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Understanding artificial intelligence:

Barriers and potential in wound care

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Foreword

The global wound burden is rising at an alarming pace due to increases in the ageing population and comorbidities and complications, such as obesity, diabetes and complex surgeries (Sen, 2021; Chen et al, 2024; Reifs et al, 2025). The World Health Organization (WHO) estimates there will be a global shortage of 18 million healthcare professionals (HCPs) by 2030 (WHO, 2016) to deliver care. To address these increasingly complex challenges, it is crucial to improve efficiency of healthcare systems, clinician education and consistency of wound care standards (The King's Fund, 2018; Sen, 2021; Gould and Herman, 2025).

Within healthcare, artificial intelligence (AI) has emerged as a promising solution to several of these challenges with demonstrated improvements in diagnosis and treatment efficiency and clinician education, and productivity (Chen et al, 2024; Rippon et al, 2024). AI promises to replicate aspects of clinician experience and intelligence and can prove to be a useful tool in increasing the scale and speed of appropriate care provision (Bajwa et al, 2021; Rippon et al, 2024). AI has the potential to encompass all aspects of wound care and clinician education and training, including wound and risk assessment, healing prediction (e.g. by assessing patient comorbidities and social and psychological factors) and delivery of evidence-based, tailored treatment (Rippon et al, 2024; Reifs et al, 2025).

The aim of this consensus is to highlight for wound care clinicians and allied healthcare associates the multidimensional potential of AI, especially for chronic and/or complex wounds. A central theme of this consensus is to highlight the crucial role that wound care clinicians will need to play in implementing AI. It is only natural that some clinicians may be wary of the impact of AI on their job security. In this publication, we strive to dispel this myth and highlight that clinicians' satisfaction with AI can only improve with a better understanding of what AI is and how it can be an addition to their toolbox. The expert panel also provide examples of implementing AI in their own wound care practices and share their learnings of improved outcomes, current barriers and areas of future need.

This consensus is not intended as a reference for highly technical AI terminology. Instead, the goal is to simplify the overwhelming amount of AI information for wound care clinicians, presenting key concepts in accessible language. We aim to help clinicians of all experience levels understand the implications and unmet needs in AI-driven wound care, empowering them to navigate their role in this rapidly evolving field.

Educating and preparing clinicians for the disruptive potential of AI is the first step towards creating effective, replicable, equitable and safe wound care systems that are increasingly needed for addressing the rising global wound care burden.

Harikrishna K. R. Nair, Chair

What is AI and how can it be applied in wound care?

Before understanding what AI is, it is important to reduce the potential fear of AI and understand its current ubiquity in the world around us. Many people around the world routinely interface with systems and devices that are AI-embedded or AI-enabled, often without realising they are doing so; some common examples include:

- Cycle duration varying according to the weight of a washing load
- Online shopping sites making recommendations based on recent purchases
- Using a search engine, digital assistant or chatbot
- Using a robot vacuum cleaner to clean the house

Whether in routine life activities or healthcare, the current AI landscape is widening at a fast pace, with several overlapping and confusing terminologies used throughout the literature. Therefore, to understand AI, it is crucial for clinicians to first simplify the definitions so they can understand its application in their routine practices.

De-mystifying AI terminologies for wound care clinicians

AI is an umbrella terminology that encompasses tools which simulate how the human mind processes information to achieve a conclusion (Rippon et al, 2024).

Artificial intelligence (AI)

Although AI as a field existed before it, the Dartmouth Conference (1956) coined this terminology and officially launched it as an academic field (McCarthy, 2006).
Today, there is no universal definition of AI; however, the word 'AI' can be used for any machine with human-like intelligence (Rippon et al, 2024). Following definition is recommended:

'AI refers to the ability of computer systems to perform tasks that would typically require human intelligence. Such tasks could include learning, problem-solving, decision-making and, more importantly, understanding natural language. In essence, the aim of AI is to create machines that can simulate human cognitive functions.'

'If a machine can do a job, then an automatic calculator can be programmed to simulate the machine'.

An excerpt defining the fundamental concept behind artificial intelligence, from the original proposal of the seminal Dartmouth Summer Research Project On Artificial Intelligence (McCarthy et al, 2006).

AI enables computers or machines to process large amounts of data (such as wound photographs and clinical notes, i.e. text), identifying patterns in these data (whether by mathematical algorithms or a set of rules such as wound assessment and diagnosis parameters) and predicting what these patterns may mean (e.g. whether a wound will heal in the future and what has worked in the past for similar wounds). It mirrors the decision-making processes of clinicians but operates at greater speed and consistency, enhancing scalability and overall clinical efficiency.

AI 'supplements and augments' clinicians' experience and intelligence by employing a range of different mathematical, statistical or logical transformations to create clinical decision support systems (Bajwa et al, 2021; Elhaddad and Hamam, 2024). These transformations use raw data to 'train' the AI system for achieving pre-defined objectives (e.g. an AI model can be trained using a repository of diabetic foot ulcer images to determine whether a newly presented photograph presents a diabetic foot ulcer). However, it is important to remember that an AI tool may not be able to provide the cognitive context that clinicians can provide (Tikhomirov et al, 2024).

To simplify the potentially confusing concepts of AI for wound care clinicians, it is important to understand the basics of these AI transformations that have shown promising results in the creation of clinical decision support systems (**Figure 1**). It is also important to remember that an AI-based healthcare system may use one or more of these transformations simultaneously (Bajwa et al, 2021).

Machine learning (ML)
ML is a software that 'learns from experience' (Mitchell, 1997; Breiman, 2001). Rippon et al (2024) define ML as: *'Systems of machines [that] acquire knowledge from data, discern patterns, and autonomously arrive at decisions, often with minimal human intervention, i.e. machines have access to information and they make decisions with little or no human interference using algorithms (a set of defined instructions). Examples: image and speech recognition, online searching.'*

ML is a sub-branch of AI that can help derive insights from clinical data, such as electronic health records (EHRs; Shickel et al, 2018). An ML system can 'learn' from new data, improve its own prediction capabilities and apply these learnings to changing clinical scenarios. For example, an ML system based on logistic regression may provide the probability of a clinical scenario, such as whether a wound is likely to heal in a given timeframe (Rippon et al, 2024). Or, an ML system may be based on more than one decision tree and combine their output to provide a single recommendation, such as 'this wound is likely to become chronic (decision tree 1) and the patient likely has the capacity for self-care (decision tree 2); therefore, dressing XYZ can be recommended as an appropriate treatment option for this patient (final recommendation or output from the AI model)'. This output can then be overseen by a clinicians to ensure accuracy of the output.

In this manner, ML can help create wound care decision support systems to improve patient outcomes and reduce clinician burden.

