

The Current State and Future Prospects for Artificial Intelligence in Dermatology



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KEYWORDS

- Artificial intelligence • Machine learning • Deep learning • Medical dermatology
- Dermatopathology • Artificial intelligence for health care • Artificial intelligence for dermatology

KEY POINTS

- Artificial intelligence (AI) can assist diagnostics in dermatology by enhancing the imaging and surveillance of skin diseases in total body photography and dermoscopy.
- With recent advances in machine learning models, AI tools can augment histopathologic analyses of digital whole slide images of skin tissue for lesion identification and diagnosis.
- AI can enable precision medicine in dermatology by the multimodal integration of patient data to guide disease prognostication and treatment selection.
- Generative AI can predict and synthesize visual reference images of skin diseases, enabling disease progression tracking, refined clinical decision-making, and improved patient comprehension.
- AI can optimize health care operations in dermatology using ambient scribing, dermatology-specific large language models, and agentic AI chatbots for patient communication.

INTRODUCTION

With recent advances in deep learning (DL), the potential for artificial intelligence (AI) applications in medicine has exponentially increased.¹ Dermatology is a specialty that primarily operates on visual observation, making the field a promising area where AI tools can potentially enhance patient skin examinations in the clinic.² Additionally, pathologists and dermatopathologists can use AI-based tools to evaluate digitized images of patient skin tissue.³ Within the sphere of AI, machine learning (ML) models are increasingly being developed and updated to assist clinicians in decision-

making, enhance diagnostic and prognostic capabilities, and improve clinical operations. In this article, we will explore multiple applications of AI in dermatology and exciting areas for future implementation that can optimize patient-care and reduce clinical administrative burden. **Table 1** lists several key concepts in ML that will be discussed.

SECTION 1: DIAGNOSTICS

With the reliance on visual evaluation in both clinical and pathologic examination, dermatology stands to benefit considerably from leveraging AI models to improve the diagnostic process. In this

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Abbreviations

AI	artificial intelligence
AUC	area under the curve
BCC	basal cell carcinoma
CNN	convolutional neural network
Cycle-GANs	cycle-consistent generative adversarial network
DL	deep learning
EHR	electronic health record
FL	federated learning
GAN	generative adversarial network
GEP	gene expression profiling
ICI	immune checkpoint inhibitor
irAE	immune-related adverse event
LLM	large language model
ML	machine learning
NLP	natural language processing
TBP	total body photography
WSI	whole slide image

portion of the article, we will focus on the application of AI to augment imaging to optimize medical diagnoses, specifically with the use of total body photography (TBP), dermoscopy, and histologic evaluation.

Digital Photography

TBP is an increasingly used form of digital photography in dermatology that records standardized whole-body photographs of patients over time for clinical surveillance. TBP software packages can incorporate AI models to optimize identification of new lesions, lesion classification, and lesion evolution.⁴ AI-based TBP has been used longitudinally to monitor the skin of patients with melanoma risk factors including a history of multiple dysplastic nevi; having greater than 50 nevi; and a family or personal history of melanoma.^{5,6} Other applications of TBP include monitoring non-melanocytic lesions, quantifying body surface area involved in a particular dermatosis, trichoscopy (evaluation of hair follicles), assessing skin contouring, documenting skin before and after procedures, and teledermatology for direct-to-patient and non-dermatology physician solutions.⁷⁻¹⁰ As such, AI-assisted TBP can assist in disease staging and the evaluation of therapeutic response for a broad range of dermatologic conditions.^{11,12} Thus far, the majority of AI-based TBP has been used to aid melanoma detection and diagnosis.¹³ In one study, 68.3% of dermatologists who employed neural network-based TBP image analysis in skin cancer screening of patients previously diagnosed with melanoma experienced greater confidence in diagnostic accuracy.¹⁴ AI-based TBP has also been employed in melanoma screening to quantify the total number of nevi of

differing sizes, which can be a time intensive process when done manually.^{15,16} These approaches can also take advantage of patient medical history to further improve the precision of risk modeling. For example, one recent implementation of TBP has incorporated both clinical and genetic meta-data to evaluate individual lesions and quantify patient risk.¹⁷

