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Artificial Intelligence in Skin Care Medical Education: Current Status, Challenges and Future Perspectives

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Abstract: Skincare education serves two connected audiences: patients and the general public, and medical students and aesthetic practitioners. Conventional teaching in both areas remains constrained—resources are unevenly distributed, consultation time is short, and content is largely one-size-fits-all—so it struggles to meet the growing demand for personalized, accessible skin-health guidance and standardized professional training. Recent progress in computer vision, large language models, multimodal generative AI, and immersive virtual reality has moved AI to the center of this field. For the public, AI tools provide visual assessment of skin conditions, round-the-clock personalized advice, plain-language explanations of ingredients, automated educational content, and continuous follow-up, making evidence-based knowledge far more reachable. For trainees, these technologies enable image-based diagnostic practice, learning paths for individual progress, risk-free virtual simulation, and automatically generated teaching materials, which relieves the shortage of quality clinical resources. However, AI still faces five obstacles in skin care practice: algorithmic bias that makes performance uneven across different skin types; hallucinated or fabricated output from generative models; overreliance on images without clinical information; biometric privacy risks; and content skewed by commercial interests. Future efforts should focus on four priorities—building datasets that represent all skin types and demographic groups, embedding clinician supervision into content workflows, fusing multi-source real-world data into scenario-based learning, and strengthening regulation. Used as a supervised adjunct rather than a replacement, AI can make skincare education more accessible, fairer, and more efficient through a sustainable human-machine partnership.

Keywords: artificial intelligence; skin care education; patient health education; dermatology medical education; large language models; virtual simulation teaching

1. Introduction

Skin diseases have a high prevalence in China. Acne vulgaris affects more than 40% of adolescents, and more than 36% of adult women report sensitive skin, which indicates a steadily growing demand for evidence-

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based dermatological information for public [1, 2]. Uneven distribution of dermatology specialists persists nationwide, and skin health educational materials for the general public remain notably scarce. Constrained by geographical limits and scheduling burdens, conventional public-health approaches fail to meets growing public demands of individualized, ongoing health education.

Dermatology is fundamentally a visual specialty. The essence of professional training lies in identifying lesions and becoming proficient in clinical skills. Traditional instructional methods, nevertheless, encounter practical hindrances. Clinical case assets are distributed unequally, educational materials for uncommon dermatological conditions are in short supply, and hands-on experience is restricted by ethical considerations, which leads to a compromise in training effectiveness and standardization [3].

Recent progress in computer vision, natural language processing and immersive technology has enabled artificial intelligence to find growing uses across multiple healthcare settings. Visual information is essential in dermatology, which is particularly well suited for AI integration. AI-assisted visual recognition has made remarkable progress in the field of dermatology. A research conducted in 2017 demonstrated that deep learning models can classify skin lesions with equal accuracy compared to certified dermatologists. This pivotal finding has driven steady expansion of AI applications in dermatology. Beyond traditional diagnostic support, AI tools are also applied to public health education and clinical training, providing new technical opportunities to digitize and individualize skin health education [4–6].

The explosive growth of generative AI and large language models (LLMs) since 2023 offered new possibilities for skin care education, including patient counseling to automated teaching material production [7, 8]. Based on current technological advances and research, this review systematically summarizes the application scenarios of AI in public skin care education and professional training, analyzes the limitations and potential risks of current practices, and discusses optimization directions for future development, so as to provide reference for the standardized and high-quality integration of AI into skin care education.

2. AI Applications in Public Skin Care and Patient Education

Public skin care education aims to share evidence-based health information, correct common skin care misconceptions among the public, and help people build up their ability to care for their own skin. Using interactive, visual and personalized technical features, AI breaks through the time and location limits of traditional popular science efforts, and solves the problem of generic, one-size-fits-all content, making it possible to deliver skin health guidance tailored to the specific needs of different groups of people.

2.1. AI Skin Image Assessment: Visualized Self-Health Education

AI skin image detection technology built on convolutional neural networks (CNNs) represents the most widely adopted AI modality in public skin health education. By capturing facial skin images via built-in smartphone cameras or portable multispectral imaging devices, the algorithm automatically identifies and quantitatively evaluates common skin concerns including seborrhea, stratum corneum barrier impairment, erythema and sensitivity, hyperpigmentation, enlarged pores and fine lines, translating abstract skin physiological states into visualized, data-rich assessment reports [9].

