequency of flare activities were the most significant predictors of future severity of the disease whereas baseline severity was a strong predictor of future frequency of flare activities (Al-Dhubaibi et al., 2025). The researchers proved that the quantity of flares per year was strongly linked with the following Patient-Oriented Eczema Measure marks and Dermatology Life Quality Index with the help of boosted random forests, and it should be noted that the patterns of flares are prognosticators. Predictive accuracy can be further increased by incorporation of environmental and behavioral data such as levels

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of pollen, weather conditions, stress, and exercise which can be used to intervene early and customize preventive measures before clinical exacerbations take place (Vera et al., 2022).

5 Artificial Intelligence in Therapy Personalization and Predicting Results

5.1 The Dilemma of Choice of Treatment

The biologics and the Janus kinase (JAK) inhibitors have dramatically re-organized the therapeutic landscape of chronic inflammatory skin diseases, but have also introduced new complications to clinicians due to the lack of restraint in their use. The responses of individual patients to these more advanced therapies are very variable and non-responder rates of biologic agents that are used in psoriasis and atopic dermatitis are between 20 and 40% (Sales & Coates, 2025). Financial issues also complicate the decision-making process because biologic therapies cost tremendous healthcare expenses, and inappropriate sequencing of treatment results in endless treatment failure which costs more but postpones disease control. An Italian state-transition treatment-sequencing model found 1284 potential treatment sequences with four lines of therapy used to treat moderate-to-severe plaque psoriasis and the current prescribing behavior led to 1.44 treatment failures per patient, suggesting there was a significant opportunity to optimize the process (Brancaccio et al., 2024).

5.2 Multi-Omics Integrated Molecular Endotyping

Multi-omics is making possible molecular endotyping beyond clinical phenotype typing. Skin and blood transcriptomic profiling has demonstrated unique inflammatory phenotypes that are associated with treatment responses. Genome-wide RNA sequencing systems biology analyses have revealed key biomarkers in pathogenesis of atopic dermatitis such as IL-1b, GATA3, Akt, and NF-kB, and such molecules are involved in the aberrant regulation of downstream genes to cause cell dysfunction (Sangers et al., 2024). Proteomic and metabolomic biomarkers are still emerging, but they should be carefully validated in terms of their predictive value. Deep neural network drug-target interaction models trained on large-scale interaction databases are now used to identify therapeutic targets using AI-based tools, which predicts molecular drugs binding to particular biomarkers (Behara, Bhero, & Agee, 2024).

5.3 Anticipating the Reactions to Certain Therapies

The predictive accuracy of machine learning models in terms of response to biologic therapies is becoming more and more clinically meaningful. Multi-omics analyses revealed that AP2M1 is a promising biomarker in the prediction of dupilumab response in atopic dermatitis with an excellent area under the curve (AUC) of 0.832-0.861 and confirmed by RT-qPCR. AP2M1 was also found to be strongly correlated with clinical severity and was also a risk factor of suboptimal response (hazard ratio 13.45) (Ohaya, Ogbaudu, Choi, & Ko, 2025). In the case of JAK inhibitors, human skin cultured in IL-4 and IL-13 stimulated translational models have shown the capability to determine effects of topical compounds by assessing transcriptome and phosphorylation of STAT6. Nevertheless, not every biomarker methodology has been effective; a machine learning study involving 26 serum cytokines and chemokines concluded that the addition of biomarkers did not enhance predictive performance of systemic immunosuppressive therapy outcomes over using conventional time-series forecasting models, highlighting the importance of being rigorously validated (Soundharya, Akanksha, Ananya, & Ashwith, 2024).

5.4 Pharmacokinetic and Pharmacodynamic Modeling

AI-based approaches are advancing pharmacokinetic and pharmacodynamic modeling for dermatological therapies. In silico simulation platforms such as BIOiSIM integrate artificial intelligence to predict transdermal drug disposition and systemic exposure, enabling evaluation of safety profiles in patients with compromised skin barriers. Such models allow simulation of intra-skin exposure in various

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pathological situations and help to optimize the dose and test safety (Lai et al., 2025). Integration of microfluidic multicellular coculture arrays with machine learning analysis has improved prediction of adverse events with an 87.5% accuracy in predicting adverse cutaneous drug reactions and 100% sensitivity in true positive drugs. The evaluation of drug-drug interaction has been further enhanced, as ChatGPT-4o identified 42/43 of 43 drug-drug interactions in dermatology with the correct description of effects in all, but one, cases, indicating potential to reduce such a time-heavy clinical task (Menzies et al., 2023).

