Barriers to AI-Enabled Mole Mapping: The Impact of Socioeconomic, Racial, Geographic, Insurance, and Tattoo-Related Factors on Early Detection

Katheryn Bell[1], Hannah Welp[2], Alicia Fields[3], Gili Amid[4], Saloni Chadha[5], Maria Guirguis[6], Kelly Frasier[7]*

[1]Indiana University School of Medicine, Indianapolis, IN, USA

[2]Lincoln Memorial University DeBusk College of Osteopathic Medicine, Harrogate, TN, USA

[3]University of Kentucky College of Medicine, Bowling Green, KY, USA

[4]Toby School of Medicine, St. George's University, Islip, NY, USA

[5]Lake Erie College of Osteopathic Medicine, Bradenton, FL, USA

[6]American University of Antigua College of Medicine and MCPHS, USA

[7]Department of Dermatology, Northwell Health, New Hyde Park, NY, USA

***Corresponding author:**

Kelly Frasier, DO, MS
Department of Dermatology, Northwell Health, New Hyde Park, NY, United States, Phone: 3105956882, Email: kellymariefrasier@gmail.com

Received : September 17, 2025
Published : December 02, 2025

ABSTRACT

Background: Digital mole mapping, integrating total body photography and lesion tracking, is increasingly used for melanoma surveillance. Artificial Intelligence (AI) integration with these technologies offers to enhance identification of worrisome lesions and provide diagnostic support. Yet, its real-world application may be influenced by many socioeconomic, racial, geographic, insurance, and tattoo-related factors that could limit equitable uptake. **Methods:** A PRISMA-guided systematic review was performed to identify barriers to AI-enabled mole mapping for melanoma detection. PubMed and Embase were searched for English-language studies published from Jan 2018 to August 2-25, combining AI, mole-mapping, and barrier-related terms. Eligible studies included original research, systematic reviews, or meta-analyses reporting at least one prespecified barrier such as socioeconomic status, race or ethnicity, skin color, geography, insurance status, or tattoos. Case reports, abstracts, and non-AI imaging studies were excluded. Two reviewers independently screened articles. Of 16 records identified, five met inclusion criteria. **Results:** Key barriers included cost, geographic inaccessibility particularly in rural settings, privacy concerns, and patient mistrust of AI. Underrepresentation of darker skin phototypes in training datasets reduced diagnostic accuracy for patients with skin of color. Tattoos were noted as potential confounders for lesion

DOI: https://doi.org/10.35702/Derm.10053

recognition, although no AI-specific studies addressed this factor. Similarly, while socioeconomic and insurance disparities are recognized in dermatology, no study directly examined insurance barriers in the context of AI mole mapping. Patients expressed support for AI as an adjunct ot physician but voiced concerns regarding data protection and the loss of human interaction. Clinicians emphasized AI's prime for triage and efficiency but stressed the need for oversight. **Conclusion:** AI-assisted mole mapping may enhance melanoma detection and patient reassurance. However, barriers related to equity, dataset diversity, and evidence gaps regarding insurance and tattoo-related barriers must be addressed to ensure safe and effective integration of AI-assisted mole mapping technologies.

Keywords: Artificial Intelligence, Dermatology, Mole Mapping, Skin Cancer, Mental Health, Geographic Location, Skin Color

INTRODUCTION

Digital mole mapping, encompassing total body photography and lesion tracking, is increasingly being utilized for skin cancer surveillance and early melanoma detection. Recent advances have integrated artificial intelligence (AI) and machine learning algorithms into these workflows, enabling automated lesion identification, risk stratification, and diagnostic support for clinicians and patients [1]. AI-based tools now range from clinician decision-support systems to direct-to-patient smartphone applications, with diagnostic accuracy in some studies approaching or surpassing the expertise of experienced dermatologists [1-3]. Although these advances are profound, the process of identifying suspicious lesions still remains complex. Factors like the variations in skin color and other patient-specific characteristics can present unique challenges to AI-assisted diagnostic approaches [4,5]. The enticing nature of AI-assisted mole mapping lies in its ability to process large volumes of imaging data and potentially reduce subjectivity. Yet, the real-world application of this tool is shaped by a range of social considerations [5-8].