Unlike text-based popular science resources, image-driven assessments are much easier for everyday users to understand and engage with. Individuals can intuitively map their own skin features to the report, establish a scientific understanding of their skin status, and correct prevalent skincare misconceptions such as trend-driven product selection, excessive exfoliation, uncontrolled chemical peeling and overuse of high-potency active ingredients, thus serving as an intuitive entry point for self-directed health education.

International evidence has confirmed that deep learning models trained on high-quality datasets can achieve equal accuracy compared to certified dermatologists in classifying benign and malignant skin lesions [10]. For consumer-facing skin care AI tools, although they do not have diagnostic authority, they demonstrate acceptable reliability in recognizing and grading physiological skin conditions, and can serve as a reference for daily care. Randomized trials have shown that mobile skin-care applications providing personalized visual feedback can significantly improve users' skin-protection behavior, which indicates a educational potential of these tools [11, 12]. Importantly, these AI-based educational tools are designed solely for public science education and general health reference, rather than formal clinical diagnosis. For individuals with suspicious cutaneous manifestations, including erythema, papules, blisters and other pathological skin lesions, professional medical institutions is strongly recommended to prevent delayed treatment.

2.2. Conversational Education via Large Language Models: Personalized Q&A and Health Counseling

Chatbots driven by large language models (LLMs) have provided skin health promotion with a novel interactive format. Since they combine natural-language interfaces with extensive knowledge bases, they are able to process queries of common skin conditions, such as acne vulgaris, rosacea, eczema, atopic dermatitis, and sensitive skin. The responses are suitable for individuals: relying on users self-reported symptoms, regional climate, way of life, and skin category, they guide individuals through disease mechanisms, triggering factors, daily skincare regimens, and precautions for topical drugs in simple, common language.

Compared to the typical 3-5 minutes for patient education in regular outpatient consultations, conversational AI enables repeated and thorough inquiries, offers tailored responses to individual issues, and effectively makes up for the restricted communication time in clinical environments [13]. For long-term skin conditions like hormone-dependent skin inflammation and atopic skin inflammation, AI has the ability to guide patients in identifying initial recurrence signs and acquiring standardized home-care procedures. It boosts treatment compliance via persistent knowledge reinforcement.

Recent benchmark research has shown that the latest LLMs are capable of producing precise, legible answers to typical dermatologic patient-education queries, and their performance is close to that of content written by dermatologists [14]. Domain-specific fine-tuning of LLMs on standardized dermatology guidelines and patient education corpora has been shown to improve answer accuracy and reduce hallucination compared with general-purpose models, making them more suitable for patient-facing education [15]. Image-feedback-based mobile interventions have demonstrated measurable educational effects on skin-care behavior. In a cluster-randomized clinical trial of 1,573 adolescents, a face-aging mobile app intervention increased daily sunscreen use from 15.0% to 22.9% ($P<0.001$) and skin self-examination from 25.1% to 49.4% ($P<0.001$) at 6 months, while reducing tanning sessions from 18.8% to 15.2% ($P=0.04$) [11]. These findings support the high application value of LLMs in grassroots health education and home-based disease self-management.

2.3. Intelligent Skincare Ingredient Analysis: Education for Rational Product Selection

Inappropriate skincare product selection is a leading contributor to skin barrier damage, sensitive skin exacerbation and allergic contact dermatitis. AI systems can be integrated with authoritative cosmetic ingredient databases (such as the *International Nomenclature of Cosmetic Ingredients*, INCI), and perform intelligent analysis of full product ingredient lists through natural language processing and efficacy prediction algorithms [16]. They interpret the core efficacy, irritation potential, sensitization risk and formulation incompatibility of each ingredient, helping users distinguish marketing rhetoric from evidence-based effects and establish a scientific "ingredient–efficacy–skin type" matching logic for product selection.