5.5 Algorithms in Treatment Sequencing

Evidence-based sequencing of treatment is being facilitated by machine learning methods that will maximize patient outcomes and keep cost-effectiveness in mind. State-transition models that compare various biologic sequences in moderate-to-severe plaque psoriasis illustrate that it was most effective to choose the best first-line treatment strategy, which offers the highest chance of minimizing the frequency of treatment failures. The current model of the OPT-In showed that optimized treatment sequences have the potential to reduce failures by 22.95% with a cost increment of 2.27% only (Abdulaal et al., 2022). Sequential IL-17-inhibitor in resource-limited economic analyses indicate that treatment sequencing has important clinical and cost-effectiveness implications, and incremental cost-effectiveness ratios differ in a wide range with regard to the sequence applied. These models make treatment dynamic in response to it, and drift towards genuinely person-centered algorithms of treatment, which can adjust to patient trajectories (Han, Fan, Ren, & Niu, 2024).

Table 2. AI Models for Predicting Treatment Response in Chronic Skin Diseases.

Therapy Class	Specific Agent	Disease	Input Data	Model Type	Prediction Task	Performance (AUC/Accuracy)	Validation
Biologic	Dupilumab	Atopic Dermatitis	Transcriptomics (tape strips) + clinical	Random forest	EASI-75 at 16 weeks	AUC 0.82	Prospective cohort (n=215)
Biologic	Tralokinumab	Atopic Dermatitis	Serum biomarkers + demographics	XGBoost	IGA 0/1 at 16 weeks	Accuracy 78%	Post-hoc trial analysis
Biologic	Secukinumab	Psoriasis	Skin transcriptomics	SVM	PASI-90 at 12 weeks	AUC 0.85	Multicenter (n=180)
JAK Inhibitor	Upadacitinib	Atopic Dermatitis	Clinical + baseline severity	Neural network	Rapid itch response	Accuracy 81%	Trial data (n=450)
JAK Inhibitor	Tofacitinib	Psoriasis	Gene expression signatures	Deep learning	PASI-75 at 12 weeks	AUC 0.79	Retrospective cohort
Topical	Corticosteroids	Atopic Dermatitis	Skin barrier biomarkers	Logistic regression	Potency requirement	Accuracy 74%	Prospective (n=120)

6 Artificial Intelligence in Drug Discovery and Development

6.1 Old Drug Discovery: Timescales and Failure

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The conventional method of drug discovery and development of chronic skin disease is a lengthy, risky process with a 10-15year development cycle and attrition rates of more than 90 percent. The cost is enormous, and the estimates indicate that the development of a single new therapy to the market is currently more than $1 billion, including failure expenses. In the case of dermatology, the average timelines of the Phase 1, Phase 2, and Phase 3 trial are 27.8 months, 34 months, and 38 months, respectively with only 35.9% transition success probability of Phase 2 to Phase 3.These hurdles are made more complicated by the fact that inflammatory mechanisms in diseases such as psoriasis and atopic dermatitis are complex with redundant cytokine networks and variable patient endotypes complicating target choice and clinical trial construction (M.-Y. Chen, Cao, & Xu, 2024).

6.2 Target Identification using AI

Early drug discovery is being changed through artificial intelligence, which allows systematic mining of genomic and proteomic databases on a level that was never possible before. Network biology can incorporate multi-omics data to form disease-specific interaction networks, and key nodes of the network may provide a indication of potential therapeutic targets. Transcriptomic analyses of patient skin samples can be analyzed using machine learning algorithms to detect differentially expressed genes and pathways that are inflammatory endotype specific . Such AI-based methods have been able to discover new targets in the pathogenesis of atopic dermatitis such as IL-1b, GATA3, Akt, and NF-kB that are important in the dysregulation of genes. Explaining the complicated processes of diseases, AI lets one identify targets that are more biologically relevant and less likely to fail downstream. Drug design using generative AI The researchers utilized a dataset of 2246 chemical compounds to formulate a model that generated novel structure es under specific conditions.