As AI-enabled tools become more widespread, uncertainty persists around their best use, the management of protected health information, and their influence on patient engagement and trust. Patient perceptions and trust of AI-assisted mole mapping are varied, with many patients expressing both positive and negative opinions [4-8]. These issues, along with a physician's evolving role within technology, warrant a further investigation into the benefits, limitations, and barriers relating to AI-assisted mole mapping in Dermatology.

METHODS

This review synthesized evidence on patient perceptions and engagement with digital mole mapping and AI in the specialty of dermatology. A PRISMA-guided systematic review of the literature was conducted to evaluate barriers to AI-enabled mole mapping/total body photography (TBP) for early melanoma and skin cancer detection. PubMed and Embase were searched for studies published between January 1, 2018-August 01, 2025, using a Boolean strategy combining AI-related terms with mole mapping and barrier terms (socioeconomic status, race/ethnicity/skin color, geographic location, insurance, tattoos). Searches were limited to English-language, peer-reviewed human studies, with additional articles identified through citation chaining. Studies were eligible for inclusion if they satisfied the following inclusion criteria: original research, systematic reviews, or meta-analyses that evaluated AI-enabled mole mapping or TBP and reported at least on prespecified barriers domain. Exclusion criteria included: case reports, editorials, abstracts, and non-AI imaging studies were excluded. Two reviewers independently screened titles, abstracts, and full texts, with reasons for exclusion recorded. Through preliminary search, 16 articles were identified and 11 were removed because they were duplicates, did not contain barrier outcomes, or included dermoscopy-only assisted AI techniques. Thus, leaving 5 studies remaining. A flow sheet depicting the search strategy and resulting studies is seen in Figure 1. Data were extracted on study characteristics, modality, barrier domains, and findings, and results were synthesized qualitatively. Studies were categorized into Tier-1 (empirical evidence of barriers) and Tier-2 (contextual evidence without barrier outcomes) to highlight both existing knowledge and evidence gaps.

Patient Perceptions and Engagement with AI-assisted Mole Mapping

Among the five included studies that specifically integrate barriers to AI-assisted mole mapping or total body photography, most studies consistently identified cost, geographic access, privacy, and trust as key barriers to implementation as seen in Table 1 [9-13]. Hona et al. and Horsham et al. reported that patients commonly noted that cost and travel distance were limitations to AI-assisted mole mapping care. In these studies, rural participants also described greater challenges in access to care than their urban counterparts [9,10]. Privacy and

DOI: https://doi.org/10.35702/Derm.10053

confidentiality with AI visits also emerged as central concerns, with participants expressing hesitation about sensitive image storage and sharing of data in AI algorithms [11]. Although, rich and diverse datasets are essential, as they enable clinicians to produce more accurate AI-driven assessments. Primero et al. highlighted the persistent underrepresentation of diverse skin phototypes in AI training datasets, underscoring the risk of reduced diagnostic accuracy in patients with skin of color [12]. And lastly, Young et. al provides a broader view of patient perceptions, noting socioeconomic and access disparities as large patient barriers, but without presenting stratified empiric data [13].

Patients generally express support for digital mole mapping and artificial intelligence (AI)-assisted tools in skin cancer screening, particularly when these technologies are used to supplement physician decision-making rather than replace it entirely. The most commonly patient-perceived benefits include increased access to care especially in underserved areas, and quicker diagnoses which may translate to catching melanomas earlier [1]. Quantitative surveys show that over 90% of respondents support the use of AI in medical approaches, and a similar proportion are willing to share health data anonymously to advance AI development [1,2,14].

However, patient concerns regarding AI-assisted diagnostic accuracy, privacy of health information, and impersonality remain prominent [3,15,16]. Interestingly, one study noted that patients perceived both more accurate diagnosis (33 participants [69%]) and less accurate diagnosis (41 [85%]) to be the greatest strength and weakness of AI, respectively [1]. Patients frequently cite the risk of errors, insufficient data protection, and the lack of human interaction as key drawbacks of solely AI-directed mole mapping models. Qualitative interviews revealed that while many patients recognize AI's potential for more precise and unbiased diagnostics, patients still worry about the algorithm's inability to be generalizable. Specifically, patients are worried about the possibility of missed cancers, especially in populations with diversity in skin color [1-3,14-16]. Opinions shift depending on personal health history, with one study finding that those with a history of melanoma welcomed AI systems for early detection of cancer more than those without a history of melanoma [2,14]. This opinion persisted among melanoma survivors even with use of AI in the home setting [2,14]. However, this information was of inconsistent quality and often caused confusion, leaving dermatologists to interpret and contextualize AI findings for pre-informed patients [3].