The advantages of AI-based TBP over other imaging modalities include the increased standardization of image intake, which reduces potential variation over time that may lead to decreased sensitivity and increases the likelihood of more accurately reproducible results.^{4,18} Specifically, TBP uses standardized positioning, lighting, and background to capture images,⁶ mitigating many potential obstacles for ML model development. Though currently used primarily in dermatology clinics, future TBP solutions may be embedded in non-dermatology settings, expanding access to dermatologic care as triaging tools for dermatology referrals (particularly in more remote and underserved settings). Moreover, 3-dimensional TBP, which incorporates dermoscopy to recreate a 3-dimensional rendering of the skin surface, is a promising application of TBP.¹⁹ Current limitations of TBP include device cost, inconsistent insurance reimbursement, time-consuming nature of performing image intake, and insufficient data to demonstrate utility across all body types and skin tones.^{4,13,20}

Dermoscopy

Dermoscopy is a technique that uses magnification and illumination to examine melanocytic lesions, diagnose non-melanoma skin cancers, and examine the hair and nails.¹⁹ Allowing for real-time magnification of the skin, dermoscopy can be combined with digital photography to track lesions over time,¹⁹ and such integration has allowed AI to be incorporated into this setting. In fact, convolutional neural networks (CNNs), AI models primarily used to analyze visual data for image processing, have been trained to determine the likelihood of melanoma and need for biopsy in dermoscopy images with a high level of accuracy.²¹ Due to this success in model development, AI-based tools have been suggested as adjunct tools for dermatologists when diagnosing clinically challenging pigmented lesions.²¹ However, CNNs may have limited diagnostic accuracy due to variation in image quality and lighting,²¹ and these models should be concurrently used by a board-certified dermatologist trained in dermoscopic evaluation. Additionally, CNN diagnostic capabilities for nail unit melanoma and mucosal melanoma from

Table 1
Definitions of key artificial intelligence methodologies

Category	Definition	Primary Use Cases
Machine Learning (ML)	An area of AI where algorithms learn patterns from data to make decisions without explicit instructions.	Diagnostic prediction, patient risk stratification, outcome prediction in dermatologic conditions.
Deep Learning (DL)	A subset of ML that uses artificial neural networks for complex data analysis.	Dermoscopic image analysis, lesion classification, skin disease diagnosis.
Convolutional Neural Network (CNN)	DL networks designed to analyze visual or spatial data.	Skin lesion detection, melanoma diagnosis, analysis of dermoscopic and clinical images.
Graph Neural Network (GNN)	DL networks designed to analyze graph-structured data.	Drug-target interactions, modeling molecular pathways, personalized dermatologic treatment planning.
Recurrent Neural Network (RNN)	DL networks specialized for sequential data processing, where outputs depend on prior inputs.	Predicting chronic dermatologic disease progression, patient monitoring over time.
Generative Adversarial Networks (GANs)	Generative DL networks that train two opposing networks for synthetic data creation.	Generating synthetic dermatologic images for data augmentation and educational purposes.
Generative AI	AI models capable of generating novel content by learning data patterns.	Personalized patient education materials, clinical decision support, generating dermatologic reports.
Contrastive Learning	ML approach that learns to differentiate between similar and dissimilar data.	Enhancing accuracy of dermatologic image analysis, improving diagnostic precision in skin diseases.
Federated Learning	Decentralized ML approach where models are collaboratively trained across data from multiple institutions.	Multicenter dermatologic research, ensuring patient data privacy during model training.