Deep learning (DL)
Deep learning (DL) is '*a class of algorithms that learns by using a large, many-layered collection of connected processes and exposing these processors to a vast set of examples*' (Bajwa et al, 2021). Building on the complexity of ML, DL has been applied in clinical decision-making processes that rely on image, speech or text recognition (Bajwa et al, 2021; Rippon et al, 2024) because when combined with holistic patient information, these types of clinical data contain interconnected networks of information. For example, 'a patient with diabetes' is a piece of information that is connected to the information, 'this patient also has a diabetic foot ulcer and heart disease'. Just as human neurons form interconnecting networks of information (called 'neural networks') to identify patterns, DL uses networks of information gleaned from data sets and recognises and predicts patterns (Rippon et al, 2024). For example, a DL-based AI tool may assess various wound images and associated patient records (collectively, 'data sets'), with each data set comprising of either exclusively diabetic foot ulcers or venous leg ulcers. The DL-tool can then use the information derived from each of these pre-existing data sets (i.e. diabetic foot ulcers versus venous leg ulcers) to deduce which group the wound image belongs to (i.e. diabetic foot ulcer or venous leg ulcer). DL has already shown promising results in AI tools aimed at identifying and classifying skin cancers (Esteva et al, 2017; Naqvi et al, 2023).

Natural language processing (NLP)
Natural language processing (NLP) is '*a method of computational analysis of language that allows a machine to understand and interpret data. Examples: text translation, speech recognition*' (Rippon et al, 2024).

NLP recognises meaningful patterns in human language and can help find invaluable clinical information from texts such as unstructured clinical notes, research articles, electronic medical records (EMRs)/EHRs and other similar clinical materials (Elhaddad and Hamam, 2024). For example, an NLP-based AI tool may use patients' routine wound care records or notes taken at each dressing change to decipher the wound status and healing journey and may help identify red flags to trigger escalation.

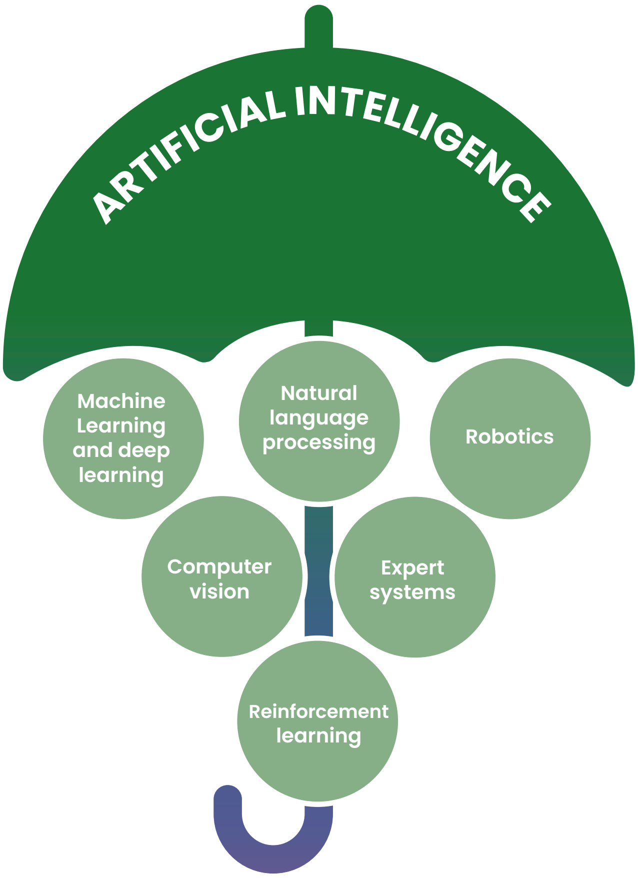
Computer vision
This is a field of AI that enables computers to 'see' and interpret images and videos. In wound

care, computer vision can be used to analyse wound images for characteristics such as tissue type and infection (International Business Machine Corporation [IBM], 2021).

Expert systems
Computer programmes can act as expert systems to draw inferences from a large knowledge base to replicate human reasoning and logic (Krishnamoorthy and Rajeev, 1996). In wound care, an expert system can be built using the knowledge and experience of wound care experts, which can then help predict and manage complexities in wound care, such as healing prediction and preventative approaches (Le and Pham, 2023).

Reinforcement learning
In this field of AI, a software system or algorithm acts as a decision-maker learning from trial-and-error 'in an uncertain environment' and 'is rewarded for optimal behaviours, and punished for undesired behaviours' (National Library of Medicine [NLM], 2025). This decision-maker can be used in wound care settings to help improve new decisions based on previously achieved care outcomes.

Figure 1. AI is an umbrella term that encompasses ML, DL and generative AI.



Generative AI
Advancing beyond DL in pattern prediction, generative AI is an application of AI that can create new content by analysing and learning from patterns and characteristics within existing data, such as images or text (Encarnação et al, 2024). The existing data set acts as the 'training data' through which generative AI learns how to create new content (e.g. Grammarly, Duolingo, Coursera and Chat GPT; Yu and Guo, 2023).

Generative AI typically uses one or more AI technologies (e.g. ML, DL and/or NLP) to achieve this goal and 'mirror' the data set it has been trained on. This AI technology has significant potential for applications in medical education (Preiksaitis and Rose, 2023).

Hallucinations in AI

When creating new content and/or deriving conclusions based on an existing data set, an AI tool generates a range of possible scenarios, not all of which may be correct or accurate. These inaccurate or misleading outputs are called 'hallucinations' (Berk, 2024).

These hallucinations may lead to dissemination of incorrect information (e.g. via Chat GPT) or present significant health and safety risks in wound care, such as misdiagnosis of wound types or incorrect dressing recommendations. In a recent study of 15 financial topics via the AI tools ChatGPT-4o, o1-preview and Gemini Advanced, the hallucination rate was found to be 20.0%, 21.3% and 76.7%, respectively, with significantly worse outcomes for recent topics (Erdem et al, 2025).

The possibility of hallucinations in AI tools requires that healthcare applications of AI are heavily regulated and consistently monitored by clinical experts for identifying any potential risks in a timely manner.

Distinction between technology and AI

It is important to differentiate between the words 'technology' and 'AI'.

Although AI can be considered a form of technology, typically, the term 'technology' describes any tools, devices or implements that collect, feed and feedback data to and from AI. A smartphone is an example of technology—a device that enables access to AI tools like ChatGPT. Similarly, in wound care, an ankle-brachial pressure index (ABPI) machine serves as a technological tool for collecting patient data. This data can then be processed by an AI system, either integrated within the ABPI machine or separately, to generate a comprehensive picture of the patient's condition. While not all technology incorporates AI, every AI tool relies on data gathered through various devices, instruments or systems.

