Review

A review of artificial intelligence in wound care

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Abstract

Our aging population, diabetes, and obesity have fueled the growth of chronic wounds seen throughout the world. Often, wounds are a marker of poor health that leads to increased mortality rates. However, the diagnosis and treatment of these wounds are challenging. Incorrectly differentiating between chronic wounds and other complex conditions can lead to adverse events. Artificial intelligence (AI) has been shown to offer some early benefits, and we hypothesized that it may enhance wound care but also carry some notable risks. We performed a detailed search using PubMed, Scopus, Cumulated Index in Nursing and Allied Health Literature, and Web of Science for AI applications in wound care. AI was found to be applied to wound diagnosis and characterization, wound monitoring for tissue change, daily therapy, and prevention and prognostics. AI made for more efficient and accurate wound assessments, less painful assessments of chronic wounds, more personalized treatment, and improved prognostic prediction capabilities. AI also allowed for more precise at-home observation and care, facilitating earlier wound treatment as needed. Challenges associated with AI included how to best allocate AI-assisted technologies equitably, how to safely maintain patient data, and how to diversify datasets for algorithm training. Because the algorithms are not transparent, validating findings may be challenging. AI presents a powerful tool in several aspects of advanced wound care and has the potential to improve diagnoses, accelerate healing, reduce pain, and improve the cost-effectiveness of wound care. More research needs to be done into how to best incorporate AI into daily clinical practice while keeping clinicians aware of the potential risks of using these evolving technologies.

Keywords: Artificial intelligence, wound healing, wound care, hard-to-heal wounds, chronic wounds, ulcers

INTRODUCTION

Wound healing is a rapidly growing multidisciplinary field drawing clinicians from diverse backgrounds including nursing, medicine, podiatry, plastic surgery, and physical therapy. The prevalence of chronic wounds has increased in association with underlying conditions, such as aging, obesity, and diabetes, which contribute to the nonhealing nature of many wounds. From 2014 to 2019, the number of Medicare beneficiaries with a wound increased from 8.2 million to 10.5 million, with the largest increase in wound prevalence in those less than 65 years of age[1]. Economically, total Medicare spending estimates for all wounds spanned $28.1 to $96.8 billion in 2014[2]. However, these numbers do not begin to capture the impaired quality of life, lost wages, and lost productivity that is too often experienced by patients and their family members. Providers face a new challenge: how to best care for an increasing number of wounds in an age of strained resources. The rapid development of artificial intelligence (AI) may be an innovative method to help reduce the burden that patients and providers face in the area of wound care.

In this review, we define AI as the ability of computers, machines, and other technology to use algorithms to simulate human intelligence and problem-solving. AI's power lies in its ability to process and interpret large amounts of data quickly and improve upon itself without the need for manual input[3,4]. AI can read electronic medical records (EMR), process images, and predict clinical outcomes, all of which can be applied to wound healing[5].

The following terminology is commonly described in AI-assisted medicine: machine learning, neural networks, natural language processing, deep learning, and computer vision[6,7]. Machine learning focuses on using computers, data, and algorithms to imitate human learning and adaptation. Neural networks are sets of interconnected algorithms that handle multiple inputs and outputs, identifying various data relationships and filtering data as needed[7]. Natural language processing comprehends language, translates texts, and recognizes speech. Deep learning extracts progressively higher-level features from data through multiple layers of processing to provide a single, high-level output. Computer vision enables computers to interpret visual input. Morris *et al.* have previously reviewed these categories in the context of the general field of surgery[7]. These AI categories can additionally be applied to various stages of wound care, improving wound diagnosis, classification, and measurement.

AI also aids wound management by assessing wounds for infection, necrosis, or healing. Additionally, AI has contributed to more personalized care and better prognosis and preventative strategies. However, AI brings challenges, including data privacy and equity of care. With appropriate safeguards and a cautiously optimistic approach to AI in wound care, we can leverage AI to make significant improvements to the field. In this review, we summarize AI advancements during stages of wound care, including diagnosis, monitoring, therapy, and prognosis and prevention. We also discuss the challenges and future directions of AI in wound care.