dermoscopic photographs has been shown to have a lower accuracy than when used to diagnose cutaneous melanoma (including glabrous skin).²¹ Furthermore, AI-based dermoscopy has been explored beyond the assessment of pigmented lesions.²² For example, Reddy and colleagues trained a CNN model to discern between benign lesions, including nevi, cysts, warts, ulcers along with malignant lesions including melanomas, basal cell carcinomas (BCCs), and squamous cell carcinomas with an area under the curve (AUC) of 0.955.²² A key criticism of dermoscopy is that it requires dermatologist-level expertise for the interpretation of dermoscopic features. However, ML-aided solutions can provide diagnostic assistance to bridge the gap in expertise between dermatologists and less trained health care providers (including primary care physicians).²² Beyond use by primary care providers, other solutions, such as the War on Melanoma initiative from the Oregon Health and Science University, have piloted the use

of dermoscopic smartphone camera lens attachments that can be directly used by patients.²³ In the future, similar initiatives can integrate AI to improve patient image quality and assist in triaging suspicious lesions.

Dermatopathology

In addition to digital photography, AI has been applied with increasing frequency to the analysis of histopathologic images, aided by the increasingly routine digitization of pathology slides. The resulting availability of whole slide images (WSIs) has enabled development of numerous DL models within digital pathology. Though computer-aided diagnostic tools, including TEGUMENT,²⁴ have been available since the late 1980s²⁵ and have been used to develop histologic differential diagnoses based on a pathologist's observations, modern ML models can evaluate and interpret WSIs independently of a clinician.²⁵ Indeed, a

recent survey of pathologists who regularly diagnosed dermatologic conditions revealed very favorable attitudes toward AI model implementation in dermatopathology, particularly for quantifying mitotic figures (historically displaying significant variation among pathologists)²⁶; assessing tumor margins; and interpreting immunostains, which can be very challenging and tedious to evaluate for a human observer.²⁷ These models have been applied with increasing frequency to many dermatologic diagnoses. For example, a recent ML model was able to reach high-sensitivity and specificity in the histologic diagnosis of BCC and even distinguish between BCC subtypes, measure tumor thickness, and assess surgical margins.²⁸ Though there are unresolved legal concerns of solely relying on such models for histopathologic diagnosis,²⁹ ML models in digital pathology can also accelerate lesion diagnosis when used as a decision support tool by a pathologist.²⁸

Furthermore, though the diagnosis of melanocytic lesions can be challenging even to the most experienced dermatopathologist, ML models have been utilized in the histopathologic evaluation and diagnosis of melanocytic lesions.³⁰ For example, using a fast random forest algorithm, Cazzato and colleagues developed a model to detect melanoma pattern defects in hematoxylin and eosin-stained slides.³⁰ This approach was only 17% discordant from the dermatopathologist consensus, which is particularly impressive given the high inter-user and intra-user discordance within human pathologist evaluation of melanocytic lesions.³⁰ These results highlight that, although the accuracy of these models leave room for improvement (and are largely dependent on the subjectivity and reliability of the ground truth), they can be used as adjunct tools to provide an independent evaluation and human-machine consensus in challenging cases.³⁰ Limitations of ML algorithms in dermatopathology include the variation of staining and processing techniques between laboratories at different institutions, which may alter the accuracy of the model depending on the dataset on which it was trained.²⁸ Recent approaches to overcome these limitations include the development of more robust image pre-processing techniques, as well as training models on larger and more heterogeneous cohorts to improve external validity.³¹

SECTION 2: PROGNOSTICS

AI is transforming dermatology by improving prognostic accuracy and guiding therapeutic decisions. With the integration of imaging, genetic

data, and clinical insights, AI has the significant potential to provide opportunities to personalize care for patients with dermatologic conditions. In this portion of the article, we will explore AI-based innovations in dermatology that can personalize prognostics and therapeutics. We will discuss the benefits, limitations, and emerging trends within this rapidly evolving field.