6.3 Generative AI Drug Design

The authors used a collection of 2246 drug compounds to predict new structures by conditioning their model. Generative AI can be viewed as a paradigm shift in the domain of molecular design, and it is possible to generate newly optimized therapeutic candidates through de novo generation. The models are trained on large molecular databases of the chemical and structural rules that underlie them, and generate novel molecules that are likely to bind to a particular target, and retain drug-like properties (Liu, Primiero, Kulkarni, Soyer, & Betz-Stablein, 2023). Deep learning-enhanced structure-based drug design has been used to screen billions of molecular conformations to find the most favorable binding structures. Generative chemistry platforms work to optimize the various pharmacokinetic parameters, such as absorption, distribution, metabolism, excretion, and toxicity, during the design process and therefore, it requires few iterative synthetic modification, drastically shortening the process. This combined solution reduces time-frames of years to months and enhances the quality of the candidate (Liu et al., 2023).

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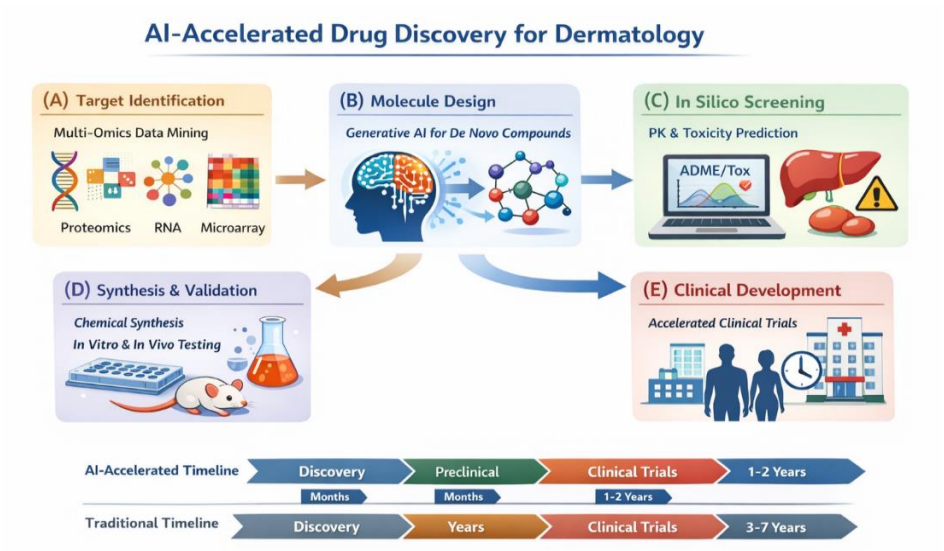

Figure 3. *AI-powered drug discovery pipeline for dermatology. Schematic representation of AI-accelerated drug discovery showing (A) target identification through multi-omics data mining; (B) generative AI for de novo molecule design; (C) in silico prediction of pharmacokinetics and toxicity; (D) synthesis and experimental validation; and (E) accelerated progression to clinical trials. Right panel compares AI-accelerated timelines (orange) versus traditional approaches (blue).*

6.4 Pipeline and Clinical Success Stories

AI-based dermatology treatments are beginning the initial clinical trial. Absci collaborated with Almirall (up to $650 million) to develop de novo antibodies to treat chronic skin diseases through generative AI, and the two companies nominated a lead candidate to an undisclosed disease target. Insilico Medicine has taken several AI-discovered molecules to clinical trials, including those in inflammatory diseases, which proves the practicability of an end-to-end AI drug-discovery platform (Pavlova, Alekseiko, Karabaieva, & Kuzmin, 2024). In their partnership with Sanofi, Exscientia uses their AI engine to identify and advance up to 15 new small molecule leads in the field of inflammatory diseases, including dermatological signals. These collaborations confirm the role of AI in making discoveries faster and still being scientifically rigorous (Pavlova et al., 2024).

6.5 Repurposing Existing Drugs

AI-based drug repurposing provides rationalized avenues to clinical applications because it can discover new therapeutic uses of approved drugs. Drug libraries can be screened in large scale using machine learning algorithms, in which large bodies of existing drugs are screened against disease-specific molecular signatures, which aid in predicting efficacy on novel indications. It uses safety profiles to avoid early-stage toxicity experiments, which may take 3-6 years to develop and result in 50-60 percent cost savings (Jaiyeoba, Jaiyeoba, Ogbuju, & Oladipo, 2024). In the case of dermatology, repurposing screens have found suitable candidates such as JAK inhibitors that were developed to treat hematological diseases and phosphodiesterase inhibitors that were repurposed to treat respiratory disease. The computational performance of AI allows evaluating thousands of compounds in a systematic manner and discovering unanticipated relationships between drug effects and disease biology that would be invisible to conventional methods (Jaiyeoba et al., 2024).