Patient trust in AI for melanoma detection is conditional and closely linked to physician oversight. The overwhelming majority of patients prefer collaborative models, where AI assists clinicians. This is in contrast to an autonomous diagnostic tool, with one study noting 94% of respondents indicating the importance of symbiosis between humans and AI [1]. The credibility of technology companies and healthcare institutions is a significant factor in patient acceptance, with higher trust placed in applications developed or endorsed by established medical organizations [1,2,15]. When faced with inconsistent results between AI and clinicians, patients consistently favor physician judgment and seek confirmatory testing [1,2,15]. And further in one study, the majority (81%; n = 491) of respondents, considered it important for a dermatologist to examine the patient, confirm the diagnosis, and discuss treatment options with them even in the context of AI [16].

Patient preferences for collaborative decision-making between AI and clinicians are echoed in other specialties, such as radiology and primary care, where AI is viewed as a valuable adjunct but not a substitute for clinical expertise [17]. Interestingly, one study found that AI was trusted somewhat more in dermatology compared to radiology and surgery. The demographic with the highest confidence in AI-assisted clinical decision making was among well-educated males of Western background who were employed or students and had not experienced hospitalization in the past year [17]. The dominant theme across each study is the importance of physician-AI symbiosis, with patients advocating for models that preserve the integrity of the physician-patient relationship while leveraging the strengths of AI for improved diagnostic accuracy and efficiency [1,2,14,15,18].

Mental Health Impacts and Patient Anxiety Related to Surveillance Technologies

Digital mole mapping is an ever-evolving technology that has played an important role in early melanoma detection and reduced mortality. Beyond the clinical benefits, AI-assisted digital mole mapping shows promise in supporting patient mental health. An obstacle faced with self-skin-examinations is accurate recollection of the evolving appearance of pigmented lesions over time. The development of mole-mapping helps addresses this barrier, specifically for those with many pigmented lesions. Studies have shown patients report

DOI: https://doi.org/10.35702/Derm.10053

high satisfaction with mole-mapping, increase adherence to regular self-examinations, and even encourage family and friends to adopt similar practices [19]. For individuals at high-risk for melanoma, cancer worry can affect quality of life and adherence to screening. Anxiety may lead to either heightened distress between screenings or avoidance of care. Digital mole mapping reduces intrusive thoughts and worry through structured surveillance, offering reassurance to these patients [20,21]. For high-risk patients, digital mole mapping provides reassurance, guidance on when to seek care, and opportunity for timely skin cancer detection [22,23]. Overall AI-assisted digital mole mapping supports early detection, patient well-being, provides reassurance, and improves quality of life, especially for those at high risk of melanoma development.

While enthusiasm for AI-assisted surveillance technology is growing, patient hesitation remains present. Both dermatologists and patients recognize the value of AI in the dermatologic field. Although, many patients emphasize the importance of preserving their relationships with providers and feel anxious about AI replacing human care [23]. With AI-assisted digital mole mapping as a surveillance tool, concerning results may arise without immediate provider support, leading to an anxiety-provoking delay until physician assessment can be provided. A common theme among respondents across studies was the preservation of human interaction. Specifically, that conversation, reassurance, and empathy remain central to the patient experience. AI lacks humanistic qualities including empathy, human touch, and eye contact: all of which are important for patients experiencing fear or uncertainty. The inability of AI to sense emotion can be especially difficult to help anxious or fearful patients. The lack of reassurance can negatively impact emotional well-being [24-26]. While these concerns signify important limitations, AI still has a meaningful role in the future of dermatology. Integration should focus on this tool as supporting providers, combining surveillance innovation with the human elements of care that patients value most.