Distinction between assessment and diagnostic tools in healthcare

It is important to make the distinction between assessment and diagnostic tools in healthcare, because this has significant implications for how medical devices are regulated in different parts of the world. For example:

- Consider a device that measures the blood pressure of a patient (device A) versus a device that 'designates' this recorded blood pressure as 'low' or 'high' (device B). The latter function is 'diagnosis', which can be performed by either a clinician or a device. Furthermore, devices A and B can be combined to create a single apparatus (device C) that performs both functions, i.e. it assesses the blood pressure and diagnoses it as 'low' or 'high'.

It is crucial to understand that regulation and approval for each of these devices (A, B and C) will be different from each other. Each of these tools will be required to undergo a separate validation to ensure regulatory approval.

Furthermore, it may be possible that these devices may embed AI tools to facilitate clinicians, requiring another set of regulations aimed at the AI component.

Why should we talk about AI in wound care?

AI implementation requires data that are amenable to AI-specific mathematical and logical operations or transformations (Anisuzzaman et al, 2022). Wound assessment yields qualitative (appearance of the wound and surrounding skin, wound boundaries, peri-wound skin status) and quantitative data (wound length/width/depth/area) that require consistent monitoring and recording to ensure wound progress can be systematically measured (Kabir et al, 2024).

The collected data, along with wound photographs, clinical notes and transcripts of telemedicine sessions, align well with common AI tools such as ML, DL and NLP. AI-driven digital platforms and systems for wound care are already in development (Anisuzzaman et al, 2022; Cunha Reis, 2025).

Successful implementation of telemedicine and the use of mobile phones and cameras in wound care has made it possible for clinicians to monitor and review wounds remotely. AI can take this process a step further by providing ease of assessment and diagnosis as well as offering recommendations for treatment and follow-up wound care (Kabir et al, 2024). This AI assistance can save invaluable clinician time and healthcare resources because in-person evaluation and follow-up by qualified wound care experts is not always realistic in routine care due to lack of accessibility or an inadequate number of trained clinicians (Kabir et al, 2024). It can also reduce travel needs and costs for patients.

Consequently, wound care has experienced a significant surge in both interest and use of AI. However, AI is frequently misunderstood or met with scepticism by clinicians and patients. Providing an overview of its current and future applications across the broader healthcare landscape could help clinicians better grasp its potential and navigate the challenges of implementing AI in wound care.

AI has shown huge potential in healthcare, with its application expanding rapidly in the last decade (Kaul et al, 2020; Bajwa et al, 2021; Alowais et al, 2023; Hirani et al, 2024). See **Box 1** for a summary of some current AI applications in healthcare.

AI is now well-established in healthcare and it is clear that current areas of use will continue to develop further, with a 47.6% compound annual growth rate expected globally by 2032. [**Figure 2**; Faiyazuddin et al, 2025].

There are also a number of exciting potential future developments regarding AI in healthcare, some of which are already being used, albeit in their infancy and others that are more speculative. **Box 2** presents some examples of potential future developments of AI in healthcare.

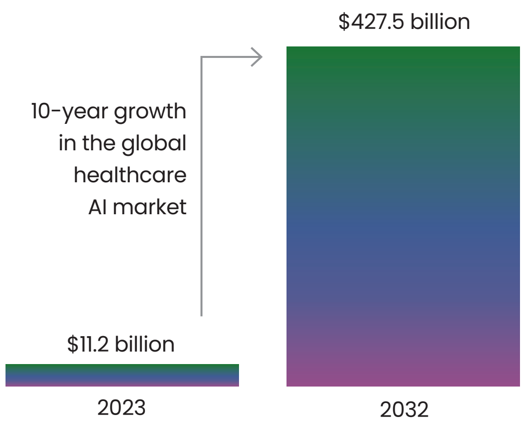


Figure 2. The projected 10-year growth of AI in healthcare (Faiyazuddin et al, 2025).

Box 1. Current applications of AI in healthcare (Kaul et al, 2020; Lee et al, 2020; Bajwa et al, 2021; Alowais et al, 2023; Hirani et al, 2024; Rudroff et al, 2024; Zaretsky et al, 2024)

- **Diagnostics:** AI is enhancing health professionals' ability to detect disease early ('computer-aided detection') and diagnose it accurately (including through use of decision support tools). A key contributor in this area is advances in the ability to analyse images accurately and in large volumes. Applications are at both individual level and population level, the latter including screening programmes (e.g. for breast cancer)
- **Personalised care and tailored treatments:** AI is enabling personalisation of care and tailoring of treatment, for example through consideration of an individual's lifestyle, demographic and genetics. AI can also analyse large amounts of population-level data to identify risk factors in sub-groups of the population
- **Predictive analytics:** The ability of AI to rapidly sift through and model vast amounts of data (both historical and real-time) brings benefits in such areas as prediction and tracking of disease outbreaks; predicting demands on services and predicting clinical outcomes
- **Drug discovery and development:** AI is helping to speed up the processes of drug discovery and development, through prediction of drug targets, creation of drug/molecular models and production of simulated data/simulated drug trials. These capabilities also offer potential for replacement of animals in drug development and testing
- **Self-care and self-management:** AI is supporting patient self-care and self-management in a variety of ways, such as gathering data, which can be shared with the patient and, in some cases, health professionals, through sensors in wearables and other devices; sharing and interpretation of images (e.g. of skin lesions or wounds) and providing support and advice, for example through chatbots or virtual assistants. AI is also aiding clinicians to support patient self-care and self-management, for example through creation of patient information resources
- **Health and care professional training and education:** AI has widespread application in the training and education of health and care professionals, including through realistic simulations, decision support tools and training resources
- **Undertaking routine tasks:** The advent of generative AI in particular is supporting health professionals in undertaking routine tasks, such as creating patient letters or discharge summaries.

Box 2. Some potential future developments in the use of AI in healthcare (Kaul et al, 2020; Lee et al, 2020; Bajwa et al, 2021; Alowais et al, 2023; Hirani et al, 2024; Katsoulakis et al, 2024; Krishnan et al, 2025).

- **Robotics:** Although there is already some integration of AI into robotics in health and care (e.g. in surgical and social robots), this area is in its infancy. It is, however, predicted to grow rapidly, supporting increased use of robots in care delivery (including personal care and undertaking technical tasks), to support wellbeing and to facilitate independent living
- **Genomic analysis:** Ongoing developments in machine learning are predicted to advance analysis of human (and other) genomes, allowing further identification of genetic mutations, facilitating development of targeted or personalised therapies and prediction of disease susceptibility
- **Real-time clinical decision support:** Increasing capabilities of AI systems are predicted to enable real-time clinical decision support, at the point of care
- **Preventative healthcare:** Advances in AI are predicted to enable more 'upstream' identification of individual and population-level risk of developing health problems and aid in developing and delivering interventions aimed at preventing disease onset or progression
- **New treatments for drug-resistant microbes:** AI-assisted drug development has recently yielded new antibiotics for gonorrhoea and methicilin-resistant *Staphylococcus aureus,* highlighting great potential for discovery of new antibiotics
- **Creating digitial twins:** AI tools are being implemented to create virtual models of patients that mimic a patient in all aspects and use real-time data to manage health conditions.