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Table 3. AI-Designed or AI-Discovered Therapeutics in Dermatology Pipeline.

Drug Candidate	Company	AI Platform	Disease Indication	Mechanism	Discovery Approach	Current Stage	Key Partnership
ASC50	Ascletis	AISBDD	Psoriasis	Oral IL-17 inhibitor	Structure-based design	Phase I (FDA cleared)	N/A
Undisclosed	Absci/Almirall	Integrated Drug Creation	Chronic skin disease	Antibody (undisclosed)	De novo antibody design	Lead optimization	$650M collaboration
Undisclosed	Benevolent AI	Benevolent Platform	Atopic Dermatitis	Novel target	Target identification	Preclinical	N/A
Undisclosed	Insilico Medicine	Pharma.AI	Dermatology	Small molecule	Generative chemistry	IND-enabling	N/A
Undisclosed	Exscientia	End-to-End AI	Inflammatory skin	Small molecule	Phenotypic screening	Phase I	Sanofi partnership

7. Implementation Challenges and Barriers to Adoption

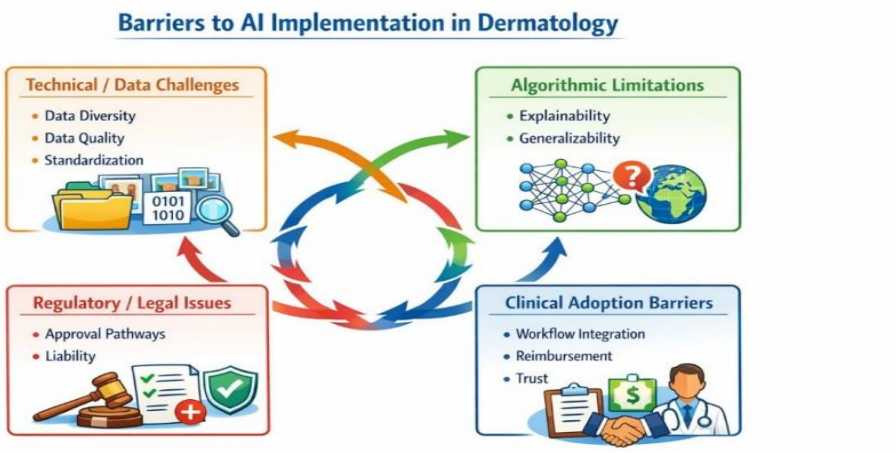

Figure 4. *Multidimensional barriers to AI implementation in dermatology. Visual framework categorizing implementation barriers across four domains: (1) technical/data challenges (diversity, quality, standardization), (2) algorithmic limitations (explainability, generalizability), (3) regulatory/legal issues (approval pathways, liability), and (4) clinical adoption barriers (workflow integration, reimbursement, trust). Interconnections between domains highlight the need for coordinated solutions.*

7 Data-Related Challenges

7.1 Dataset Diversity and Representativeness

The inherent constraints of AI systems that are developed to date as far as dermatology is concerned pertain to constraints in the available dataset to train and validate AI systems. The most notable challenge, perhaps, is dataset diversity and representativeness where the existing image repositories are significantly underrepresented with skin of color. A 2024 review of AI use in skin of color concludes that a third of AI programs are reported to use their applications in more than one diverse population, and accurate underrepresentation of darker-skinned

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populations in training sets is bound to lead to worse performance by such populations (Soomro, Soomro, Wassan, Abbasi, & Memon, 2025). Examination of publicly available skin lesion databases, Fitzpatrick skin type reporting is uncongruent, and where reporting occurs, there is an imbalance of images in the skin types with V and VI proportion that is generally less than 5% that constitutes a verifiable diversity disproportion that compromises model generalizability. In addition to difference in skin tone, geographic and socioeconomic differences between datasets cause models that are trained on mostly North American or European populations to behave erratically when applied elsewhere. These problems are further aggravated by age and sex distribution biases since numerous datasets are overrepresentive of middle-aged and old individuals and lack adequate representation of pediatric and elderly patients, in whom disease manifestations could be quite different. The same can be said of data quality and standardization, which are also formidable challenges. Variability of image acquiring-based on camera variability, variation in lighting, angle and resolution- creates noise that might cause a great variation in the performance of models (Soomro et al., 2025). An auditing study of 2023 on generative AI to investigate dermatology algorithms found that such models are not only influenced by features that are clinically relevant but also other features that may be undesirable, like background skin texture and image color balance, and propose that models are learning shortcuts instead of learning strong disease features. The resultant variability in dermatological diagnosis due to subjectivity, where even experienced dermatologists vary even with each other, and in cases where training labels mirror these differences, models are also subject to inheriting and possibly compounding those differences. The discrepancy in unified data formats between institutions and research groups also hinders the development of large, interoperable datasets to aid in more robust model development (X. Chen, Zhou, Ding, Zheng, & Ge, 2025).