Once users enter their skin profile, the system screens for suitable ingredient categories and flags components that are likely to irritate, which makes users easier to select suitable skincare productions. Moreover, AI systems can also makes exaggerated product claims easier to recognize, and abuse of high-concentration active formulations becomes less likely to occur, which reduce the risk of skin barrier damage and contact dermatitis [17]. Moreover, the ingredient-analysis process functions as a form of rational skincare education. By making full ingredient lists transparent and interpretable, the ingredient-analysis process can progressively improve public skincare literacy and shift consumer decision-making from marketing-driven to ingredient-driven [16].

2.4. Multimodal Generative Content: Lowering Knowledge Comprehension Thresholds

The multimodal generation capability of generative AI has greatly enriched the content formats for skin health education. Based on specific educational themes, AI can automatically produce multimedia content including schematic diagrams of skin physiological structures, animations of disease progression, and short videos demonstrating proper skincare maneuvers, which significantly lower the threshold for knowledge acquisition.

AI-generated content can further enhance public dermatological education. For instance, three-dimensional (3D) reconstructions of the stratum corneum's structure allow dynamic visualization of the sequence of epidermal barrier damage and repair, helping the public intuitively understand the rationale for moisturization and barrier restoration. As for photoprotection, AI can illustrate the differential penetration and damage mechanisms of UVA and UVB across the epidermal and dermal layers, which may effectively strengthen public awareness of sun protection.

Such visual content adapts well to the communication characteristics of short-video and social media platforms. With low production cost and high output efficiency, it enables mass production of specific science materials and alleviates the shortage of health education content supply. Research has shown that visual popular science content achieves significantly higher knowledge retention than text-only content, and offers notable advantages in improving communication efficacy and public acceptance. The latest text-to-video generative AI can further produce standardized educational short videos in groups, which increases content output efficiency. Dermatology-related accounts have already leveraged such tools extensively on short-video platforms [18].

2.5. Longitudinal Follow-Up: Sustained Health Education

Skin self-management is a sustained, long-term process that evolves continuously. Single-session health education is usually insufficient to prevent users from relapsing into their old habits. AI-powered platforms can help solve this problem. They let users take skin photos routinely and store these records over time. Algorithms track how skin features evolve by comparing serial images, and time-series data can tell whether a patient's skin is getting better or worse. The platforms can also send custom care notifications based on seasons and surrounding environmental conditions. For example, sun-safety reminders pop up more often during high-UV summer months. When autumn and winter bring dry air, the advice shifts toward skin-barrier repair and moisturizing routines. People with chronic skin conditions gain extra support from periodic home-care tips and follow-up notifications. In this way, health education can be extended beyond scheduled outpatient visits and adjusted to each user's real-life circumstances. This follow-up procedure embeds educational content within users' day-to-day skin-care practices. It routinely sends out notifications and review key knowledge based on the spacing-effect learning principle. This approach helps users develop durable, evidence-based skin-care habits. It also relieve two common limitations of single-session educational interventions: rapid memory decay and restricted transfer of behaviours to real-world settings. Among people suffering from chronic skin disease such as acne and rosacea, continuous AI-supported follow-up may improve patients' ability to manage their condition and reduce relapse risk. It indicates that structured educational input combined with reminder-based support can obtain concrete improvements in patients' adherence to topical treatment [19].

3. AI Applications in Professional Dermatology and Aesthetic Education

For medical students, dermatology residents and clinicians engaged in aesthetic practice, competence-building focus three main goals: accurate identification of skin lesions, development of robust clinical reasoning skills, and mastery of hands-on procedural skills. AI tools can improve specialist training by building knowledge bases, offering skill-practice opportunities, and expanding access to teaching materials. These benefits help reduce the inequalities caused by unevenly distributed clinical teaching resources.

3.1. Image-Assisted Teaching: Enhancing Lesion Recognition and Differential Diagnosis

Morphological recognition of skin lesions is the foundational capacity for dermatology professionals. Traditional teaching relies on limited images and clinical cases, which are not able to guarantee sufficient reading practice and case diversity for students. By integrating massive clinical photographs, dermoscopy images and pathological data, AI builds a large-scale teaching case database and provides abundant reading training resources.