Despite these recent advances, further work is required, with many AI applications in healthcare, including some that are widely available or marketed commercially, still requiring considerable research, development and testing (Rippon et al, 2024). The role of clinicians will be central in addressing these challenges and improving AI applications.

Wound care burden

AI is transforming digital health and telemedicine, a domain that has already seen significant application in wound care (Bai et al, 2024). With the escalation in wound prevalence and increasing burden on clinical and healthcare workforces globally, there is a need to improve efficiency and productivity of the existing workforce (WHO, 2016; Sen, 2021). There is also an urgent need to train new clinicians in managing this projected rise in people living with chronic wounds (WHO, 2016).

These unmet needs have already been recognised by wound care clinicians worldwide, with AI applications in wound care being developed and tested globally.

Application of AI in wound care practice

Several imaging-based healthcare fields have experienced significant advancements in recent years due to AI implementation (Faiyazuddin et al, 2025). AI has been applied in the field of radiology, supporting patients and healthcare systems amid a global shortage of radiologists: approximately a third of all radiologists in the US now use AI in their clinical work (Tanno et al, 2025). In an effort to reduce image assessment time and improve the speed of lung cancer diagnosis, the Yorkshire Imaging Collaborative of the NHS has implemented AI to support image analysis and decision-making for the estimated 400,000 X-ray images taken annually across the participating trusts (West Yorkshire Association of Acute Trusts, 2025). Within the fields that require magnetic resonance imaging (MRI) for accurate visualisation and diagnosis, AI has been used in numerous applications in image synthesis, parameter assessment, image segmentation and other aspects of diagnostics (Shimron et al, 2023).

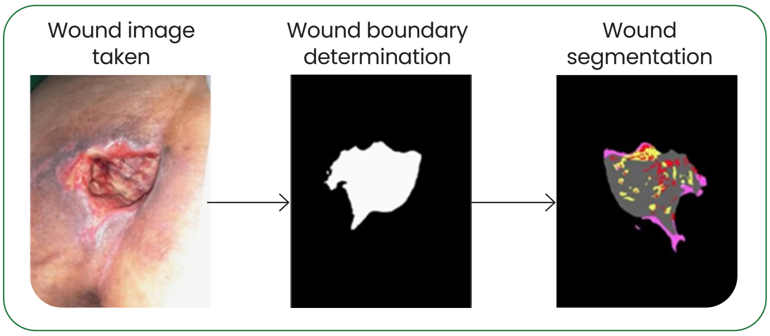
These outcomes in other imaging-based healthcare fields highlight how AI has great potential at each stage of wound care.

Wound assessment and diagnosis

When assessing a wound, clinicians employ visual observation to determine wound location, dimension (area and depth), peri-wound status, tissue classification, type of exudate and signs of infection (World Union Of Wound Healing Societies [WUWHS], 2025). As wound photographs have become a standard tool in routine wound care, AI may be used to:

1. Augment and clarify wound photographs (e.g. manipulation of lighting, contrast, saturation and focus)
2. Interpret the wound status to assist in accurate identification, diagnosis and monitoring (e.g. by designating wound and peri-wound boundaries and tissue type).

A. Basic steps in assessing wound boundary and tissue types



B. The first step in building an AI algorithm to determine the edges and tissue type for a wound (left); example output of an AI algorithm for wound assessment (right).

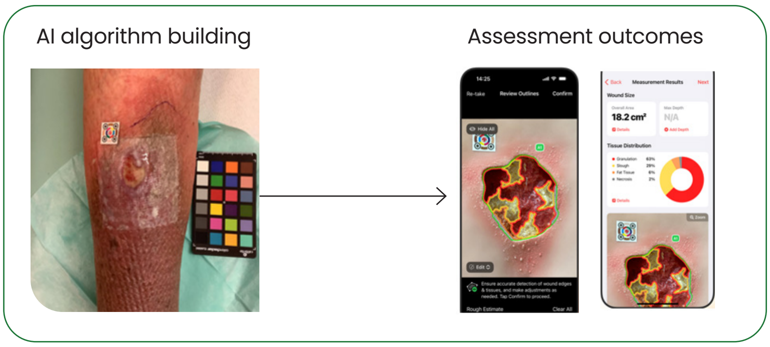


Figure 3. Examples of AI implementation in wound assessment (images courtesy of Sebastian Probst; Stefanelli et al, 2025).

Recent publications have demonstrated the effectiveness of these applications during wound and tissue assessment. Reifs et al (2023) assessed several AI-based wound imaging methods for detection of region of interest, area calculation and tissue classification. The wound photographs obtained by smartphones yielded reliable results and the authors were able to define wound contour and measurement with a high inter-rater reliability, resulting in accurate tissue classification (Reifs et al, 2023). In a recent study of diabetic foot ulcers, an AI-based assessment and classification tool demonstrated high accuracy, precision and recall in distinguishing between ulcer versus non-ulcer photographs (Bansal et al, 2024).

Anecdotal evidence shows experiences of implementing AI-based wound classification via wound photographs recorded in an outpatient setting: an AI model was trained on sample wound photographs where the percentage of slough and dead tissue had already been calculated by a HCP. The objective of the AI model was to assess new wound photographs, estimate the tissue type and recommend the optimal dressing. **Figure 3** outlines the steps this AI tool takes in order to assess a wound and provide measurable outputs.

Prediction of healing

Numerous global initiatives are actively working to enhance wound healing predictions through AI-driven methods. A groundbreaking trial within the National Health Service (NHS) has introduced DeepView, a reliable healing predictor tool designed to estimate burn wound depth. This innovation has led to outstanding assessment outcomes and informed clinical recommendations, with clinicians praising its portability and imaging quality, both of which were rated as excellent (NHS, 2024).

In a new wound care initiative, wound photographs are assessed using an AI tool, which triggers case escalation if any red flags are detected. Additionally, AI-powered smartphone cameras are being used to scan patients' bodies and identify pressure ulcer hotspots, areas at risk of ulcer development. This technology has enabled clinicians to take proactive measures in pressure ulcer prevention.

Validation of collected data

In Canada, geographic constraints make in-person patient assessments challenging. To address this, e-consulting has been introduced, allowing local and community staff to consult specialists or registered clinicians via an electronic system that facilitates wound image sharing.

To enhance accuracy and accountability, an AI-powered image analysis tool has been integrated into the consulting system. This tool ensures that only high-quality wound images are recorded by automatically rejecting substandard photographs, such as grainy images or those where the peri-wound skin is not clearly visible. This approach strengthens data reliability while supporting clinicians in delivering more effective wound care assessments.