Precision Medicine

In addition to augmenting the diagnostic process, AI can be leveraged to enable the promise of precision medicine through the improved prognostication of dermatologic conditions and the facilitation of treatment selection based on an integration of a wide range of clinical data, including molecular biomarkers and genomic information.³² Traditionally, prognostic models and clinician decisions have relied on staging systems that categorize disease severity based on static clinical and histopathologic features. However, these conventional approaches fail to account for individual patient variability, which significantly influences disease progression and therapeutic outcomes. AI offers a powerful solution by analyzing multidimensional patient data to dynamically refine risk assessments, predict disease trajectories, and personalize treatment recommendations.

Though real-time AI-driven prognostication is currently limited by dataset diversity, regulatory hurdles, and electronic health record (EHR) integration, these hurdles are likely to be resolved in the future through regulatory advancements, the development of large multi-institutional AI-ready cohorts, and the seamless integration of molecular registries into EHRs.

Deep Learning and Key Definitions

DL, a subset of ML, serves as the computational backbone of AI-driven precision medicine. It utilizes multilayered neural networks to analyze complex biomedical data, enable AI to identify patterns, refine risk assessments, and support clinical decision-making.³³

In dermatology, DL models, including CNNs for image analysis³⁴ and recurrent neural networks for temporal data analysis,³⁵ enhance diagnostic accuracy, prognostic predictions, and treatment selection. Advanced models like generative adversarial networks (GANs) further aid in synthetic image generation, augmenting training datasets for AI applications.³⁶ These diverse techniques allow for multimodal data integration, combining imaging, genetic profiles, and clinical insights to refine personalized medicine approaches (**Table 1**).

Multimodal Data Integration

With the use of AI-driven models, multimodal data integration is transforming the development of personalized medicine tools in dermatology. By synthesizing diverse data sources, multimodal AI techniques including enable the identification of complex patterns that would be difficult to detect through traditional methods.³⁷ This approach enhances diagnostic precision, refines risk stratification, and improves therapeutic decision-making, offering a more comprehensive, individualized understanding of disease progression and treatment response.³⁸

Melanoma has been the focus of notable, AI-based innovations in precision medicine. For example, ML algorithms have driven advancements in melanoma prognostication by synthesizing diverse datasets into actionable insights.³⁹ Wan and colleagues demonstrated the power of ML in predicting early-stage melanoma recurrence using clinical and histopathologic data.⁴⁰ The authors used Gradient Boosting models to achieve AUCs of 0.845 (internal) and 0.812 (external), and to identify key predictive features, such as Breslow thickness, mitotic rate, and social determinants (e.g., insurance type, median income).⁴⁰ These findings highlight the value of multimodal data in refining patient-specific risk stratification and informing targeted interventions, such as enhanced surveillance or adjuvant immunotherapy.⁴⁰ Additionally, Wei and colleagues combined digital photography, histopathologic data, and clinical information extracted from EHRs into a multimodal learning framework for enhancing diagnostic accuracy, improving patient outcomes, and assisting health care providers in making more informed-decisions regarding skin cancer treatments.⁴¹ The authors also demonstrated that integrating multiple data modalities improves the performance of AI-driven diagnostic models, leading to more precise and reliable skin cancer detection and classification.⁴¹ Such models improve recurrence predictions and stratification efforts, paving the way for personalized interventions.

Furthermore, the introduction of immune checkpoint inhibitor (ICI) therapy has revolutionized the management of advanced-stage (stage III – IV) melanoma,⁴² and ICIs have also recently been approved for the management of high-risk early-stage (stage IIB/IIC) melanoma.⁴³ However, these treatments are associated with a high burden of morbid and potentially life-threatening toxicities known as immune-related adverse events (irAEs), of which cutaneous irAEs are among the earliest and most common to occur.^{44–46} Moreover, not all patients with melanoma will experience disease

recurrence following surgical therapy,⁴⁰ and ICIs are only effective in approximately half of treated patients.⁴⁷ Given these nuances, the appropriate selection of melanoma patients for ICI therapy is necessary to ensure the most clinically and cost-effective therapeutic strategy,⁴⁸ which underscores the need for comprehensive decision support tools that AI can provide.^{49,50}