To overcome the scarcity of teaching materials for rare dermatoses, generative diffusion models have been increasingly used to synthesize photorealistic skin lesion images, expanding the availability of rare-case teaching resources and supporting differential diagnosis training. Multimodal LLMs can further enrich image-based teaching by automatically generating structured medical records, differential diagnosis tables, and pathophysiological explanations alongside each lesion image, forming self-contained, interactive learning units [20]. Moreover, AI-assisted image-reading training improves students' recognition of basic lesion morphologies and may accelerate the development of clinical reasoning competence [21].

3.2. Adaptive Learning: Customized Professional Competency Development

Traditional unified-progress teaching fails to accommodate students with different knowledge bases. Adaptive learning represents a core advantage of AI-enabled education. Machine learning algorithms track learning behavioral data, analyze error patterns, identify knowledge blind spots, construct individual competency profiles, and deliver targeted exercises, cases and learning materials to customize personalized learning pathways.

Unlike one-size-fits-all education programs, data-driven adaptive learning adapts instruction to individual learners, precisely addressing competency gaps and demonstrably enhancing learning efficiency and training quality. Such systems are especially valuable in dermatology, where standardized residency training and continuing medical education must accommodate wide variability in students' baseline competencies [22].

3.3. Virtual Simulation Practical Training: Low-Risk Skill Development

Clinical skills are vital competencies for aesthetic doctors and dermatologists. Traditional hands-on training on real patients or models faces high ethical risks. Integrated with virtual reality (VR), augmented reality (AR) and physical simulation technology, AI builds highly immersive procedure simulation scenarios covering basic skincare, chemical peeling, preoperative evaluation of energy-based therapy, skin biopsy and other scenarios. Students can repeatedly practice procedural workflows, master operation standards, and learn to identify risks and manage complications without bearing the ethic risk of real clinical operations.

The latest AI-integrated VR systems incorporate real-time motion tracking and haptic feedback, providing immediate corrective feedback on students' operation angle, intensity, and duration, thereby significantly shorten the process of skill acquisition [23]. Virtual simulation tools have three strengths: they are repeatable, highly standardised, and raise no ethical concerns. For these reasons, they work as a helpful add-on to clinical instruction. Students can build acquaintance with standard protocols and strengthen their awareness of safety hazards before they carry out real-world clinical work [24].

3.4. Intelligent Teaching Material Generation: Improving Teaching Resource Supply

High-quality teaching materials are fundamental to successful clinical training. However, developing conventional educational materials consistently related to heavy time and workload burdens on clinical faculty. Based on course objectives, teaching syllabi, and the target students, LLMs can quickly produce case discussion questions, PPT lecture scripts, standardized patient-education documents, and exam items. Thus, teachers are relieved of heavy lesson-preparation workloads, and devote their energy to interactive teaching and clinical supervision.

AI can also reorganize existing materials, breaking knowledge points into a structured teaching knowledge base that supports quick retrieval, associative exploration, tiered instruction, and self-study [5]. However, automatically generated teaching content is not always factually reliable, so professional teachers should review and revise it before classroom use to keep it clinically accurate and standardized [8].

4. Current Limitations and Potential Risks

The technical limits of today's AI systems inevitably color what they can teach. Most training datasets for skin images are built predominantly from light-skinned subjects, so algorithm performance drops noticeably on darker skin—for conditions such as post-inflammatory hyperpigmentation and hidradenitis suppurativa, recognition accuracy falls sharply [25]. The consequences are twofold: the public receives assessments and advice that may be wrong, and trainees are left with gaps in their grasp of lesion morphology across skin tones, which weakens the all-around clinical judgment they need to develop.

LLMs, for their part, can "hallucinate": they may deliver advice that sounds perfectly authoritative but is clinically off-base, especially for complex dermatoses and for vulnerable groups such as pregnant women, children, and immunocompromised patients [26]. Compounding this, most AI education tools look only at images and never ask about onset triggers, medical history, or allergies. The resulting advice stays shallow, glosses over genuinely complicated cases, and can mislead both lay users and learners.