METHODS

A literature search was performed using freely accessible online databases, including PubMed, Scopus, Cumulated Index in Nursing and Allied Health Literature, and Web of Science, from publication to July 20, 2024. Keywords included "wound healing", "hard-to-heal wounds", "wound care", "artificial intelligence", "machine learning", "deep learning", "neural network", and "arterial, venous, diabetic, pressure, or chronic wounds and ulcers". Articles were included for their specific discussions on the use of AI in common chronic human wound diagnosis, management, prognosis, and prevention.

RESULTS AND DISCUSSION

AI in wound diagnosis

Wound diagnosis is challenging yet crucial to treatment. Chronic wounds most commonly include diabetic foot ulcers, pressure injuries, arterial ulcers, and venous insufficiency ulcers. Other less common disease states are often present where diagnoses are not obvious, such as pyoderma gangrenosum and inflammatory ulcerations. Treating the wound commonly involves treating the underlying condition, thus making proper diagnosis critical and the first step in treatment [Figure 1].

Experienced clinicians who have the training to properly diagnose chronic wounds are limited. For medical students and physicians, formal wound care training is sparse. A survey of fifty American medical schools reported that the average number of educational hours spent on the physiology of tissue injury and wound healing over all four years of medical school was just 4.7 h[8]. More than 47% of surveyed nurses in an inpatient setting stated that they "did not accept wound care as a nursing task", and more than half of the nurses failed to provide wound care discharge education[9]. Because of the lack of standardized education on wound care, knowledge is often picked up through practitioner experience, creating a varied knowledge base. The lack of standardized education has also led to the creation of organizations working to address this issue. The Wound, Ostomy, and Continence Nurses Society is one of those organizations that provides standardized education to nurses to help fill the need for trained wound providers. AI can similarly help standardize and expand that base with an unlimited number of "experiences", or data. For example, by inputting hundreds of images of different wounds into a database, AI can examine a new wound's image, "compare" it to the ones in the database, and report information about the new wound.

Several researchers have utilized AI to differentiate between challenging-to-diagnose wounds [Table 1]. For example, pyoderma gangrenosum is easily misdiagnosed as cellulitis, diabetic foot ulcers, abscesses, and other processes. The misdiagnosis of pyoderma gangrenosum can expose patients to risks that are associated with its treatment and delay care for other causes of ulceration[10]. It can lead to prolonged hospitalization, unnecessary procedures, and increased medical costs for the hospital and the patient. Birkner *et al.*, however, developed a deep convolutional neural network to differentiate pyoderma gangrenosum from conventional leg ulcers with a higher sensitivity than trained dermatologists[11]. This technology can help prevent misdiagnosis.

Similarly, Hüsers *et al.* studied image detection and classification algorithms for venous leg ulcers and diabetic foot ulcers, and their algorithms of the YoloV5 ("You-Only-Look-Once") family resulted in a high precision (0.94)[12]. With such high precision, this technology could serve as a tool for double-checking physicians, enhancing their confidence that they are accurately diagnosing and treating patients.

Several deep learning tools, involving superpixel segmentation and a convolutional neural network, have been created to classify pressure and diabetic wound images with higher accuracy than what had been done in the past[13-16]. One model, "Alexnet architecture", attained about 99% accuracy, 99% sensitivity, and 99% specificity[16]. Such high values are necessary for monitoring the progress of healing. Mohammed *et al.* used an AI digital application to capture quality wound images and calculate wound surface area faster than clinic staff using a standard digital camera, saving about two minutes on each wound assessment[17].