One such recent solution has been a multimodal AI model developed at New York University, which combines histopathologic images with clinical and demographic data to predict ICI response in metastatic melanoma.⁴⁹ This model achieved an impressive predictive accuracy, with AUCs ranging from 0.800 to 0.805, significantly outperforming traditional methods. Additionally, this pipeline applied DL algorithms to analyze histopathologic slides, extracting patterns indicative of immunotherapy response.⁴⁹ These features, when combined with clinical variables, such as age, sex, and disease stage, improve patient stratification. Notably, this approach relies on standard clinical data, eliminating the need for specialized imaging and making implementation more feasible.⁴⁹ Future refinements may incorporate additional biomarkers and immune profiling to further enhance predictive accuracy.

Gene expression profiling (GEP) is another molecular data modality that stands to benefit from multimodal integration. By analyzing the activity of thousands of genes simultaneously, GEP enables a deeper understanding of cellular function across different disease states. This approach has been particularly valuable in oncologic and inflammatory skin diseases, where molecular profiling enhances risk stratification and supports more individualized treatment strategies.⁵¹ The integration of AI and ML has considerably expanded the utility of GEP, allowing for more precise assessments of disease behavior and therapeutic outcome,⁵² though controversy remains about the most appropriate settings in which to implement these tools.⁵³ Traditional analytical methods often struggle to process the vast datasets generated by gene expression studies⁵⁴; however, AI-driven models can identify hidden patterns, correlations, and predictive biomarkers that would otherwise be missed. For example, the Deep Neural Network Integrating Prior Knowledge framework leverages self-supervised techniques to integrate gene interaction relationships, gene expression profiles, and molecular topology.⁵⁵ This approach has shown enhanced prediction accuracy and robustness for drug responses.⁵⁵

Beyond integrating genetic and histopathologic data, AI has significantly advanced EHR data

mining.⁵⁶ Text mining techniques using AI, such as large language models (LLMs) and natural language processing (NLP), are increasingly utilized to extract structured insights from unstructured clinical notes.⁵⁷ This includes therapeutic response assessment, where AI-driven text mining methods can dynamically retrieve clinically relevant metrics, such as body surface area for disease tracking, which are typically documented in EHRs but not routinely structured.⁵⁸ Thus, AI-assisted EHR mining supports both clinical decision-making and quality-of-care reporting, such as through the Medicare Incentive Payment Systems.⁵⁹ Afshar and colleagues developed an NLP DL model named Substance Misuse Algorithm for Referral to Treatment Using Artificial Intelligence for AI-driven text mining of EHRs to screen hospitalized patients in real time for opioid use disorder.⁶⁰ This system integrates unstructured clinical data from EHRs through AI-driven tools like the Clinical Text Analysis and Knowledge Extraction System to extract key medical concepts, which are then fed into a CNN model for prediction. Results are delivered to clinicians as actionable best practice alerts.⁶⁰ This system demonstrated high sensitivity and specificity during testing,⁶⁰ showcasing the transformative potential of AI-driven tools in augmenting clinical workflows. Importantly, the integration of these systems into routine care has been facilitated by cloud-based infrastructures and iterative design processes, although challenges like cybersecurity⁵⁶ and calibration drift remain.⁶¹ Therefore, the study by Afshar and colleagues exemplifies how real-time AI applications in EHR mining can enhance early detection and intervention strategies, paving the way for broader adoption across other clinical scenarios including those in dermatology.⁶⁰