Physician Perspective: AI in the context of digital mole mapping

Clinicians largely view AI-assisted digital mole mapping as a promising tool, particularly for its potential to improve diagnostic accuracy, streamline workflows, and enhance patient care pathways. These belief systems hold strong provided that AI influence serves as a support system rather than a replacement. A qualitative interview study found that many clinicians recognized the potential of AI to improve diagnostic accuracy and informed decision making when thoughtfully integrated into clinical practice [27]. Surveys of dermatologists and general practitioners similarly show optimism regarding AI's role in facilitating early melanoma detection, standardizing lesion analysis, and aiding storage and retrieval of imaging data [28]. One study highlighted a general practitioner who described an AI-based app correctly flagging a suspicious mole that was later confirmed as melanoma, underscoring AI's value in triage and early detection [27]. Explainable AI (XAI) has further improved clinicians' confidence and trust in AI-assisted tools. Studies show that systems providing dermatology-oriented explanations significantly increase both diagnostic accuracy and physician trust compared to conventional "black box" AI outputs [29]. These small changes in AI can help smooth the transition for AI-assisted integration into not just melanoma diagnosis, but specifically mole mapping for long-term tracking purposes.

Real-world examples demonstrate these benefits in practice. The UK National Health Service recently implemented Skin Analytics' AI tool Derm in several hospitals to assist with urgent skin cancer assessments. The system captures lesion images using an iPhone-based platform, enabling rapid triage of suspicious lesions and allowing dermatologists to prioritize complex cases. Nearly half of patients received immediate all-clear results, reducing wait times and anxiety [27]. Although these advantages are apparent, clinicians continue to express ongoing concerns. AI lacks the ability to incorporate full clinical context, such as patient interviews and palpation [28]. Other concerns include bias of the algorithm for underrepresentation of diverse skin tones, limitations in model generalizability, and the risk of overreliance without human oversight [29]. Overwhelmingly, and similar to a patient's viewpoint, physicians view AI as a decision-support tool rather than a replacement for clinical judgment. Success depends on thoughtful implementation, rigorous validation, and maintaining physician control to ensure equitable, safe, and effective integration into dermatologic practice.

Structural and Demographic Barriers: Skin Color, Tattoos, and Data Diversity

Despite the promising opportunity for using artificial

DOI: https://doi.org/10.35702/Derm.10053

intelligence in melanoma detection, clinicians must acknowledge the limitations of AI-based systems in accurately identifying clinically relevant melanocytic lesions. The accuracy and generalizability of AI-assisted methods are challenged by underrepresentation of skin of color and potentially, the presence of tattoos. Some features of a lesion may make it more or less likely to go undetected. These include faint pigmentation, lentiginous or large lesions, grouped lesions, and small palmoplantar lesions [30]. In one study, undetected clinically relevant melanocytic lesions were most likely to be located on the trunk (n=19) and followed by the face (n=8) [30]. Other factors that may make it more likely to miss lesions are hair, clothing, skin folds, and camera angles [30]. To improve detection, patients should be encouraged to remove body hair before appointments and fully undress for imaging [30].

Aside from factors that patients could control, AI-based systems also need to improve recognition of the above-mentioned lesion-specific characteristics [30]. This is evidenced by detection in one image and being undetected in another view of the same lesion [30]. Further, the performance of AI-based systems is also limited by the quality and representativeness of its training data [31, 32]. If the training data sets are small, this will preclude limited accuracy in making effective diagnoses [33]. Misdiagnosis risk is also prevalent in those with rare genodermatoses including albinism and xeroderma pigmentosum, and patients at an increased risk for skin cancer due to solid organ transplantation [33].

The lack of skin of color lesions can lead to an inherent bias and exacerbate already existing health care disparities [31,32]. For instance, The International Skin Imaging Collaboration: Melanoma Project, one of the largest archives of pigmented lesions, has data collected predominantly from fair-skinned patients in the United States, Europe, and Australia [31]. AI systems require training data that represents all skin types; otherwise, they risk reproducing the same shortcomings long observed in dermatology textbooks [31]. While melanoma is more common in the non-Hispanic and non-Black patient population, patients of all skin types should benefit from the use of AI-based systems and the potential for early detection [31].

There are few documented cases of melanoma arising within tattoos [34]. As many melanoma lesions have dark pigmentation, darker pigments used in tattoos may mask a concerning lesion and lead to delays in diagnosis [35]. During a skin exam, close and meticulous examination of tattoos should be done. Further, patient education should encompass that tattoos should not be placed over preexisting melanocytic nevi or any premalignant lesions [35]. Cited as a known clinical confounder likely to affect AI localization, tattoos' dark pigment may obscure pathology. However, there are no AI-specific tattoo-related studies listed currently in the literature, warranting further investigation into this potential threat to lesion identification.