AI is quick and efficient, facilitating noncontact optical assessment of a patient's wound, which can potentially reduce pain and risk of infection. It also allows non-providers to assess wounds, which is crucial as they often require daily assistance from family members, friends, or nonmedical caretakers. For example, Lau *et al.* developed a smartphone application to perform real-time detection and staging classification of

Table 1. Summary of AI advancements in wound diagnosis

Study	AI framework and/or computational system	Outcome
Identification and classification		
Birkner *et al.*[11]	Deep convolutional neural network trained with images of pyoderma gangrenosum and leg ulcers	Differentiate pyoderma gangrenosum from conventional leg ulcer
Hüsers *et al.*[12]	Image detection and classification algorithms of the YOLOv5, trained with 885 images of either wound	Identify and classify venous leg ulcers and diabetic foot ulcers
Swerdlow *et al.*[13] and Zahia *et al.*[14]	Convolutional neural network	Segmentation and classification of pressure injury images
Chang *et al.*[15]	Deep learning based on superpixel segmentation	Pressure ulcer diagnosis
Eldem *et al.*[16]	"Alexnet architecture", a deep learning tool	Classify pressure and diabetic wound images
Lau *et al.*[18]	Smartphone application using a deep learning-based object detection system	Detection and stage classification of printed images of pressure injury wounds
Sizing		
Mohammed *et al.*[17]	"Swift", a noninvasive digital tool using AI	Capture color calibrated images to identify wound boundaries, surface area, and depth
Chan *et al.*[19]	Mobile device application using YOLOv4, validated with 144 photos	Detect length, width, and area of diabetic foot ulcers
Tissue identification		
Aldoulah *et al.*[20]	SEEN-B4 deep learning framework	Assess erythematous regions compared to an eschar or dry crust
Veredas *et al.*[21]	Neural networks and Bayesian classifiers	Identify tissue types in wound images
Lien *et al.*[22]	Neural network model trained with three rounds of active learning	Detect the growth of granulation tissue in diabetic foot ulcers
Liu *et al.*[23]	EfficientNet deep learning model	Create color-coded regions to identify ischemia and infection based on real patient images of diabetic foot ulcers
Viswanathan *et al.*[24]	AI-enabled noninvasive device, Illuminate®, capable of autofluorescence imaging	

AI: Artificial intelligence; SEEN-B4: Swish-ELU EfficientNet-B4.

Figure 1. Schematic of the elements that comprise wound care.

printed images of pressure injuries using a deep learning-based object detection system[18]. It has an accuracy of 63%, specificity of above 85%, and sensitivity of 73%[18]. The app itself claims to provide a "reasonable pressure injury staging support tool for lay carers"[18]. With a moderately high specificity and moderate sensitivity, providers should rely on this tool as a way to confirm suspected diagnosis rather than as a diagnostic tool itself. The technology specifically aimed to assist nursing home carers in accurate wound assessment and care planning to avoid downstream infection and hospitalization if the wound was otherwise not detected[18]. Another mobile device application, described by Chan *et al.*, can detect the length, width, and area of diabetic foot ulcers all without touching the ulcer[19].

Aldoulah *et al.* present a novel Swish-ELU EfficientNet-B4 (SEEN-B4) deep learning framework that specializes in the accurate assessment of erythematous regions compared to an eschar or dry crust[20]. Similarly, Veredas *et al.* used neural networks and Bayesian classifiers to design a computational system for automatic tissue identification in wound images[21]. Lien *et al.* used AI to detect the growth of granulation

tissue in diabetic foot ulcers[22]. In the same type of wound, Liu *et al.* and Viswanathan *et al.* used AI to create color-coded regions to identify ischemia and infection based on real patient images[23,24]. These advancements in wound identification and assessment naturally lead to their application in wound management.

AI in wound management

Many smartphone applications (apps) have been designed to facilitate wound monitoring at home, where most wound management happens. These apps assess pictures of wound tissue with automatic color and measurement calibration, remove background "noise", and use a factorization-based segmentation to classify and assess chronic wounds accurately[25,26]. One app can also detect subsurface tissue oxygenation of wounds[27]. Poor wound oxygenation can delay healing, and catching these complications early on could help prevent further deterioration.

Researchers are also aiming to sync data gathered from these apps with patients' EMRs to offer providers up-to-date information for wound healing. Previously, patients had to manually measure their wounds at home, take pictures of their wounds without necessarily knowing if they were infected or had changed, and send the images to the practice, then wait for a response. Now, AI-assisted apps connected to medical records allow patients to input a single photo and receive several outputs, including the wound's dimensions, classification, possible presence of infection or ischemia, and tissue types. This information can be synced with the EMR for immediate access by providers to further guide the patient.