On the commercial side, two problems intertwine: privacy and the commodification of science communication. Facial images carry both biometric and health data, and when storage, transmission, and usage controls are lax—as they often are, to varying degrees, across commercial tools — leakage and misuse become real risks, and public confidence erodes [27]. Some apps meanwhile use "free skin testing" or "science Q&A" as bait, tying these entrances to cosmetic sales and exaggerating how severe users' skin problems are in order to push partner products. Content shaped this way drives consumers toward irrational purchases, can worsen skin damage, and chips away at both the public-good nature and professional credibility of skin health education.

5. Future Directions

In light of these problems, future work should be steered by three principles—standardization, equity, and security—and advance on four fronts: data governance, collaboration mechanisms, technology integration, and regulation.

5.1. Building Balanced, Standardized, Population-Specific Skin Datasets

Fixing algorithmic bias has to start at the data source. Multi-center collaboration across regions and ethnic groups is needed to assemble standardized skin-image collections that cover a wide range of skin tones, ages, and ethnicities, with rare diseases and special populations given priority. For China specifically, a dedicated skin-image database should be built first, one that draws on different regions, skin types, and disease categories [28]. Uniform imaging and annotation protocols will keep data consistent, curb bias, and raise accuracy across populations. Federated learning and similar privacy-preserving approaches allow many institutions to train together without exchanging raw data, so datasets grow richer without compromising privacy.

5.2. Implementing Clinician-in-the-Loop Collaborative Education

AI's place in skincare education should be that of an assistant, nothing more. Content production should run as a closed loop—AI drafts, specialists review and calibrate, and the model is updated from the feedback—and every piece of popular-science or teaching content should pass specialist review before release, keeping hallucination in check and clinical accuracy intact [26]. Labor can then be divided by complexity: AI handles routine questions and standardized instruction, while specialists take on difficult cases, design the core curriculum, and oversee quality. In this human–machine model, AI buys efficiency and clinicians guarantee standards [26]. For dermatology-specific LLMs, continuous fine-tuning on clinician feedback can keep shrinking hallucination rates and firming up content reliability.

5.3. Expanding Scenario-Based Education through Multi-Source Data Fusion

Education should also stop leaning on single images. Fusing wearable and environmental inputs—UV intensity, humidity, ambient temperature—with a user's skin condition, lifestyle, and care routines would yield a far fuller skin-health profile [29]. From such multi-dimensional data, guidance can be tailored: outdoor workers get high-protection regimens, people in dry, cold climates get barrier-repair advice, and the sleep-deprived get reminders about inflammation control. The result is a dynamic, continuous learning system that follows users across all life situations.

5.4. Improving Regulation and Clarifying Product Boundaries

None of this will hold together without a solid regulatory base. Specifications for AI skincare education products need to be drafted sooner rather than later: popular-science tools must be clearly separated from medical diagnostic AI, non-medical tools must be barred from issuing diagnostic conclusions, and covert illegal practice has to be pursued. Commercial tools should be supervised so that educational and marketing content stay apart, product placement is controlled, and false advertising disguised as science communication is punished. Data-security and privacy rules likewise need tightening, forcing companies to safeguard users' biometric and health information [28].

6. Conclusion

Artificial intelligence has clearly sped up the digital transformation of skincare education and proved its worth on both fronts. The public now absorbs skin-health knowledge more readily, and scientific skincare literacy along with self-care ability have visibly risen. Professional training benefits too: AI offsets the resource shortages of conventional teaching and makes talent cultivation more efficient and more individualized.

None of this changes the fact that today's AI remains bounded by algorithmic bias, hallucination, incomplete information, privacy concerns, and commercial slant. Its technical limits are such that it can never take over the educational role and core value of human professionals. Accordingly, future directions of AI in skin care field should adhere to the principles of "assisted positioning, professional oversight, and standardized development." By improving dataset construction, optimising human-machine collaboration mechanisms, integrating multi-source data, and strengthening regulatory frameworks, AI can be deeply integrated into skincare education to build a safer, fairer, and more efficient human-machine collaborative education ecosystem, ultimately serving population skin health and the cultivation of high-quality professionals.

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References

1 Li Y, Hu T, Xia X, *et al*. Knowledge, Attitude, and Practice Toward Photoaging in the Chinese Population: a Cross-Sectional Study. *Scientific Reports* 2024; **14**(**1**): 5196. https://doi.org/10.1038/s41598-024-55691-5.