Finally, the emergence of federated learning (FL) provides an opportunity to train and test AI solutions across institutions without the need for

centralized data storage, which has been a source of delay in developing AI innovations in health care due to the need for time-consuming cross-institutional data sharing agreements.^{62–64} This approach addresses privacy concerns and regulatory barriers, enabling institutions to collectively train AI models without sharing sensitive patient data.⁶⁵ A notable example is a study published in *JAMA Dermatology*, which utilized FL to classify invasive melanoma versus benign nevi across 6 hospitals.⁶² The federated model not only preserved patient privacy but also demonstrated superior generalizability to external datasets, achieving an area under the receiver operating characteristic curve (AUROC) of 0.91 compared to 0.90 for centralized model.⁶² These results underscore the potential of FL to democratize AI adoption, particularly in resource-limited settings where data-sharing barriers have historically hindered innovation.

In summary, multimodal data integration driven by AI technologies is transforming dermatology by enabling personalized therapeutic strategies and improving prognostic accuracy. By synthesizing diverse datasets including genetic information, imaging, biomarkers, and EHR data, AI-powered tools highlight the potential to optimize patient-care and streamline clinical workflows. These innovations not only enhance diagnostic precision but also reduce waste by directing costly treatments, such as ICIs, to patients most likely to benefit. With the rapid expansion in the availability of such tools, increasing efforts will be required to ensure their integration into EHRs to facilitate rapid and seamless clinical adoption.

Generative Artificial Intelligence

Generative AI is a subset of AI where models use advanced NLP to comprehend text and generate responses in specific formats by learning patterns

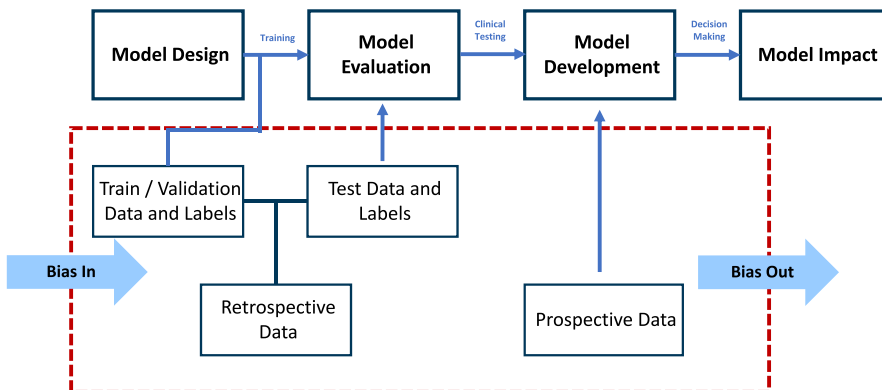


Fig. 1. Overview of AI model pipeline.

from data inputs (**Fig. 1**).^{66,67} These models excel in creating realistic and innovative outputs, making them valuable tools in health care for tasks, including simulating disease progression, modeling therapeutic responses, and generating personalized treatment plans. Within dermatology, generative AI holds the potential to revolutionize care by enabling advanced predictive modeling, synthesizing multimodal data, and even generating visual representations of disease states for training and diagnostics.

One of the most compelling applications of generative AI in dermatology is its ability to stimulate disease progression visually using cycle-consistent GANs (Cycle-GANs).⁶⁸ These models can generate potential future presentations of lesions based on their initial dermoscopic images.⁶⁹ Jütte and colleagues have demonstrated how Cycle-GANs can be leveraged to depict the evolution of melanoma from benign nevi to malignant states, creating synthetic images that reflect patterns of disease transformation.⁶⁸ These simulations can enhance both clinician training, offering dynamic visual aids to improve diagnostic accuracy, and patient education, illustrating how key changes including increased asymmetry or pigmentation dispersion signify malignant transformation. These visualizations also enhance the asymmetry (A), border (B), color (C), diameter (D), and evolution (E) (ABCDE) framework for melanoma evaluation,⁶⁸ quantifying lesion evolution in ways that could refine diagnostic criteria and improve early detection strategies. While the results highlight the transformative potential of generative AI, challenges remain, including artifacts in the generated images and the need for real-world validation through dermatologist feedback and longitudinal studies.⁶⁸