One example of this kind of technology is "The Wound Viewer", developed by Zoppo *et al.*[28]. The Wound Viewer is an AI-powered, portable medical device that leverages sensors and algorithms to remotely collect and analyze clinical data, including three-dimensional wound measurements and tissue composition, and upload interpretations to the EMR[28]. Guadagnin *et al.* created an image mining-based system that automatically interprets tissue types and colors from pressure ulcers, while making selected relevant visual information available to providers in the medical record[29]. Given the rapid deterioration of wounds, daily monitoring is crucial to ensure proper healing and timely treatment adjustments.

Daily monitoring can inform adjustments to wound treatment, since chronic wounds are, by definition, difficult to treat due to a number of underlying health conditions. Pressure injuries occur due to localized damage to the skin and underlying soft tissue, usually over a bony prominence[30]. This damage is often a result of prolonged pressure, shear, and/or frictional forces[30]. Patients who have sensory deficits have an absent pressure feedback response that results in prolonged pressure over a period of time[30]. The way to prevent and heal these types of injuries is to avoid that prolonged pressure. This is especially difficult for those who are unable to sense pressure or those with mobility and activity challenges, like patients in wheelchairs. These patients also experience more friction/shear when transferring from chairs to other surfaces, are more likely to experience nutritional deficiencies, and have more moisture around their wounds. Sensory perception, mobility, activity, friction/shear, nutrition, and moisture are factors of the Braden Scale, a widely used scale that assesses six physical categories that affect wound healing[31].

Researchers have developed AI that tackles several of the factors included on the Braden Scale, aiming to facilitate the wound healing process. To address challenges in mobility, sensory perception, and activity, Gabison *et al.* used data from a noncontact system of load cells placed under a bed[32]. The data were used to determine whether a patient was left-side lying, supine, or right-side lying with 94% accuracy[32]. Danilovish *et al.* used an inexpensive "off-the-shelf" camera to classify a patient's positions into four different postures with 95% accuracy[33]. Artificially intelligent load cells and cameras could eventually alert caregivers when a

patient needs repositioning, enhancing effective healing.

Several AI-assisted technologies already aim to reposition patients automatically. Ni *et al.* developed an AI mattress that utilized three-dimensional InterSoft technology to detect bony prominences and redistribute pressure[34]. They studied this mattress on a 79-year-old male with left-sided hemiplegia, a need for positional changes, a sacral ulcer measuring 2.5 × 2 × 3 cm³ at five months of standard treatment, and an overall Braden score of 12, indicating a high risk of pressure injuries[34]. The AI mattress had an active pressure sensory array that ensured correct positioning and calculated pressure every second[34]. It used results from a first-time scan as a baseline to locate areas of bony prominences and employed a color-coded scheme to indicate areas at the highest risk for pressure injury[34]. As a result, the mattress redistributed pressure off those highest-pressure areas[34]. After four weeks of AI mattress usage, the wound measured shrunk in size, the patient reported more comfort, and he had healthier tissue types[34].

Recent advances in AI have also been employed through other methods to facilitate wound healing. One example includes the AI bandage. Kalasin *et al.* created a smart bandage with a flexible sensor and deep neural network algorithm[35]. The bandage has MXene, a new class of graphene-like two-dimensional transitional metal carbon, which enhances its conductivity and sensory capabilities[35]. It also has a wound dressing made of poly(vinyl acrylic) gel combined with polyaniline that can react to the wound's pH level[35]. The wound dressing generates a voltage that responds to changes in pH, indicating different stages of healing[35]. The deep learning network processes the voltage to classify the wound's healing stage with 95% accuracy[35]. Healthcare professionals can make informed decisions about wound treatment based on the data.