Consensus recommendation: AI tools can be used to validate clinical recordings (e.g. ensuring wound images are of appropriate quality). Similar approaches should be adopted across the world, especially in remote areas or regions with limited access to qualified wound care clinicians (e.g. images can be used to assess whether compression therapy has been applied correctly).

Clinical education

AI applications have already demonstrated promise in virtual medical education. Using a system consisting of automatic tutoring and assessment tools, AI-based medical education has the adaptability required to provide feedback to the learner and recommend new training materials (Chiu et al, 2023; Encarnação et al, 2024). AI can also track long-term learning trends to improve knowledge gaps and provide opportunities tailored to the needs of each clinician in their specific clinical setting (De Gagne et al, 2023).

An example of using an AI tool in training saw trainee clinicians receiving medical education via virtual reality scenarios to familiarise them with wound types with common challenges in assessment and treatment. The integration of AI-based virtual reality scenarios was found to significantly enhance both learning and knowledge retention. To further improve this training system, efforts are now focussed on incorporating wound-specific odours into the simulations, allowing clinicians to gain firsthand experience in identifying and familiarising themselves with malodour.

AI systems also exist to help prepare course materials and assessments (Lee et al, 2024). For scientific accuracy, these systems can be programmed to search for information only from pre-specified, reliable sources (e.g. NICE guidelines, Cochrane publications).

Clinical note-taking and preparing discharge summaries

For appropriate treatment delivery, it is crucial to ensure accurate and timely documentation of clinical notes in EHRs/EMRs (Balloch et al, 2024). However, this is known to increase clinicians workload, potentially contributing to increased cognitive burden as well as burnout (Muhiyaddin et al, 2022). In a simulated study of an AI tool for improved EHR documentation, an AI tool increased documentation quality and reduced consultation time by approximately 26%, without any significant decrease in patient-facing time or increase in erroneous content entries (Balloch et al, 2024).

Various AI tools used in the NHS for preparation of discharge notes/summaries have already proven helpful in saving clinician time. In a preliminary study by Clough et al (2024) to assess the potential of AI in preparing a high-quality discharge summary, all discharge summaries generated by AI were of high-quality when compared to summaries generated by junior doctors (100% versus 92%).

Further implementation of these AI tools across wound care settings has the potential to make cost- and time-savings and reduce clinician burden.

Improving the future of wound care with AI

Tools employing AI are advancing rapidly across healthcare settings. However, their successful implementation in wound care remains hindered by significant challenges and barriers. These include concerns around data quality and accessibility, clinician scepticism, regulatory constraints and the need for clear integration pathways within existing workflows. Addressing these obstacles is essential to harness AI's full potential in enhancing wound care practices.

Current barriers to implementing AI in wound care

Several barriers currently exist, such as data-related or technical challenges.

Data-related challenges

Wound care clinicians currently face several types of data-related challenges in implementation of AI tools:

- Data quality and availability
  - AI algorithms require large, high-quality data sets for training (Khalid et al, 2023). In wound care, data can be highly variable due to differences in wound types, patient conditions and imaging techniques. Images taken by untrained individuals (e.g. by patients/carers and in the absence of medical imaging support) or on low-quality devices can introduce errors in the AI model generated using these images
  - Standardised data collection protocols are often lacking in wound care, especially for people living with chronic wounds, which tend to require long-term care provided by both registered and unregistered healthcare staff; this can lead to inconsistencies and biases in the data (Atkin and Probst, 2025). Additionally, important meta-data (e.g. patient age, gender, comorbidities), which is crucial to facilitate training of AI, is often lacking. This can lead to gaps when training an AI model
  - There remains a challenge in building a quality database for AI, as image quality and consistency across the wound journey can vary: even for the same wound through its healing journey, there may be variations in the photographs in terms of lighting, distance from the camera or impact of skin tone.

Consensus recommendation: AI systems rely on high-quality data to provide reproducible and accurate outputs (e.g. clinical recommendations or predictions). To support training of AI systems, wound care clinicians need to be aware of the importance of data quality for routinely collected data and of the need for meta-data that must accompany wound images. There is a need to educate clinicians on the definition and components of meta-data to ensure consistent data recording and input throughout the patient journey.

- Data privacy and security
  - Wound care involves sensitive patient data, raising concerns about privacy and security (Liu et al, 2025). Robust data protection measures are essential to prevent unauthorised access and breaches when developing AI models that require patient images.

Technical challenges

- Algorithm accuracy and reliability
  - AI algorithms/transformations must be highly accurate and reliable to ensure patient safety because errors in wound assessment or treatment recommendations may have serious consequences (Ganesan et al, 2024).
- The 'Black Box' problem
  - Some AI algorithms, particularly DL models, operate as 'black boxes', meaning that it can be difficult to understand how they arrive at their decisions (Dynatrace, 2021). This lack of

transparency may have significant clinical and regulatory implications, making it challenging to validate the algorithm's performance and identify potential errors; it also presents problems in terms of accountability for clinical decisions (IBM, 2024a).

- Potential for 'hallucination'
  - Generative AI systems can create incorrect or misleading outputs, due to factors including insufficient training data, biases or incorrect assumptions. These 'hallucinations' can be realistic and convincing (Alowais et al, 2023).

Consensus recommendation: For AI challenges, such as hallucination or the Black Box problem, it is crucial to prepare appropriate and relevant training programmes so current and future clinicians can understand how to employ critical thinking and clinical judgement when interpreting results produced by AI models.

- Integration with existing systems
  - Integrating AI-powered wound care tools with existing EHRs/EMRs can be complex and challenging due to variations in these systems and the regulations or restrictions associated with each (Liu et al, 2025). In the global wound care landscape, poor IT infrastructure and a mosaic of EHR/EMR systems are prevalent, each of varying quality and compatibility, which can hamper AI integration and cross-system functioning/collaboration.

Consensus recommendation: Poor IT infrastructure can lead to a bottleneck in the adoption of AI and its integration with existing systems. The scale of this problem requires commitment from global wound care communities and health services at organisational, regional and national level, especially as equitable achievement of this goal is limited by financial constraints in many areas globally.

Ethical and practical challenges

Several factor contribute to these challenges, including:

Bias in clinical data

If the training data is biased, the AI algorithm will likely be biased, leading to disparities in care for different patient populations and potentially compounding existing inequalities (Webster et al, 2022). For example, if the wound data primarily consists of images from patients with light skin tones, the AI algorithm will be less accurate in analysing wounds in patients with dark skin tones (Rochon et al, 2024). Or, bias may also be introduced from commercial sources, leading to their own product being identified for treatment.

Consensus recommendation: It is crucial to ensure that the development, training and use of AI systems does not create or compound inequalities.