2 Li D, Chen Q, Liu Y, *et al*. The Prevalence of Acne in Mainland China: a Systematic Review and Meta-Analysis. *BMJ Open* 2017; **7**(**4**): e015354. https://doi.org/10.1136/bmjopen-2016-015354.

3 Hansra NK, O'Sullivan P, Chen CL, *et al*. Medical School Dermatology Curriculum: Are We Adequately Preparing Primary Care Physicians? *Journal of the American Academy of Dermatology* 2009; **61**(**1**): 23–29. e1. https://doi.org/10.1016/j.jaad.2008.11.912.

4 Esteva A, Kuprel B, Novoa RA, *et al*. Dermatologist-Level Classification of Skin Cancer with Deep Neural Networks. *Nature* 2017; **542**: 115–118. https://doi.org/10.1038/nature21056.

5 Chan KS, Zary N. Applications and Challenges of Implementing Artificial Intelligence in Medical Education: Integrative Review. *JMIR Medical Education* 2019; **5**(**1**): e13930. https://doi.org/10.2196/13930.

6 Chen R, Zhang Y, Choi S, *et al*. The Chatbots Are Coming: Risks and Benefits of Consumer-Facing Artificial Intelligence in Clinical Dermatology. *Journal of the American Academy of Dermatology* 2023; **89** (**4**): 872–874. https://doi.org/10.1016/j.jaad.2023.05.088.

7 Yang R, Tan TF, Lu W, *et al*. Large Language Models in Health Care: Development, Applications, and Challenges. *Health Care Science* 2023; **2**(**4**):255–263. https://doi.org/10.1002/hcs2.61.

8 Lewandowski M, Kropidłowska J, Kvinen A, *et al*. A Systemic Review of Large Language Models and Their Implications in Dermatology. *Australasian Journal of Dermatology* 2025; **66**(**4**): e202–e208. https://doi.org/10.1111/ajd.14484.

9 Lim ZV, Akram F, Ngo CP, *et al*. Automated Grading of Acne Vulgaris by Deep Learning with Convolutional Neural Networks. *Skin Research and Technology* 2020; **26**(**2**): 187–192. https://doi.org/10.1111/srt.12794.

10 Han SS, Kim MS, Lim W, *et al*. Classification of the Clinical Images for Benign and Malignant Cutaneous Tumors Using a Deep Learning Algorithm. *Journal of Investigative Dermatology* 2018; **138**(**7**):1529–1538. https://doi.org/10.1016/j.jid.2018.01.028.

11 Brinker TJ, Faria BL, De Faria OM, *et al*. Effect of a Face-Aging Mobile App–Based Intervention on Skin Cancer Protection Behavior in Secondary Schools in Brazil: A Cluster-Randomized Clinical Trial. *JAMA Dermatology* 2020; **156**(**7**): 737. https://doi.org/10.1001/jamadermatol.2020.0511.

12 Buller DB, Berwick M, Lantz K, *et al*. Smartphone Mobile Application Delivering Personalized, Real-Time Sun Protection Advice: A Randomized Clinical Trial. *JAMA Dermatology* 2015; **151**(**5**): 497–504. https://doi.org/10.1001/jamadermatol.2014.3889.

13 Zhang Y, Chen R, Nguyen D, *et al*. Assessing the Ability of an Artificial Intelligence Chatbot to Translate Dermatopathology Reports into Patient-Friendly Language: A Cross-Sectional Study. *Journal of the American Academy of Dermatology* 2024; **90**(**2**): 397–399. https://doi.org/10.1016/j.jaad.2023.09.072.

14 Kamminga NCW, Kievits JEC, Plaisier PW, *et al*. Do Large Language Model Chatbots Perform Better Than Established Patient Information Resources in Answering Patient Questions? *A Comparative Study on Melanoma. British Journal of Dermatology* 2025; **192**(**2**):306–315. https://doi.org/10.1093/bjd/ljae377.

15 Mantena S, Johnson A, Oppezzo M, *et al*. Fine-Tuning LLMs in Behavioral Psychology for Scalable Health Coaching. *npj Cardiovascular Health* 2025; **2**(**1**): 48. https://doi.org/10.1038/s44325-025-00083-5.