AI in wound prognosis

Chronic wounds are hard-to-heal due to a complex web of contributing factors including immunocompromise, poor blood circulation, and chronic inflammation, resulting in often bleak prognoses. Accurate prognosis requires comprehensive data collection, and researchers have applied AI to this challenge. Topaz *et al.* developed a natural language processing application that selected detailed wound information from free text clinical notes, gathering comprehensive data on wound comorbidities, risk factors, and underlying contributors[36]. With a strong ability to extract relevant data, AI can be leveraged to predict outcomes and prognoses. Robnik-Sikonja *et al.* used machine learning to analyze the effects of wound, patient, and treatment attributes on wound healing rates[37]. Ngo *et al.* studied how machine learning could use textural features from thermal images of venous leg ulcers to predict delayed healing outcomes[38]. They achieved a 79% sensitivity and 60% specificity with a Bayesian neural network[38]. With moderate sensitivity but mild specificity, clinicians will still need to rule out false positives to avoid unnecessary treatment.

Chen *et al.* similarly used AI to assess images of pressure ulcers for tissue changes, wound stages, and healing conditions[39]. These researchers aimed to provide clinicians with valuable information to guide treatment decisions and resource allocation.

With the creation of AI-assisted technologies like mattresses and bandages, appropriate resource allocation becomes crucial. Following the ethical principles of justice, resource allocation typically prioritizes those with the most dire conditions or those who stand to benefit the most and avoid the worst prognoses. Studies have examined wound healing prediction rates, but AI can also predict wound incidence. Alberden *et al.* created a machine-learning model to predict the development of pressure ulcers among surgical critical care patients[40]. The predictions are made from data in the patient's EMR, differentiating it from other models

that might require input from clinicians[40]. Similarly, Cai *et al.* developed a machine-learning model that used factors including age, surgical procedure, weight, and disease category to predict a patient's risk of pressure ulcers after cardiovascular surgery[41]. Lee *et al.* created an algorithm to predict nursing home patients at risk for pressure ulcers with 81% accuracy[42]. Lustig *et al.* developed a machine-learning algorithm for early detection of deep tissue injuries in the heel[43]. They trained the model with a database of six consecutive daily measurements of sub-epidermal moisture, which is an established biophysical marker that can detect pressure ulcer formation[43]. The algorithm resulted in a strong power to predict deep tissue injury in the heel the next day, with a sensitivity and specificity of 77% and 80%, respectively[43]. With the sensitivity and specificity being moderately high, clinicians may be able to use this tool as a diagnostic guide; however, clinical decision making must still be applied. Several studies explored an algorithm to identify certain risk factors associated with diabetic foot ulcer development[44-46]. These models can be applied to various wound types to predict which patients are most at risk of developing hard-to-heal wounds. Healthcare providers can allocate resources accordingly and work to prevent those injuries from happening.

Once those injuries do occur, complications are possible, and AI-assisted technologies can predict outcomes based on an array of inputted data. For example, poorly managed diabetic foot ulcers may result in amputation. Manual scoring systems help providers determine which ulcers are most at risk, but they do not capture as much data as AI can, leading to less accurate predictions. Schäfer *et al.* used machine learning with certain socioeconomic risk factors, such as household income, ethnic background, and changes in family status, to predict incidence and amputation risk for diabetic foot ulcers[47]. Xie *et al.* used demographic features, medical and medication history, clinical and laboratory data, and various ulcer classifications in a machine-learning model to predict which hospitalized patients with diabetic foot ulcers would undergo amputation[48]. The researchers demonstrated a 0.90, 0.85, and 0.86 predictive ability for non-amputation, minor amputation, and major amputation outcomes, respectively[48]. These predictions can help providers with wound management and resource allocation.

Challenges with AI in wound care

Although AI has the potential to significantly impact wound care, it raises several challenges [Figure 2][49]. The World Health Organization outlines six challenging yet crucial regulatory areas for thoughtful implementation of AI in health: transparency and documentation, risk management, data validation with clear indications of intended use, ensuring unbiased and quality data, safeguarding privacy and data security, and fostering collaboration among regulatory bodies to secure safe usage of AI[50].