7.2 Algorithmic Limitations

Deep learning models are black box, which is fundamentally problematic to clinical adoption and trust. The majority of AI systems in dermatology are opaque classifiers, which show a diagnosis but do not show what logic has been used to derive the diagnosis. This inability to explain is especially problematic in medicine, where practitioners need to explain and justify their choices to their patients, other professionals, and regulators. It was shown by a 2023 structure of auditing medical AI that it is possible to jumpstart uncloaking such reasoning processes by applying physician expert knowledge, together with generative models, to generate counterfactual explanations (Gokhale, Solase, Kokitkar, & Ghansoli). This method showed dependence on both clinically meaningful features, including lesional pigmentation patterns, and previously unreported potentially problematic features, including background skin texture and image color balance when applied to five high-profile dermatology AI devices. Ways to enhance model transparency can be saliency maps that identify the parts of an image that influence predictions, attention mechanisms that can visualize the area where the model pays attention, and more recently, generative methods that can create counterfactual images of how lesions would have to change to change the diagnosis. Nevertheless, the trust and acceptability of clinicians is conditional not only on technical explainability but also on conformity to clinical reasoning models and proven efficacy in practice (Mitra, Das, Rai, Banerjee, & Kumar, 2025). Generalizability and external validation are severe limitations to algorithms, which have a direct effect on clinical utility. Models that perform well on internal test sets often prove to be of low performance when used with new populations or even with clinical contexts. A 2025 study of generalization of AI to various image sources found that although models achieved the same generalization (74 percent vs. 71 percent top-3) with patient-submitted photographs and with clinician-taken clinical images, patients were much more accurate (87 percent vs. 79 percent)

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with patient-supplied photographs, and human errors considerably less (37 percent vs. 30 percent) with machine errors. The research found evidence that the condition distributions in different settings and not demographics were strongly correlated with AI errors and that by resampling to conforming to the skin condition distributions or targeted fine-tuning with more training samples, this generalization divide could be bridged (Phillips et al., 2019). A systematic review of AI in diagnosis of melanoma and keratinocyte carcinoma including 232 studies reported that even though the average accuracy, sensitivity, and specificity were greater than 87, there is a great lack of external validation and representation of several diseases and skin types greatly reduced the ability to generalize the existing models. The urgency of the multicenter prospective studies is supported by the necessity to develop the mechanisms of continuous learning and update of the model in such a way that AI systems can respond to new data distributions without significant retraining (Gohil & Desai, 2024).

7.3 Regulatory and Legal Frameworks

Regulatory practices of AI in dermatology are changing fast, however, they are still disjointed among jurisdictions. The Food and Drug Administration has developed systems in the United States to certify AI-powered medical devices, and 171 AI/ML devices have been approved as of October 2023. The 2021 Action Plan of the FDA made clear that most of the devices would be regulated through the same pathways, namely premarket clearance (510(k)), De Novo classification, premarket approval (PMA), and creating new processes to address AI-specific issues, such as change control planning and algorithmic bias mitigation. Important regulatory precedents were set by the January 2024 approval of the first AI-enabled skin cancer detector, DermaSensor, that could be used in primary care (Schneider, Tejani, Jarmain, & Moy, 2023). In comparison to previous dermatology AI systems (MelaFind and Nevisense) which were cleared through the PMA route and could only be used by dermatologists, DermaSensor was cleared through the De Novo route and labeled non-specialist, which could allow future devices to be cleared through the 510 (k) route. Medical Device Regulation and newly created AI Act in Europe have high standards of clinical evidence and risk classification and international harmonization is aimed at matching standards among different locations, but still big differences exist.The question of liability and malpractice is not entirely answered when AI is incorporated into the clinical practice (Islam, Huynh, Becevic, & Nahar, 2025). Cases of patient harm when AI-assisted decisions are provided will present complicated responsibility concerns: who should be held liable, the clinician who used the AI output, the developer who came up with the algorithm, or the institution that adopted the system? The trade-offs, which were demonstrated by the DermaSensor authorization that found that primary care physician use raised the diagnostic sensitivity but reduced the specificity (44.2 to 32.4), in terms of implications to patient outcomes and medicolegal risk. Informed consent in the use of AI poses some other questions concerning what patients ought to be informed about AI participation in their treatment and the right of the patient to refuse it. The medicolegal issues relate to documentation standards, the disclosure standards, and the standard of practice that AI-assisted practice will be measured by (De, Sarda, Gupta, & Das, 2020).