- Clinician trust and acceptance
  - Concerns among wound care clinicians regarding job or role displacement are an important issue (Frey and Osborne, 2017; Jiang et al, 2017; Ahmed et al, 2023), making clinicians hesitant to adopt AI-powered tools, especially if they do not fully understand or trust them (Ahmed et al, 2023).
- Regulatory and ethical approval
  - AI-powered wound care devices and software must undergo rigorous testing and regulatory approval before they can be used in clinical practice. Additionally, data-sharing across organisations, sectors (e.g. public to private, or health and care systems to higher education institutions) and countries can be complex, and data protection regulations (locally or at

regional/national level) may make this difficult or even impossible. It is worth noting that regulatory guidance in this area is constantly being updated by world governments (e.g. the latest updates from UK government were released in February 2025; Medicine & Healthcare products Regulatory Agency [MHRA], 2025).

✔ **Consensus recommendation:** Robust regulation of AI and sound data protection are important. However, they can present challenges in the development, training and adoption of AI in healthcare. Wound care professionals need to work alongside organisational leads, regulators and policy makers to ensure there is a balance between governance and scope for innovation in AI.

- Cost and accessibility
  - The cost of developing and implementing AI-powered wound care solutions can be substantial, which could limit their accessibility in resource-limited settings.
- Patient privacy and safety concerns
  - It is inevitable that good-quality wound images will be central to the evolution of AI systems in wound care. With patients and clinicians routinely using their smartphones to record and share these photographs (including those wounds in intimate body areas), there is a need to ensure protection of patient privacy and dignity. Currently, not all people living with wounds may fully understand the future impact and usage of their wound's photographs.

Box 3 suggests steps which AI designers and healthcare professionals need to take, in some instances in collaboration with organisational leads, regulators and policy makers, to overcome the challenges and barriers to adoption of AI.

Box 3. Suggested steps to reduce concerns and barriers to AI implementation (Queen and Harding, 2019; Bajwa et al, 2021; Ahmed et al, 2023; Alowais et al, 2023; Rippon et al, 2024)

Addressing healthcare professionals' concerns and barriers
- Dispel myths regarding AI 'taking our jobs'
- Learn more about the benefits of AI and share learning with others
- Focus on how AI can improve the efficiency and effectiveness of human interaction, rather than replacing it
- Employ innovative data annotation methods to facilitate AI training
- Focus on ways in which AI can enhance patient care
- Engage in multidisciplinary approaches to identify constructive solutions to challenges posed by AI
- Recognise that human judgement and clinical reasoning are not infallible and that there are limitations to current best evidence
- Be willing to embrace technology and support others in doing so, especially those that may appear more 'technophobic'

Addressing patients' concerns and barriers
- Develop more robust AI techniques and models
- Ensure that privacy and data security are robust and uses of data are transparent
- Ensure that training of AI systems does not create biases or compound inequalities
- Focus on how in which AI can improve the efficiency and effectiveness of patient-clinician interaction, rather than replacing it
- Focus on ways that AI can enhance patient care and improve the patient experience

The role of wound care clinicians in AI systems

The role of wound care clinicians is central at each stage of AI system development.

Authentication of AI system at each step of development and roll-out

The potential of AI in wound care lies in diagnostics and prediction for improving wound care (e.g. using a wound image to determine aetiology and predict healing outcomes). One of the largest obstacle to achieving this potential is ensuring AI technologies are customised for wound care applications. Wound care clinicians are well placed to provide AI engineers the context (e.g. the impact of the wound, the patient and the clinical setting) required to ask the right questions and create an effective model.

Figure 4 depicts a stepwise development of an AI model and outlines the stakeholders involved in each step: this further highlights how clinicians are crucial at each step of the development of an AI model for wound care.

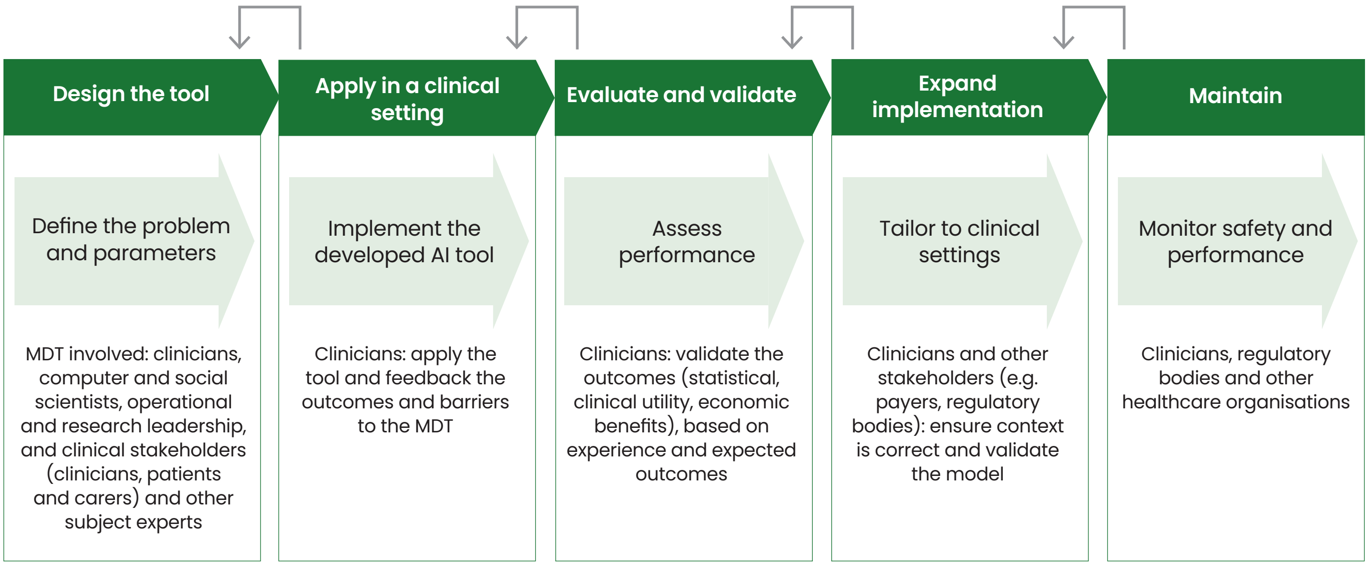


Figure 4. The stages in the development of an AI model and the crucial role of clinicians and other stakeholders at each step. *Abbreviation: MDT: multidisciplinary team.*

Implementation of AI recommendations

Once an AI model has provided recommendations for care, clinicians may be able to implement these recommendations and deliver the care, which is often complex, including wound debridement, dressing application and changes, exudate management and addressing other physical, cognitive or psychological challenges that a person with wound(s) may experience. However, clinicians must also use professional judgement and not solely rely on the AI recommendations.