Socioeconomic, Geographic, and Insurance-Related Disparities in Access

In those with multiple melanocytic nevi and a higher likelihood of developing skin cancer, digital mole mapping is a noninvasive technique that may reduce overall healthcare costs and lead to better dermatologic outcomes. Yet, there are multiple disparities to access. Socioeconomic status, insurance coverage, geographic location, ethnicity, gender, and age, are just some of the many difficulties that patients may face in regards to their skin health.

Poor socioeconomic status in patients has shown to lead to decreased dermatologic care due to high costs of insurance and healthcare visits. Research suggests that people who do not receive routine checks present with thicker tumors and advanced disease [36]. In a study by Tripathi et al., patients with Medicaid or Medicare coverage and uninsured patients were less likely to receive outpatient dermatologic care than privately insured patients, again highlighting the effect of insurance on routine skin care [37]. Although other studies discuss the impact of insurance status on care outcomes and accessibility, there appears to be no evidence in the literature regarding insurance barriers in the specific context of AI-assisted mole mapping likely due to its novelty. Minority populations are especially vulnerable, with recent evidence showing that minority melanoma patients who present to the public hospital were more likely to have a lower socioeconomic status [38,39]. The increased incidence of minority populations, such as Hispanic and Asian communities, having a growing melanoma incidence further fuels a need for change [38,39]. A retrospective cohort study in Ontario, Canada found that advanced age (95% CI 1.37–1.72), male sex (95% CI 1.05–1.20), and lowest socioeconomic status quintile (95% CI 1.12–1.38) were significantly associated with advanced melanoma [40]. All of these factors leading to advanced disease further

DOI: https://doi.org/10.35702/Derm.10053

emphasizes the need to address healthcare disparities in dermatology.

Underserved populations in rural communities may lack access to early melanoma detection, including digital mole mapping techniques, due to increased distance from clinics and transport difficulties. This disparity may then lead to advanced disease and decrease odds of survival. A study by Pollitt et al., found that high-school educated individuals were less likely to have received a physician skin examination within the year before diagnosis, showing that low education status also has a negative effect on skin cancer detection [41]. This effect is likely in some part due to misconceptions about skin cancer in skin of color [42]. Early detection of skin cancer plays a role in survival, thus it is vital to continue to equalize access to dermatologic surveillance. There is a need for further research and formal discussion on dermatologic disparities and misconceptions affecting disadvantaged individuals.

Implementation Challenges and Opportunities for Equitable AI Integration

Integrating AI into digital mole mapping for melanoma surveillance presents challenges with regards to equity of care. As noted in previous discussion, AI models demonstrate reduced diagnostic accuracy for skin of color patients due to underrepresentation in the datasets that AI is programmed with, leading to disparities in early detection [43]. Socioeconomic factors such as limited access to advanced imaging technology and healthcare further worsen the issue of inequity particularly for rural or underserved areas [44,45]. Insurance coverage is also an important factor to consider because without adequate reimbursement for AI-based diagnostic tools, integration into clinical practice will remain limited [46]. Cultural factors and personal reasons including tattooed skin can interfere with the AI algorithm ability to accurately assess skin lesions, causing another hurdle in early detection efforts.

Opportunities exist to enhance the equitable integration of AI in melanoma surveillance despite all the noted challenges. Being able to integrate skin of color patients into robust AI learning datasets may reduce disparities among these patients [44]. Collaborations between technology developers, healthcare providers, and the community are essential to ensure that AI tools are accessible and effective for patients of all various skin tones [45]. Increasing awareness and access as well as promoting insurance coverage for AI-based diagnostics can also help support equitable AI integration [46]. Overcoming these challenges will facilitate the development of AI systems that contribute to improved early detection and outcomes in melanoma care.