SkinGPT-4,⁷⁰ introduced by Juexiao Zhou and colleagues, integrates generative AI into dermatologic diagnostics. By analyzing skin images, this model provides actionable insights and treatment recommendations, with a focus on expanding accessibility to underserved regions. SkinGPT-4 represents a paradigm shift toward democratized dermatologic care, illustrating generative AI's role in breaking geographic and resource barriers. Its interactive interface also offers potential for remote diagnostic support, reducing reliance on in-person consultations while maintaining diagnostic accuracy.⁷⁰ However, limitations, such as potential biases in training data and reliance on internet connectivity, must be addressed to ensure equitable access and effective implementation.

Lastly, SkinGEN⁷¹ represents a groundbreaking framework designed to enhance diagnostic transparency and trust through visual explanations.

By leveraging vision-language models and advanced generative techniques, SkinGEN produces synthetic reference images that align with diagnostic outputs, offering clinicians and patients a clearer understanding of AI-driven recommendations.⁷¹ This innovative approach bridges the gap between complex AI models and end-users, fostering improved diagnostic confidence and patient engagement during consultations. By providing visually intuitive outputs, SkinGEN not only supports clinician decision-making but also empowers patients to better comprehend their diagnoses and treatment options. Nevertheless, challenges persist, particularly in ensuring the accuracy and fidelity of generated images, especially when dealing with rare or atypical dermatologic presentations. Future refinements, such as expanding diverse datasets and refining generative algorithms, are critical for broadening its clinical applicability.

Limitations and Challenges

The integration of diverse data types is essential for enhancing diagnostic accuracy and personalized treatment outcomes.⁷² Despite the recent advances described earlier, challenges remain, including biases in training datasets (see **Fig. 1**), ensuring equitable access to AI-driven tools, and addressing issues of scalability and patient privacy.^{56,73-75} The complexity of integrating large, heterogeneous datasets, the need for large-scale validation studies, and the potential for algorithmic bias highlight the necessity for continued research and refinement before multimodal AI frameworks become commonplace in clinical practice.⁷⁶

Anticipated challenges include regulatory barriers in adopting AI-driven tools and balancing innovation with cost-effectiveness and clinical utility. However, the cost-efficiency and resource optimization offered by these systems underscore their transformative potential in an increasingly resource constrained health care environment. Future developments, such as FL and the inclusion of molecular biomarkers, promise to refine predictive accuracy and broaden the impact of these tools. As AI continues to evolve, multimodal data integration is poised to advance equitable, efficient, and highly personalized care in dermatology and beyond.

SECTION 3: ARTIFICIAL INTELLIGENCE FOR HEALTHCARE OPERATIONS

Along with diagnostic and prognostic applications, AI has the ability to optimize health care operations in dermatology, especially due to recent advances in LLMs.⁷⁷ Health care operations refer to the

systems utilized to deliver patient-care, including clinical and administrative aspects,⁷⁸ and are thus pivotal to how dermatology clinics operate. In this portion of the article, we will examine how AI can be applied to optimize health care operations within dermatology to reduce administration burden and improve patient-care.

Ambient Scribing

Recent advances in AI and ML have led to the development of digital scribes—systems that can record physician-patient encounters and generate clinical documentation, automating the roles of human clinical scribes to optimize health care operations.^{79,80} Digital scribes are promising solutions for reducing the clinical documentation burden that has been linked to increased risk of physician burnout,⁸⁰ making these AI models ideal for dermatology clinics with traditionally high patient volumes. Ambient scribing involves recording provider-patient conversations with automatic speech recognition, converting audio into text, and then summarizing information in structured physician notes.⁸⁰ Emerging AI ambient scribing platforms have capabilities of EHR integration for streamlined documentation, automated billing, and multilingual support.⁸¹ Such platforms have been shown to reduce documentation time for providers using the platform,⁸² increasing direct patient engagement and interaction.⁸¹ While these systems are far from perfect,^{83,84} further refinement of these tools is likely to entirely replace human-based scribing and achieved increased documentation accuracy, reduce documentation time, and reduce documentation costs.