Transparency regarding how patient data will be used is crucial for building societal trust. Mitigating risk by safely integrating AI into clinical practice, training algorithms without bias, and ensuring data quality control will contribute to safer and more accurate AI. Integrating AI into clinical practice and syncing patients' EMRs with data gathered from AI-assisted technology demands time, effort, and appropriate safeguards to protect patient data. Considering that AI is usually trained with patient data, and AI can better achieve its goals if trained with a large quantity of high-quality and diverse data, care must also be taken to protect databases of patient information. Compromised data could deter patients from sharing their information in the future.

Ensuring that patients feel comfortable sharing data is important for creating diverse databases. Resource-limited populations are more likely to be excluded from databases, leading to biased outputs. As AI becomes more capable of improving wound management, care should be taken to implement it in an equitable manner [Figure 3]. AI-assisted technologies may be costly, creating barriers to resource-constrained practices. To address these issues, being mindful of regulatory guidelines and collaborating between
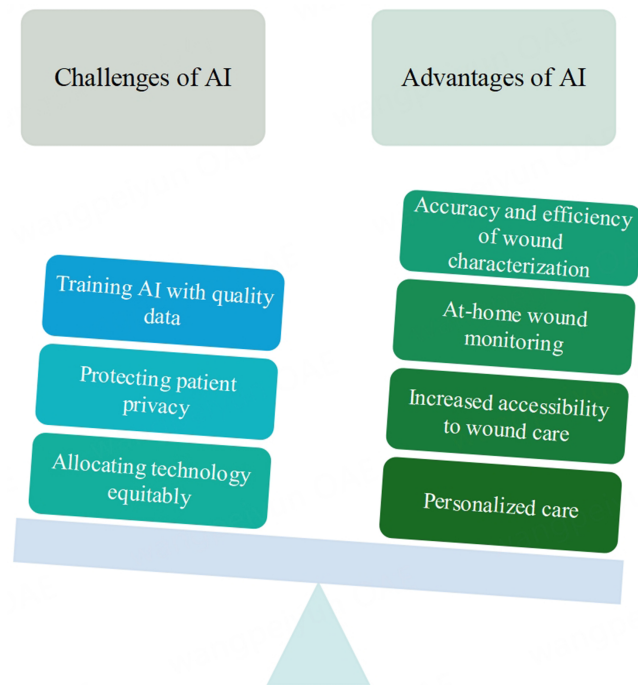
Figure 2. Visual diagram of the challenges and advantages of AI in wound care. AI: Artificial intelligence.
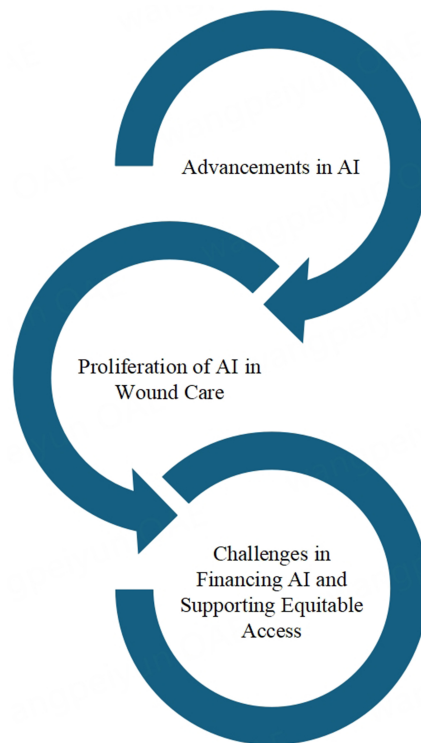

Figure 3. Schematic demonstrating the challenges arising from the proliferation of AI. AI: Artificial intelligence.

patients, providers, lawmakers, and ethicists will be vital to ensuring the ethical and safe implementation of AI in wound care[7,49,51].

As AI aims to improve prognostic prediction, providers should be aware of the challenges associated with communicating poor prognosis to patients. Providers might become fatigued when addressing treatment options for patients with unfavorable prognoses. Patients may question the validity of AI, and providers should be prepared to have such discussions. Although AI is prepared to analyze infinite amounts of data and suggest prognoses, providers must be equipped to discuss all those findings comprehensively.