CONCLUSION

Digital mole mapping and AI surveillance technology are increasingly being integrated into dermatology practices through their enhancement of lesion identification and diagnostic support, especially to those of higher risk for melanoma. Patients are relatively enthusiastic in regard to these enhancements especially when used alongside their physicians. In regards to patient anxiety and mental health outcomes, preserving the physician-patient relationship is key for patients to accept AI-assistance technology, and barriers such as geographic accessibility, privacy and trust still persist. For clinicians, AI offers increased diagnostic accuracy and streamlined workflows. Although, concerns arise as AI is unable to integrate the full clinical context and some clinicians may over-rely on this technology. Structural and demographic barriers pose challenges in accuracy and generalizability due to underrepresentation of darker skin phototypes, potential interference from tattoos, and the need for diverse, high-quality datasets to avoid bias and errors. Additionally, socioeconomic status and geographic location further compound these disparities, as underserved populations will still face limited access to AI-assisted dermatologic care. The absence of explicit barriers regarding insurance coverage and tattoo-related factors represents a significant evidence gap and highlights the need for further research in these areas. The future for the integration of AI depends on expanding diagnostic accuracy to address and reduce disparities ultimately enhancing detection and improving the overall well-being of patients.

ACKNOWLEDGEMENTS

No acknowledgements to be made. No external funding, grants, or financial support were received for completion of this work.

CONFLICT OF INTEREST

The authors declare no conflict of interest related to this manuscript.

DOI: https://doi.org/10.35702/Derm.10053

REFERENCES

1. Nelson CA, Pérez-Chada LM, Creadore A, Li SJ, Lo K, Manjaly P, et al. (2020). Patient Perspectives on the Use of Artificial Intelligence for Skin Cancer Screening: A Qualitative Study. JAMA Dermatol. 156(5):501-512.

2. Jutzi TB, Krieghoff-Henning EI, Holland-Letz T, Utikal JS, Hauschild A, Schadendorf D, et al. (2020). Artificial Intelligence in Skin Cancer Diagnostics: The Patients' Perspective. Front Med (Lausanne). 7:233.

3. Schick TS, Höllerl L, Biedermann T, Zink A, Ziehfreund S. (2023). Impact of Digital Media on the Patient Journey and Patient-Physician Relationship Among Dermatologists and Adult Patients With Skin Diseases: Qualitative Interview Study. J Med Internet Res. 25:e44129.

4. Fried L, Tan A, Bajaj S, Liebman TN, Polsky D, Stein JA. (2020). Technological advances for the detection of melanoma: Advances in diagnostic techniques. J Am Acad Dermatol. 83(4):983-992.

5. Strzelecki M, Kociołek M, Strąkowska M, Kozłowski M, Grzybowski A, Szczypiński PM. (2024). Artificial intelligence in the detection of skin cancer: State of the art. Clin Dermatol. 42(3):280-295.

6. Primiero CA, Rezze GG, Caffery LJ, Carrera C, Podlipnik S, Espinosa N, et al. (2024). A Narrative Review: Opportunities and Challenges in Artificial Intelligence Skin Image Analyses Using Total Body Photography. J Invest Dermatol. 144(6):1200-1207.

7. Beltrami EJ, Brown AC, Salmon PJM, Leffell DJ, Ko JM, Grant-Kels JM. (2022). Artificial intelligence in the detection of skin cancer. J Am Acad Dermatol. 87(6):1336-1342.

8. Brancaccio G, Balato A, Malvehy J, Puig S, Argenziano G, Kittler H. (2024). Artificial Intelligence in Skin Cancer Diagnosis: A Reality Check. J Invest Dermatol. 144(3):492-499.

9. Hona THTP, Yates P, Yip D, Loescher LJ, Damian DL, Janda M, et al. (2023). Consumer views of melanoma early detection using 3D total-body photography: cross-sectional survey. Int J Dermatol. 62(12):1636-1642.

10. Horsham C, Loescher LJ, Yates P, Janda M. (2022). The experience of 3D total-body photography to monitor nevi: results from an Australian general population-based cohort study. JMIR Dermatol. 5(1):e33504.

11. Horsham C, Loescher LJ, Yates P, Janda M. (2022). Consumer perceptions of privacy and confidentiality in 3D total-body photography for melanoma screening. J Med Imaging Radiat Oncol. 66(8):1045-1052.

12. Primiero CA, Cota GF, Manoharan S, Saad S, Papakostas D, Caffery LJ, et al. (2024). Opportunities and challenges in artificial intelligence skin image analyses using total body photography: a narrative review. J Invest Dermatol. 144(6):1203-1211.