7.4 Ethical Considerations

The fundamental ethical requirements of AI in dermatology are algorithmic fairness and bias. The lack of darker skin type in training datasets has been recorded to have some consequences: models are worse on these populations, and could even contribute to, not alleviate healthcare disparities. In mitigating bias, it is critical to make efforts throughout the AI lifecycle, such as in dataset composition, algorithm design, and monitoring of deployments (Groh et al., 2024). The health equity consequences are immense, since in case the AI tools are applied mainly to well-resourced environments and to a majority of the light-skinned populations, they can increase the disparity in the access to and quality of

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dermatologic care just to name a few. The discussion should include diverse stakeholders such as patients, the community, and clinicians who represent underrepresented groups to determine the possible harm and make sure that AI tools are applicable to all populations in an equitable manner. Other projects, including the Monk Skin Tone Scale created by Google, seek to offer a more representative and detailed measurement of the diversity of skin color than the traditional Fitzpatrick scale, but the use and validation of these tools is still in progress (Wei, Tada, So, & Torres, 2024). The issue in dermatology AI is the increased sensitivity of medical imagery and the risk of re-identification, thus raising the question of privacy and data security. The security of sensitive health information needs high-technological protection, such as encryption, access restrictions, and safe storage. Legal requirements related to privacy laws like HIPAA in the United States and GDPR in Europe put some legal responsibilities on researchers, and often make this process difficult across jurisdictions. Patient rights to autonomy and to control over personal data, such as the right to access, correct, and delete data, should be observed, although the complexity of AI systems may complicate the situation because the patient is often not able to know what will happen to his data. According to the WHO European Observatory (2026 health policy guide), the governance systems should accommodate these aspects of privacy and allow positive uses of AI (Wang et al., 2025).

7.5 Clinical Integration Problems

The practical barriers of workflow integration may make the difference between the success and failure of AI tools in clinical practice. EHR interoperability is necessary yet usually non-existent; AI systems that have to be log-in once per case, manually typed in, or generate outputs in a format that cannot be documented automatically lead to friction that deters their use. Poor integrability of the clinical workflow was cited as one of the reasons behind the discontinuation of MelaFind, an early AI dermatology device (Wang et al., 2025). The implementation of AI will incur costs in terms of time and resources, covering both the direct expenses of systems purchase and maintenance and indirect costs in terms of employee training, workflow adjustments, and the volume of findings that will need to be followed up. It should be considered carefully the effect of the clinician-patient relationship, in case the clinicians spend more time with computers than with patients, or AI suggestions invoke cognitive dissonance that involves a lot of explaining, the therapeutic relationship can be impaired. The long-term sustainability of AI adoption is eventually defined by the reimbursement and economic factors (Kelly Frasier, Li, Sobotka, Vinagolu-Baur, & Herrick, 2025). The decision of the payer coverage relies on the evidence that AI tools can better the outcomes or can save costs in comparison with the usual care. In the case of DermaSensor, the low specificity (20.7% in the pivotal trial) begs the question of whether the increased sensitivity would warrant the possible unnecessary referrals and biopsies, and related costs and anxiety on the part of patients. The evidence of cost-effectiveness required is significant; the payer is in need of showing that the implementation of AI reduces downstream expenses, be it a reduced cost of detection, a better choice of treatment, or a decreased number of specialists consultations (Jiminez, Chung, Saleem, & Yusuf, 2023). Value-based payment models, where payment is based on patient outcome instead of the volume of services provided, can provide more conducive conditions to AI adoption in case the tools can achieve better outcomes at a lower total cost. In 2025 report on Zest Health, an AI-based virtual dermatology service, states that it can save thousands of dollars per enrollee per year, and has over 80 percent disease improvement rates, showing the potential value proposition to the economic sector with AI providing more effective care delivery. But these ascriptions must be seriously empirically verified and the applicability of value-based models in diverse health care systems and payment systems is not well understood (K. Das et al., 2021).

