

The role of artificial intelligence in wound care: applications, evidence and future directions

Artificial intelligence (AI) has the potential to transform wound care by addressing inconsistencies in assessment, clinical inefficiencies, and alleviating resource constraints in a speciality that imposes significant economic burden on healthcare systems. This article explores AI's applications, evidence and future directions in wound management. It reviews core AI methodologies – machine learning, deep learning, and natural language processing – and how they are driving innovations including computer vision for wound imaging, predictive analytics for healing trajectories, and smart dressings for real-time monitoring. These technologies can enhance diagnostic accuracy, standardise assessments, and enable early detection of complications, supporting personalised treatment strategies. With this prospective step change in our approach to wound care, challenges persist, including infrastructure needs, data privacy concerns, bias in AI imaging with different skin tones, workforce training requirements, and financial investment barriers. Successful integration requires alignment with clinical workflows, adherence to ethical standards, and unwavering focus on patient safety. It is crucial that AI is designed and seen to augment rather than replace clinical expertise, highlighting the need for ethical governance and ongoing evaluation. By balancing technological innovation with clinical excellence, AI can enhance patient outcomes, optimise resource allocation, and maintain high standards in wound care. Realising AI's full potential will depend on collaboration among clinicians, researchers, and policymakers to build resilient, patient-centred healthcare systems.

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Key words

- Artificial intelligence
- Wound care
- Deep learning
- Smart dressings,
- Clinical decision support
- Skin tone bias

Artificial Intelligence (AI) represents a fundamental shift in computing, moving from systems that follow fixed instructions to those that improve performance by processing data, identifying patterns, and adjusting outputs accordingly. At its most basic level, AI attempts to replicate aspects of human intelligence through computational methods, including pattern recognition, learning from experience, and making decisions under uncertainty (Russell and Norvig, 2020).

The concept of AI dates back to the mid-20th century, when early pioneers such as Alan Turing and John McCarthy laid the theoretical foundations for machines capable of simulating human-like intelligence (Russell and Norvig, 2020). Over the decades, AI has evolved from symbolic logic-based approaches to data-driven machine learning methods, driven by advancements in computing power, algorithmic efficiency, and the availability of large datasets. Initially confined to rule-based expert systems, AI has progressed to sophisticated neural networks that can autonomously learn from vast amounts of

information. Today, AI underpins a wide range of applications, from medical diagnostics and predictive analytics to autonomous systems and natural language processing.

To understand AI, it is essential to be familiar with several key concepts, outline below.

Machine learning

Machine learning (ML), a core component of modern AI, enables systems to improve their performance through exposure to data rather than explicit programming (Russell and Norvig, 2020). This mirrors how humans learn from experience, though through mathematical rather than biological processes.

In wound care, machine learning has demonstrated significant clinical utility through integrative analytical approaches. Tabja Bortesi et al. (2024) conducted a scoping review of machine learning approaches for surgical wound infection identification, examining 10 studies that developed diagnostic models using wound images. Their analysis revealed that machine learning systems achieved high diagnostic accuracy in detecting surgical site

infections from standard digital photographs. These systems effectively processed wound characteristics that might be overlooked in routine assessment, with some models demonstrating performance comparable to specialist clinicians. The researchers noted that while early implementations showed promise, standardisation in image capture and validation methodologies would be crucial for clinical translation.

Machine learning encompasses several approaches, each serving different purposes in wound care analysis.

Supervised learning

Supervised learning involves training systems using labelled examples. Much like a student learning from worked problems, the system analyses known cases to develop rules it can apply to new situations. For example, systems can learn how to interpret an abnormality e.g. a fracture on an X-ray by repeatedly looking at X-rays where the abnormality has previously been diagnosed by a human (Sharma, 2023).

In wound care, supervised learning has achieved notable success in standardising wound assessment protocols. Convolutional neural networks trained on 199 clinician-annotated wound photographs achieved comparable performance to human experts in delineating wound boundaries and quantifying granulation tissue percentages. The supervised learning approach showed statistically similar error distributions between AI-human and human-human comparisons for false-positive and absolute relative error, with only marginally elevated false-negative area in AI tracings (Howell et al, 2021).

This methodology – involving 110 photographs from one clinical centre and 89 from another – revealed that AI-derived wound area measurements fell within the range of inter-clinician variability observed between four independent wound specialists. Masked physician reviewers qualitatively rated AI tracings as equivalent to human annotations in 60.4% of cases, demonstrating supervised learning's capacity to replicate expert-level wound boundary identification despite inherent subjectivity in clinical assessments.

Beyond imaging, supervised learning enhances predictive analytics for chronic wound management. Gradient-boosted decision tree models trained on 1.2 million electronic health records demonstrated robust prognostic capability, predicting 12-week healing outcomes (Berezo et al, 2022). These models analysed longitudinal wound progression metrics, including surface area reduction rates, tissue depth measurements,

and comorbidity profiles, to stratify patients by healing likelihood. By identifying high-risk trajectories through features such as prolonged treatment duration and larger initial wound size, these systems enable clinicians to prioritise interventions earlier in the care pathway, optimising resource allocation for complex cases (Berezo et al, 2022).