16 Bennike NH, Oturai NB, Müller S, *et al*. Fragrance Contact Allergens in 5588 Cosmetic Products Identified Through a Novel Smartphone Application. *Journal of the European Academy of Dermatology and Venereology* 2018; **32**(**1**):79–85. https://doi.org/10.1111/jdv.14513.

17 Ananthapadmanabhan KP, Mukherjee S, Chandar P. Stratum Corneum Fatty Acids: Their Critical Role in Preserving Barrier Integrity During Cleansing. *International Journal of Cosmetic Science* 2013; **35**(**4**): 337–345. https://doi.org/10.1111/ics.12042.

18 Campbell J, Williams K, Woolery-Lloyd H. DermTok: How TikTok Is Changing the Landscape of Dermatology Patient Education. *Journal of Drugs in Dermatology* 2023; **22**(**3**): 302–304. https://doi.org/10.

36849/JDD.6676.

19 Svendsen MT, Feldmann S, Tiedemann SN, *et al*. Improving Psoriasis Patients' Adherence to Topical Drugs: a Systematic Review. *Journal of Dermatological Treatment* 2020; **31**(**8**): 776–785. https://doi.org/10.1080/09546634.2019.1623371.

20 Goktas P, Gulseren D, Tobin AM. Large Language and Vision Assistant in Dermatology: a Game Changer or Just Hype? *Clinical and Experimental Dermatology* 2024; **49**(**8**): 783–792. https://doi.org/10.1093/ced/llae119.

21 Donoso F, Peirano D, Longo C, *et al*. Gamified Learning in Dermatology and Dermoscopy Education: a Paradigm Shift. *Clinical and Experimental Dermatology* 2023; **48**(**9**): 962–967. https://doi.org/10.1093/ced/llad177.

22 Mangion SE, Phan TA, Zagarella S, *et al*. Medical School Dermatology Education: a Scoping Review. *Clinical and Experimental Dermatology* 2023; **48**(**6**): 648–659. https://doi.org/10.1093/ced/llad052.

23 Mao RQ, Lan L, Kay J, *et al*. Immersive Virtual Reality for Surgical Training: A Systematic Review. *Journal of Surgical Research* 2021; **268**: 40–58. https://doi.org/10.1016/j.jss.2021.06.045.

24 Gladstone HB, Raugi GJ, Berg D, *et al*. Virtual Reality for Dermatologic Surgery: Virtually a Reality in the 21st Century. *Journal of the American Academy of Dermatology* 2000; **42**(**1**): 106–112. https://doi.org/10.1016/S0190-9622(00)90017-3.

25 Nasir M, Tahir MZ, Zhou SK. Reducing Skin Tone Bias in Dermatology AI Via Sketch-Guided Multimodal Fusion. *Scientific Reports* 2026. https://doi.org/10.1038/s41598-026-59316-x.

26 Omiye JA, Gui H, Rezaei SJ, *et al*. Large Language Models in Medicine: The Potentials and Pitfalls: A Narrative Review. *Annals of Internal Medicine* 2024; **177**(**2**): 210–220. https://doi.org/10.7326/M23-2772.

27 Kounidas G, Cleer I, Harriss E, *et al*. Usability Evaluation and Reporting for Mobile Health Apps Targeting Patients with Skin Diseases: a Systematic Review. *Clinical and Experimental Dermatology* 2025; **50**(**2**): 387–394. https://doi.org/10.1093/ced/llae378.

28 Sangers TE, Kittler H, Blum A, *et al*. Position Statement of the EADV Artificial Intelligence (AI) Task Force on AI-Assisted Smartphone Apps and Web-Based Services for Skin Disease. *Journal of the European Academy of Dermatology and Venereology* 2024; **38**(**1**): 22–30. https://doi.org/10.1111/jdv.19521.

29 Huang X, Chalmers AN. Review of Wearable and Portable Sensors for Monitoring Personal Solar UV Exposure. *Annals of Biomedical Engineering* 2021; **49**(**3**): 964–978. https://doi.org/10.1007/s10439-020-02710-x.