13. Young AT, Vora NB, Cortez J, Tam A, Yeniay Y, Afifi L, et al. (2021). The role of technology in melanoma screening and diagnosis. Pigment Cell Melanoma Res. 34(2):288-300.

14. Po Harvey Chin Y, Hsin Huang I, Yu Hou Z, Yu Chen P, Bassir F, Han Wang H, et al. (2020). User satisfaction with a smartphone-compatible, artificial intelligence-based cutaneous pigmented lesion evaluator. Comput Methods Programs Biomed. 195:105649.

15. Gaube S, Biebl I, Engelmann MKM, Kleine AK, Lermer E. (2024). Comparing preferences for skin cancer screening: AI-enabled app vs dermatologist. Soc Sci Med. 349:116871.

16. Lim K, Neal-Smith G, Mitchell C, Xerri J, Chuanromanee P. (2022). Perceptions of the use of artificial intelligence in the diagnosis of skin cancer: an outpatient survey. Clin Exp Dermatol. 47(3):542-546.

17. Yakar D, Ongena YP, Kwee TC, Haan M. (2022). Do People Favor Artificial Intelligence Over Physicians? A Survey Among the General Population and Their View on Artificial Intelligence in Medicine. Value Health. 25(3):374-381.

18. McRae C, Zhang TD, Seeley LD, Anderson M, Turner L, Graham LV. (2025). Patient Perceptions of Artificial Intelligence and Telemedicine in Dermatology: A Narrative Review. JMIR Dermatol. DOI: 10.2196/75454.

19. Weinstock MA, Nguyen FQ, Martin RA. (2004). Enhancing skin self-examination with imaging: evaluation of a mole-mapping program. J Cutan Med Surg. 8(1):1-5.

DOI: https://doi.org/10.35702/Derm.10053

20. Habgood E, McCormack C, Walter FM, Emery JD. (2021). Patients' Experiences of Using Skin Self-monitoring Apps With People at Higher Risk of Melanoma: Qualitative Study. JMIR Dermatology. 4(2):e22583.

21. Moye MS, King SM, Rice ZP, DeLong LK, Seidler AM, Veledar E, et al. (2015). Effects of total-body digital photography on cancer worry in patients with atypical mole syndrome. JAMA Dermatol. 151(2):137-143.

22. Young AT, Vora NB, Cortez J, Tam A, Yeniay Y, Afifi L, et al. (2021). The role of technology in melanoma screening and diagnosis. Pigment Cell Melanoma Res. 34(2):288-300.

23. Li Z, Koban KC, Schenck TL, Giunta RE, Li Q, Sun Y. (2022). Artificial Intelligence in Dermatology Image Analysis: Current Developments and Future Trends. J Clin Med. 11(22):6826.

24. Young AT, Amara D, Bhattacharya A, Wei ML. (2021). Patient and general public attitudes towards clinical artificial intelligence: a mixed methods systematic review. Lancet Digit Health. 3(9):e599-e611.

25. Nelson CA, Pérez-Chada LM, Creadore A, Li SJ, Lo K, Manjaly P, et al. (2020). Patient Perspectives on the Use of Artificial Intelligence for Skin Cancer Screening: A Qualitative Study. JAMA Dermatol. 156(5):501-512.

26. Jutzi TB, Krieghoff-Henning EI, Holland-Letz T, Utikal JS, Hauschild A, Schadendorf D, et al. (2020). Artificial Intelligence in Skin Cancer Diagnostics: The Patients' Perspective. Front Med (Lausanne). 7:233.

27. Partridge B, Gillespie N, Soyer HP, Mar V, Janda M. (2025). Exploring the Views of Dermatologists, General Practitioners, and Melanographers on the Use of AI Tools in the Context of Good Decision-Making When Detecting Melanoma: Qualitative Interview Study. JMIR Dermatol. 8:e63923.

28. Yee J, Rosendahl C, Aoude LG. (2024). The role of artificial intelligence and convolutional neural networks in the management of melanoma: a clinical, pathological, and radiological perspective. Melanoma Res. 34(2):96-104.

29. Chanda T, Hauser K, Hobelsberger S, Bucher TC, Garcia CN, Wies C, et al. (2024). Dermatologist-like explainable AI enhances trust and confidence in diagnosing melanoma. Nat Commun. 15(1):524.