Continuous patient monitoring for individualised treatment

Healing, especially for patients with complex or non-healing wounds, is a physiological process that requires weeks and even months to complete (Cullen and Gefen, 2023). Some wounds may never heal and a significant number of complex wounds (e.g. diabetic foot ulcers) often recur or become infected (Armstrong et al, 2023; Fletcher et al, 2024). Throughout the journey of individuals living with complex wounds (see **Box 4** for definition of complex wounds), holistic monitoring and assessment remain the gold standard to underpin timely intervention. However, this process demands substantial clinician time and resources for each patient and wound. By harnessing

Box 4: Preferred terminology for nonhealing versus complex wounds.

A recent consensus from the WUWHS (2025) recommended adaptation of the term 'complex wounds' in contrast to 'non-healing wounds'. It was noted that the term 'complex wounds' encompasses both non-healing wounds as well as those at risk of becoming non-healing (e.g. in people living with diabetes; Fletcher et al, 2024).

AI's ability to efficiently process vast amounts of data, clinicians can optimise resource utilisation, enhance productivity, and improve efficiency, ultimately supporting them in achieving the highest standards of wound care.

Compassion and care

Empathy and compassionate care for people living with wounds is a fundamental requirement for improving patient outcomes such as engagement with treatment (ultimately increasing healing rates; Nembhard et al, 2023) and reduction in psychological and social distress (ultimately improving immune function due to lower stress; Schakel et al, 2019). However, with the rising challenges of an ageing population and shortage of healthcare workforce, there is a significant lack of resources for providing empathetic care for people living with wounds (Probst et al, 2025).

With AI implementation, there is potential for wound care clinicians to save time for empathic care delivery.

Patient communication

Effective communication can help patients become more engaged with their treatment and build trust in clinicians (Probst et al, 2025), making it easier for clinicians to identify symptoms, and individual barriers that a patient may be experiencing. Ultimately, this results in improved support with timely wound care interventions to remove healing barriers associated with nutrition, mobility issues and pain management (Queen and Harding, 2019; Probst et al, 2025). It can be challenging for an inexperienced wound care clinician to effectively identify and understand patient barriers. Access to experienced clinicians for guidance and support is essential, ensuring that decisions are evidence-informed and patient-centred. AI tools can assist in analysing data and providing recommendations, but their effectiveness depends on clinician expertise in interpreting and applying those insights. Without access to knowledgeable professionals, AI-driven recommendations may lack the nuanced understanding required for optimal wound care.

MYTH

Clinicians think clinically, not computationally, and are, therefore, not well-equipped to advise on developing AI tools for wound care.

TRUTH

Clinicians thinking 'clinically' has historically been crucial to bringing both technology and AI to wound care. When creating and integrating new tools into practice, clinicians are best-placed to provide the practical tips and identify potential barriers that are needed for development, implementation and validation of these tools.

MYTH

AI implementation may prove costly to healthcare systems as the algorithms may recommend advanced treatments and dressings to achieve optimal outcomes.

TRUTH

AI algorithms must be created based on scientific evidence and realistic targets (e.g. for a patient with pressure ulcer, the AI algorithm can be weighted towards routine repositioning and not towards managing with the most advanced and costly dressing available).

Which AI tools do wound care clinicians require?

Wound care clinicians require the following AI tools:

Diagnosis, assessment and healing prediction tools
The field of wound care is vast and each wound aetiology may require a specialised set of AI tools. However, in broad terms, AI systems will be required to identify wound aetiology, tissue types, presence/absence of infection and a holistic patient and wound assessment in their respective healthcare setting – the ultimate objective being improving patient outcomes and saving clinician time and resources.

Table 1 highlights the requirements for developing AI tools specialised for major aetiologies of chronic wounds.

Table 1: Requirements for developing AI tools for major aetiologies of chronic wounds (Reifs et al, 2023; Bansal and Vidyarthi, 2024; Wongvibulsin et al, 2024).

Wound aetiology	Requirements/unmet needs for an AI tool
All aetiologies (e.g. venous leg ulcers, lymphoedema and palliative wounds)	• A patient app to identify early signs of skin damage • Chatbots or virtual assistants to guide self-care/escalation • Wound assessment and measurement (identification of tissue type, presence/absence of infection or chronic inflammation, identification of altered pH or oxygen levels) • Wound healing prediction • Escalation planning • AI-generated transfer or discharge letters/summaries
Diabetic foot ulcers	• Assess wound images; augment for interpretation • Diagnose and classify the ulcer • Differentiate between granulation, slough, ischemia, necrosis and infection • Create a holistic picture using information about the patient, wound and clinical setting • Predict healing trajectory and recommend appropriate dressings/ treatments
Pressure ulcers	Identify risk factors and direct to a care pathway by: • Use of ML or DL to assess EPRs of patients who did or did not develop pressure ulcer • Diagnosis and categorisation of ulcer: creating a holistic picture using information about the patient, wound and clinical setting • Sensors to identify inflammatory markers (e.g. underneath NPWT devices) • Identification of at-risk areas/early damage (e.g. via subepidermal moisture [SEM] scanners) • Manage risks (e.g. pressure monitoring mats and programmable repositioning devices or preventative equipment) • Robotics for repositioning
In addition, there is a need for an embedded function within the tools above to provide distinction between pathologies versus symptomatic disease • Provide holistic patient and wound picture so short-term and long-term interventions and management goals can be decided upon.	

Clinical care-related tools

Several areas of unmet need [Table 2] in wound care were identified where AI-based tools can help improve outcomes and productivity.

Table 2: The potential functionalities that AI tools for wound care may embed.

Unmet need	Goal of the AI tool
An MDT interface that connects different wound care clinical settings (community, acute, settings specialised in comorbidities such as diabetes)	• Monitor the wound healing journey • Understand when a patient should be referred to specialists • Connect with local referral pathways
A wound care provision system similar to 'National Health Service [NHS] 111'	• Direct patients with wound-related care needs away from Accident and Emergency [A&E] (e.g. a patient with a wound may simply visit the A&E department because their dressing is leaking)
A function embedded in the wound care system to assess cost-effectiveness of healing strategies	• Build a case for implementing advanced adjunct therapies • Ensure long-term cost-saving for wounds that are unlikely to heal with traditional treatments
A function to ensure all clinical decisions are aligned with local guidelines	• Ensure each clinical decision and treatment is legally compliant
Data security functions	• Ensure protection of patient data on clinicians' personal smartphones which they often use to record wound photographs
A function to connect locally available resources (e.g. treatments, dressings) with AI recommendations	• Ensure the AI tool recommendations are based on what is realistically achievable and not on who has sponsored the AI tool

Consensus recommendation: There are thousands of published case studies already available in wound care literature. These images may form the foundation for developing the tools and objectives outlined in **Tables 1** and **2**.