Patient Education and Communication

The recent introduction of LLMs has streamlined the ability of clinicians to educate patients regarding their medical conditions. For example, DermGPT⁸⁵ is a dermatology-specific LLM that has been used to develop patient handouts with information relevant to their diagnoses, treatments, and post-visit care. These reports are able to reference the most up-to-date literature^{85,86} and can be generated rapidly at point-of-care and customized for each patient. Moreover, LLMs have also been highly useful in communicating with payers, particularly in obtaining insurance authorization for medical management, which can otherwise be a highly time-consuming process.⁸⁷ Indeed, a recent survey of health care stakeholders demonstrated an increasing interest in applying generative AI to improve health care operations, especially through improved clinician productivity, patient engagement and quality of care, and administrative efficiency.⁷⁷

Furthermore, AI chatbots offer a reliable means of facilitating patient communication. Using interactive conversational models, AI chatbots directly enhance patient communication with the ability to provide initial responses to patient inquiries without requiring the immediate presence of a health care provider or administrator.⁸⁸ Such inquiries include patient appointments requests, whether these patients are aiming to book, modify, or cancel their appointments.⁸⁹ These systems are able to integrate multiple factors, including patient medical history, length of prior appointments, prior appointment no-show rate, number of medical appointments same day as the planned visit, distance from clinical facility, and other factors to most appropriately schedule the dermatology visit.⁹⁰ Furthermore, by interacting with the patient directly, these solutions are able to collect clinical information regarding patient presenting concerns and can triage appointments based on the urgency of a visit. As such, AI-powered chatbots are sophisticated virtual agents on call at any time of the day, including hours outside of the business day, to alleviate the administrative workload placed on dermatology clinics. Furthermore, AI chatbots can also contact patients via voice calls or texts to provide appointment reminders⁸⁹ and can be trained in various languages to facilitate communication with patients of diverse backgrounds,⁹¹ thus reducing patient call volumes and associated staffing costs. Although the applications of AI chatbots to dermatology are numerous, provider oversight is warranted as the risk for misinterpretation is still present. As such, AI chatbots must continue to be rigorously tested to ensure they can communicate patients effectively and direct patients to providers for further medical support if needed.

SUMMARY

In this article, we have discussed developments in AI and ML and their transformative potential within the field of dermatology. As these technologies continue to advance along with the rapid expansion of health care databases, we highlight the ways in which AI will revolutionize diagnostic, prognostic, and operational processes in dermatology. While further training and validation efforts are required for large-scale adoption, AI tools have the potential to enhance patient-care while minimizing the resource demands on an on dermatologists and the field of medicine in general.

CLINICS CARE POINTS

- AI tools in TBP can enable the rapid detection and precise longitudinal monitoring of skin

lesions, enhancing melanoma screening and surveillance.

- CNNs can significantly augment dermoscopy, but clinician oversight remains crucial due to variability in the quality and lighting of dermoscopic photographs.
- AI can leverage ML models to assist in the histopathologic evaluation of digital slide images to increase the accuracy of skin lesion diagnosis and differentiation, but pathologist oversight remains required to account for differences in models and slide processing techniques between institutions.
- Multimodal AI-based integration of the imaging, clinical, and genetic data of patients can refine patient-specific melanoma prognosis and guide therapy selection, permitting targeted therapies through precision medicine.
- AI-driven scribing along with patient communication and education can reduce both the administrative burden placed on clinics and the documentation burden faced by dermatologists, improving the quality of patient-care.

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