30. Winkler JK, Kommoss KS, Toberer F, Enk A, Maul LV, Navarini AA, et al. (2024). Performance of an automated total body mapping algorithm to detect melanocytic lesions of clinical relevance. Eur J Cancer. 202:114026.

31. Adamson AS, Smith A. (2018). Machine learning and health care disparities in dermatology. JAMA Dermatol. 154(11):1247-1248.

32. Fried L, Tan A, Bajaj S, Liebman TN, Polsky D, Stein JA. (2020). Technological advances for the detection of melanoma: advances in diagnostic techniques. J Am Acad Dermatol. 83(4):983-992.

33. Strzelecki M, Kociołek M, Strąkowska M, Kozłowski M, Grzybowski A, Szczypiński PM. (2024). Artificial intelligence in the detection of skin cancer: state of the art. Clin Dermatol. 42(3):280-295.

34. Brusasco M, Spagnolini S, Mazzoni L, Magi S, Scarcella G, Stanganelli I. (2025). Melanoma arising in tattoos: a case series and scoping review of the literature. Cancers. 17(5):767.

35. Lebhar J, Jacobs J, Rundle C, Kaplan SJ, Mosca PJ. (2024). Skin cancers arising within tattoos: a systematic review. JAAD Int. 16:133-143.

36. Harvey VM, Patel H, Sandhu S, Wallington SF, Hinds G. (2014). Social determinants of racial and ethnic disparities in cutaneous melanoma outcomes. Cancer Control. 21(4):343-349.

37. Tripathi R, Knusel KD, Ezaldein HH, Scott JF, Bordeaux JS. (2018). Association of Demographic and Socioeconomic Characteristics With Differences in Use of Outpatient Dermatology Services in the United States. JAMA Dermatol. 154(11):1286-1291.

38. Wich LG, Ma MW, Price LS, Sidash S, Berman RS, Pavlick AC, et al. (2011). Impact of socioeconomic status and sociodemographic factors on melanoma presentation among ethnic minorities. J Community Health. 36(3):461-468.

39. Hu S, Parmet Y, Allen G, Parker DF, Ma F, Rouhani P, et al. (2009). Disparity in melanoma: a trend analysis of melanoma incidence and stage at diagnosis among whites, Hispanics, and blacks in Florida. Arch Dermatol. 145(12):1369-1374.

DOI: https://doi.org/10.35702/Derm.10053

40. Mavor ME, Richardson H, Miao Q, Asai Y, Hanna TP. (2018). Disparities in diagnosis of advanced melanoma: a population-based cohort study. CMAJ Open. 6(4):E502-E512.

41. Pollitt RA, Swetter SM, Johnson TM, Patil P, Geller AC. (2012). Examining the pathways linking lower socioeconomic status and advanced melanoma. Cancer. 118(16):4004-4013.

42. Lin RR, Lee J, Maderal AD, Elman SA. (2024). Rural Health Disparities in Skin Cancer Amplified Among Skin of Color. J Drugs Dermatol. 23(6):480-484.

43. Grzybowski A, Jin Y. (2023). Challenges of artificial intelligence in medicine and dermatology. J Am Acad Dermatol. 89(1):1-3.

44. Hu S, Parmet Y, Allen G, Parker DF, Ma F, Rouhani P, et al. (2009). Disparity in melanoma: a trend analysis of melanoma incidence and stage at diagnosis among whites, Hispanics, and blacks in Florida. Arch Dermatol. 145(12):1369-1374.

45. Brancaccio G, Balato A, Malvehy J, Puig S, Argenziano G, Kittler H. (2024). Artificial intelligence in skin cancer diagnosis: a reality check. J Invest Dermatol. 144(3):492-499.

46. Berk-Krauss J, Polsky D, Stein JA. (2017). Mole mapping for management of pigmented skin lesions. Dermatol Clin. 35(4):439-445.

Citation: Bell K, et al. (2025). Barriers to AI-Enabled Mole Mapping: The Impact of Socioeconomic, Racial, Geographic, Insurance, and Tattoo-Related Factors on Early Detection. Dermis. 5(6):53.

DOI: https://doi.org/10.35702/Derm.10053