Validation tools for data quality and outcomes

As AI tools evolve at a fast pace, there is variation in existing data in terms of quality, consistency and bias. Therefore, it is crucial to develop a wound care guideline for accurate and adequate data collection (e.g. patient images, wound dimensions, meta-data). The purpose of this guideline should be to establish clear protocols for data recording, ensuring accuracy and consistency. Additionally, it should identify common errors that could compromise data validity, preventing its effective use in AI tools. By addressing these issues, clinicians can enhance data quality, leading to more reliable AI-driven insights in wound care. Any outcomes generated by an AI tool must be validated by experienced clinicians and subject experts.

Consensus recommendation: For all of clinical tools and functions, it is crucial to ensure that validation is undertaken as per recommended clinical and scientific methodology.

Data-sharing platforms

Within wound care settings, there is a significant unmet need of adequate data sharing between regions, hospitals and MDT settings. For example, although different types of EHRs/EMRs are currently in use throughout wound care settings, these systems do not 'communicate' with each other, leaving a huge gap in understanding the overall wound care landscape. There should be equity in the sharing of clinical data at each step of the patient journey – from initial assessment to patient monitoring and clinicians' feedback.

There is a need to develop a unified AI platform that can connect the variety of different wound care apps currently in use both regionally and globally. The current lack of compatibility and inter-operability causes a significant waste of resources for clinicians and healthcare systems, and results in sub-optimal patient outcomes. For example, a clinician may choose to use a wound care app for guidance on care pathways and treatment strategies. However, they are also required to document the same data in their local EHR/EMR system, resulting in duplicated efforts and lost time. Streamlining data integration between AI-driven wound care tools and EHRs/EMRs could significantly enhance efficiency, reducing administrative burdens for clinicians.

Furthermore, it is crucial that the coding systems between wound care apps and EHRs/EMRs are identical, ensuring accurate and consistent data recording. However, it is challenging to achieve this goal due to the extent of governance required for each step of this coding development process and for accessing patient data. Private investors and developers of an AI tool are likely to own the copyright and may require the user to pay for a subscription, making it difficult to align different apps and EHR/EMR systems.

Finally, other decision-makers in a healthcare ecosystem may also benefit from these data-sharing platforms. For example, payers may be able to access an interface that summarises analytics and resource utilisation, resulting in informed decision-making by all stakeholders (Kabir et al, 2024).

Wound care specialisation tools

It is important to help clinicians achieve wound care specialisation once AI tools are available to reduce the time spent on routine care decisions. This upskilling of healthcare force can help address the chronic under-resourcing and lack of experienced wound care clinicians (Queen and Harding, 2019; Probst et al, 2025).

A 'step-up' AI tool for clinician education could be developed to gradually enhance decision-making complexity for trainee clinicians. This tool would generate assessment outcomes and provide real-time feedback on scenarios tailored to different wound aetiologies and varying levels of clinical severity. Ideally, such an AI system should be trained on real-world data, allowing clinicians to engage with actual wound photographs and patient-specific factors and outcomes. This approach would ensure practical, experience-based learning, helping trainees refine their diagnostic and treatment strategies in a controlled yet clinically relevant environment.

Consensus recommendation: Alongside AI-based medical education systems, it is crucial to develop a knowledge-retention strategy for clinicians to ensure that AI implementation does not lead to erosion of wound care skills that are learnt and reinforced over time.

Patient communication tools

AI has potential in empowering patients for self-care. For example, with the availability of patient knowledge platforms such as NHS websites, patients are now likely to be more informed as to why a wound has developed on their lower limb and how receiving compression therapy is a long-term need. Effective and consistent communication with their clinicians may result in improved outcomes, which may not be possible otherwise. In this regard, AI can be the partner that clinicians require to emphasise the urgency of required care and the need for prompt intervention for the patient, improving engagement and, ultimately, healing outcomes. For example, AI-based apps or chat bots may be useful in helping patients decide if they need to seek help.

Furthermore, AI-based patient communication tools can provide the crucial support clinicians may require in routine work, such as the need for translators. Employing AI tools purpose-built for translating patient communication can help clinicians overcome the language barrier when a human translator is not available.

Ethical considerations

There are several ethical considerations in implementing AI in wound care.

Lack of AI-oriented guidelines in wound care
This is a significant issue for overall scientific and ethical validation of new AI tools. To address this situation, it is crucial to adapt data quality, integrity and management guidelines that are compliant with patient privacy regulations. Development of any AI tools for wound care must also account for systemic health inequity and inequality to ensure skin tone and social barriers are appropriately reflected in each AI algorithm, with each model's shortcomings and potential bias clearly highlighted for the users.

It is crucial to ensure that the principles of patient privacy, security, and informed consent are upheld.

Potential increase in burden of care
AI tools bring potential to wound care, but they also introduce challenges such as increased clinician burden and legal risks. If an AI system flags a critical issue but the healthcare workforce lacks the capacity to respond promptly, this could lead to negative patient outcomes, liability concerns and accountability gaps for all stakeholders.

To mitigate these risks, healthcare organisations must ensure clear implementation strategies, define responsibilities and establish protocols for handling AI-generated alerts. Additionally, robust AI governance frameworks and clinician education can help balance efficiency with ethical accountability in AI-assisted wound care.

It is paramount to ensure AI implementation supports clinicians in improving outcomes and does not lead to increased administration and fears of litigation.

Laws for copyright infringement, disinformation and criminal activities
Potential legal issues present potential risks through intentionally malicious behaviour, such as cheating by students who may employ AI to produce content; it is also possible to create 'deepfakes' using generative AI to give the appearance that someone said or did something they did not do, constituting crimes of identity fraud and disinformation (Feuerriegel et al, 2024; IBM, 2024b). Furthermore, a risk of either intentional or unintentional copyright infringement exists, the latter being when generative AI closely reproduces an original work without the intention to infringe copyright (Feuerriegel et al, 2024; IBM, 2024b).

Conclusions and future recommendations

With its immense capacity to process large amounts of data, AI has the potential to empower wound care clinicians. The current reactive care approaches to wound management can be replaced with proactive interventions by promptly identifying wounds that are likely to become chronic. This shift toward predictive and personalised treatment approaches can be made possible with large-scale development and implementation of AI-based wound care tools. However, it is important that clinician experience is incorporated at every step of this process to ensure clinical needs are met and user experience improved.

Although AI can replicate certain aspects of clinical decision-making processes on a larger scale and with greater speed, the experience and knowledge of wound care clinicians remains at the heart of AI development, implementation and evolution. It is increasingly important that wound care clinicians improve their awareness of AI's potential in wound care provision, education, regulation and guidelines.

This publication has outlined key areas in wound care where AI can play a transformative role. To ensure its effective implementation, it is crucial to address logistical barriers and ethical considerations while developing guidelines that evolve alongside rapidly advancing AI technologies. Establishing clear protocols will help clinicians integrate AI seamlessly into practice, balancing innovation with patient safety and accountability.

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