Current gaps and the future of AI in wound care
Thus far, AI has been leveraged to process large amounts of data quickly and accurately, proving useful for wound diagnosis and characterization, management, treatment, and prognosis prediction. With advancements in AI-assisted technology, considerations for equitable access must be addressed. Understanding how this technology will be funded, whether through insurance, individual payers, government and public funding, or hybrid models, is crucial for equitable access. Wound management itself, even without AI-assisted technology, is expensive, and there are a plethora of available options for dressings, antibiotics, and more. Powerful and detailed AI algorithms could be used to help sort which methods of management might be most cost-effective given a patient's insurer. Utilizing the most cost-effective methods of management from the onset of wound diagnosis could help save on downstream costs.

Additionally, integrating developed smartphone apps into clinical practice, rather than just a trial setting, should be studied. Considering the incorporation of AI into digital platforms used by healthcare providers, such as EMRs, may allow for real-time wound analysis. If AI technology can be implemented in rural areas, providers might be able to guide remote wound care. However, once AI is integrated into these settings, identifying who will supervise the data, whether the provider, hospital, or a third-party data analytics group, will be paramount to seamlessly incorporating accurate and accessible AI-assisted technology into wound care.

Of the current studies on AI advancements in wound care, very few report demographic data. Fewer reported AI-assisted technology's accuracy, sensitivity, and specificity stratified by racial background. This is particularly important for image-based detection methods, where an accurate AI-assisted technology should be able to adequately diagnose wounds regardless of skin color. Further reporting on demographics will improve transparency and reduce bias from AI-assisted technology. Diversifying datasets for AI training will also ensure less biased data and improve output accuracy.

Of note, patients from diverse backgrounds may heal in clinically different ways. Keloids are more likely to develop after injury in those of African and Asian ancestry[52]. Hypertrophic scarring is more likely to occur in those with darker skin colors[53]. Not only will demographically diverse data provide insights into these conditions, but AI may be able to predict when these complications might occur. Kim *et al.* used a neural network structure along with multinominal logistic regression to identify that scar severity was positively associated with postoperative itching and pain[54]. They found that postoperative adhesion/tightening and induration/edema were negatively correlated with scar severity in patients. More research must be done to further predict keloid and hypertrophic scarring development in patients.

Additional research can be done into predicting wound healing complications such as sepsis and necrotizing fasciitis. Although AI's prognostic ability for both cases has been studied, they have not been studied in the context of wound healing[55-57]. AI can be leveraged in molecular biology as well. So far, most of the technologies that analyze wounds have focused on the wound itself. However, wounds are often accompanied by a heterogeneous array of exudates, calluses, edema, maceration, and excoriations. Wound healing is often impacted by the specific type and amount of bacteria that are in the wound. Research into

using AI to analyze wound exudates, periwound areas, and bacteriology could facilitate more accurate assessments of healing[58]. Nanotechnology with AI may offer a promising way of identifying bacteria and their characteristics in wounds, though the idea has not yet been fully studied. Similarly, research into genetic risk factors for certain wounds could pave the way for better prognostics.

CONCLUSION

AI stands to meaningfully impact wound diagnosis, management and therapy, and prognosis. Its ability to draw conclusions from relevant data in EMRs, patient images, and entered criteria allows for efficient and effective guidance. AI can help guide treatments outside the clinic as well, eventually making for more equitable care. While ensuring equitable access, diverse datasets, and data security presents challenges, further research can help address these issues and mitigate potential harms.

Being receptive to the improvements AI can offer while also addressing challenges as they arise will be crucial to the safe use of new technology in wound care. The field of medicine is constantly evolving, but cautious optimism will allow for the deliberate integration of empowering AI usage in wound care.

DECLARATIONS

Authors' contributions
Conceptualization, writing - review and editing, writing - original draft: Ganesan O
Writing - review and editing: Morris MX, Guo L
Conceptualization, project administration, writing - original draft, writing - review and editing: Orgill D

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