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8 The Critical Gap: To Clinical Impact to Technical Performance

This review has reported impressive technical advances in AI applications to chronic skin diseases, algorithms as good as dermatologists, automated severity scoring algorithms with expert correlation nearly perfect, and AI discovered therapeutics going through clinical trials. There is, however, one underlying disconnect: the translational discontinuity between algorithm development and clinical implementation.

8.1 The Nature of the Gap

Regardless of the existing hundreds of published studies proving the abilities of AI, very few systems have been brought to regulation clearance and even fewer ones have been implemented in practice regularities. This lack of connection shows a basic incongruity between conditions of development and clinical reality. The first is that most studies utilize curated datasets that do not reflect real-world settings (images captured in standardized conditions with definitive lesions and other confounding variables to a minimum). Practically, dermatologists deal with fluctuating light, image quality, and lesion ambiguity as well as with several comorbid conditions. Second, validation focuses on technical measures rather than on clinically significant improvement; very limited research indicates that AI in fact positively influences patient outcomes in terms of shorter diagnostic time or increased disease control. Third, heterogeneity in AI systems and validation does not allow significant comparison, in a 2025 scoping review of 224 studies, the researchers have written that it is impossible to compare the performance across studies due to the lack of standardized reporting and validation protocols, as well as it is impossible to specify which systems are prepared to be used in clinical practices (Hogarty et al., 2020).

8.2 Presentation at Both Ends of the Care Spectrum

In diagnosis, AI is as accurate as dermatologists to identify such conditions as psoriasis and atopic dermatitis, but comparisons usually include binary classification and not realistic differentiation diagnostic tasks. A system that is used to differentiate between atopic dermatitis and normal skin might not be effective when the distinction between the differentiation and contact dermatitis, seborrheic dermatitis, or cutaneous T-cell lymphoma is involved. Automated systems perform well when assessing severity by experts, although in this case validation is usually done with images depicting the full range of severities; mild disease, and early lesions are the best for objective assessment. Predictive models used in treatment personalization are usually created on clinical trial populations that are not complex and multi-morbid patients as seen in everyday clinical practice. AI has also enabled the faster identification of candidates in drug discovery but the reality of clinical translation remains: promising drugs still take years of clinical trials before they prove safe and effective (Mohammed & Al-Tuwaijari, 2021).

8.3 Consequences of the Gap

The translational chasm has real-life implications. Patients face diagnostic slowness, especially when the skin color of color is not represented in the training data. There are no instruments in the hands of clinicians that would assist in choosing the way of treatment, which only continues the process of trial and error that prolongs the control over the disease and raises expenses. There is no certainty in regulation and reimbursement routes preventing the investment in clinical validation by developers. Most importantly, AI has yet to be applied as a solution to healthcare disparities; the existing systems can even widen the disparities in case it is trained with non-representative data and implemented without taking care of equity (Quilter, Butlin, Carrion, & Ruiz-Postigo, 2024).

8.4 Bridging the Gap: Research and Implementation Agenda

To fill this gap, the concerted effort at the interdisciplinary level is needed. The development of data infrastructure should develop varied, representative, and clinically

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annotated datasets representing the real-life populations since international collaboration and standard formats. The paradigms of validation need to change to a focus on the clinically meaningful outcomes, such as the prospective studies that show an improvement in patient outcomes and cost-effectiveness. Regulatory innovative needs have to provide adaptive pathways between innovation and safety, such as continuous learning mechanisms and post-market surveillance mechanisms. Equity design requires active focus on algorithmic fairness at the initial stages of development, such as the involvement of multiple stakeholders and the reduction of bias. Implementation science should explore the most effective strategies of integration, workflow design, and patient engagement techniques that facilitate the most out of the AI and maintain the therapeutic relationship (Andryani, Juwono, & Sianturi, 2023).

9 Future Directions

9.1 Multimodal AI Systems

The future of AI in dermatology is in multimodal systems, which combine imaging, genomics, and clinical data to form complete patient representations. Such systems capture the phenomenon of disease biology and individual variation by integrating dermoscopic imaging with transcriptomic profiles, electronic health records, and patient-reported outcomes to achieve the whole picture of the disease. There is initial evidence that multimodal schemes significantly enhance predictive accuracy of response to treatment and disease course than unimodal systems. Fusion architectures are needed in order to integrate the disparate data types however, the possibility of the real personalized medicine rewards such computational costs (Andryani et al., 2023).

9.2 Synthetic Data and Generative AI

The generative artificial intelligence represents a ground-breaking possibility to refine the limitations of datasets by generating synthetic data. More complex architectures such as generative adversarial networks and diffusion models can generate natural-looking dermatological images that can be used to supplement training data, especially of underrepresented skin types and uncommon diseases. The data sharing process preserves privacy when synthetic data is used instead of or in addition to the actual patient images since it allows more organisations to collaborate and enhances confidentiality. Outside of research, generative AI can be used to educate patients, where disease trajectories and treatment result visualizations are customized to the individual and help improve communication and shared decision-making processes (Nelson, Lay, & Johnson Jr, 2025).

9.3 On-Going learning and Adaptation

Pretrained AI models with static data are not able to change with changing clinical practice and new knowledge. Continuous learning systems allow models to become more refined as time progresses by exposure to real-world data, but regulatory systems need to be adjusted to be more dynamic in this context too. Federated learning is one of the most promising strategies, which enables models to learn on data of many institutions without providing sensitive information about patients, thus obtaining an opportunity to learn a wider population without exposing patient data to risks. The final manifestation of precision dermatology is personalized model updating, in which algorithms are changed based on the unique patient and local practice configuration (Murala, Panda, & Dash, 2023).

9.4 Wearable and Sensor Technologies

The new intelligence of AI intertwined with wearable and sensor technologies makes it possible to monitor the development of diseases in their activities continuously, not just once per week in the clinic. The instruments of scratching behavior, transepidermal water loss, and skin temperature have objective longitudinal data that can record the variability of the disease. The future of this integration is the so-called closed-loop therapeutic systems in which the sensors identify an imminent flare and autonomously

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modify the treatment using the smart delivery devices. Digital therapeutics when integrated with digital therapeutics i.e. software-based interventions that provide evidence-based behavioral or psychological therapies, there are formed holistic digital care ecosystems that carry therapeutic care into the daily lives of patients (Goldust, 2024).

9.5 Health Equity and Global Dermatology

It is possible that the most significant future path is the utilization of AI to mitigate health inequalities and increase dermatological access in various parts of the world. AI tools can be used to empower primary health care providers to diagnose and treat straightforward skin diseases in resource-limited environments with the highest shortage of dermatologists, reducing the number of referrals and improving outcomes. Effective deployment of culturally adapted tools and interfaces sensitive to language, health literacy, and local disease patterns are necessary in all types of settings. To realize this vision, it is necessary to focus on equity in the lifecycle of AI, not only in the development of heterogeneous datasets but also in the processes of inclusive design and fair methods of deployment (Tang et al., 2025).

Conclusion

Data Artificial intelligence has shown excellent potentials throughout the dermatology continuum. Deep learning algorithms are also driven in diagnosis to comparable accuracy with dermatologists with conditions such as atopic dermatitis, psoriasis and acnes with median diagnostic accuracy of 89-94%. Automated scoring has a high correlation with expert scoring in the severity assessment, which allows objective and reliable measurement of the disease. In drug discovery, AI systems have shortened the time to candidate identification by years to months with the first AI-based dermatology therapeutics in clinical trials via technology company-pharmaceutical leader partnerships. The Imperative of Crossing the Translational Gap. Although these technical successes have been achieved, there remains a critical issue between the development of algorithms and clinical practice. There are a small number of systems that are cleared by the regulators and even smaller that have become part of standard practice. Such a disconnection is symptomatic of severe inadequacies: training datasets are not diverse, validation is focused on technical measures, rather than patient outcomes, and regulatory frameworks are outpaced by technical capabilities. Skin of color patients continue to be underrepresented, which only contributes to health care disparities and not eliminates them. It is up to all the stakeholders to pull together in order to bridge this gap. Scientists need to focus on different datasets creation and clinical meaningful validation. Clinicians have to be involved in the development and implementation science of AI tools. Regulators have to establish dynamic channels of ongoing learning systems and remain safe and fair. Industry has to invest on strict clinical testing and fair implementation process. The long-term vision is the AI-enabled precision dermatology systems that combine multimodal information to provide customized diagnosis, choice of treatment and monitoring of each patient, however, skin type or geographic location. This vision will be possible only with the long-term effort to ensure a commitment to translational research that changes technical capability into quantifiable patient benefit.

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