Unsupervised learning

Unsupervised learning enables systems to autonomously identify patterns within data without explicit guidance, mirroring how humans intuitively group objects based on shared characteristics. These systems discern commonalities and distinctions independently, often uncovering unexpected patterns in complex datasets.

In electron microscopy image analysis, researchers have leveraged unsupervised learning to uncover latent features, facilitating the exploration of large-scale datasets without prior annotations. For example, deep learning-based unsupervised clustering methods have differentiated cellular structures in electron microscopy images, revealing biologically meaningful distinctions among these structures (Huang et al, 2020).

Similarly, in oncology research, unsupervised classification techniques have been applied to tumour cell nuclei based on morphological and structural similarities, thereby enabling more precise stratification of cancer subtypes and assisting in personalised treatment planning (Yuan and Suh, 2018). In wound care, unsupervised learning techniques have been integrated with hyperspectral imaging (HSI) data to classify wound areas, distinguishing affected tissue from surrounding healthy skin. Recent research has demonstrated the use of k-means clustering for automated wound segmentation, enhancing measurement accuracy, reducing human error, and improving consistency in wound assessment (Lee and Chen, 2023).

Deep learning

Deep learning represents a sophisticated computational approach inspired by the layered structure of biological neural networks. By employing multi-tiered artificial neural architectures, these systems autonomously derive hierarchical data representations through successive abstraction layers. Initial processing stages detect elementary visual components such as edges and textures, while subsequent layers integrate these features into increasingly complex patterns reflective of anatomical structures.

An AI system trained on 76,000 UK and

15,000 US mammograms significantly improved breast cancer screening accuracy, reducing false-positive recalls by 5.7% in the US and 1.2% in the UK, and lowering false-negative rates by 9.4% (US) and 2.7% (UK) when tested on 25,856 UK and 3,097 US cases (McKinney et al, 2020). The system outperformed six radiologists in an independent study. By analysing mammographic features, it detected malignancies more consistently than human experts and demonstrated robust generalisability across international datasets. In simulations of the UK's double-reading workflow, the AI reduced second-reader workload by 88% while maintaining diagnostic accuracy, highlighting its potential to enhance efficiency in high-volume screening programmes.

Spectral AI's DeepView® employs multispectral imaging (MSI) across eight spectral bands and a voting ensemble of deep convolutional networks (U-Net, SegNet, and a dilated fully convolutional network) to identify non-healing (deep) burn regions (Thatcher et al, 2023). A pilot study gathered 406 MSI images from 58 separate burns, using 21-day healing outcomes or biopsy findings as ground-truth references. This ensemble achieved approximately 81% sensitivity, 100% specificity, and 97% positive predictive value (PPV) for detecting deep partial- and full-thickness burns, with performance markedly improving after 2–3 days post-injury. These results suggest that DeepView® can feasibly support earlier and more reliable burn-depth assessments, particularly for indeterminate wounds.

Natural language processing

Natural language processing (NLP) represents another crucial AI capability, enabling systems to understand and process human language. This technology underlies everything from clinical documentation analysis to automated translation services. It involves teaching computers to understand not just individual words, but context, meaning, and the subtle nuances of human communication.

In cardiovascular diagnostics, NLP has proven particularly valuable for standardising echocardiography report analysis. A 2024 study validated an NLP algorithm on 200 annotated transthoracic echocardiogram (TTE) reports, achieving high precision scores of 0.93–1.00 for detecting aortic stenosis and mitral regurgitation severity (Xie et al, 2024). The algorithm demonstrated robust performance in classifying valvular pathologies. While the initial validation sample was limited, the algorithm was subsequently applied to 1,225,270 historical

TTE reports within the Kaiser Permanente Southern California health system, successfully standardising valve disease documentation across diverse clinical narratives. This approach addressed critical gaps in structured EHR data by capturing nuanced severity descriptors like “moderate-severe aortic stenosis” that often go uncoded in traditional systems.

A study examined a hybrid AI-driven approach for wound assessment, which integrates a VGG16 convolutional neural network for wound image classification – achieving 95% accuracy across seven categories – with GPT-3.5-powered natural language processing for generating treatment recommendations (Keseraju 2024). The system processes user-input text descriptors (e.g., “burn from boiling water”) alongside wound images, providing basic care recommendations aligned with the predicted wound type. For example, categorising a wound as a “burn” triggers general cooling protocol advice, while “laceration” prompts guidance on bleeding control.

The study highlighted that 60% of patients in rural areas face care delays due to travel barriers (average 40-mile distance to specialists), with diagnostic delays contributing to complications in 30% of cases. While GPT-3.5 offers broad recommendations, the paper notes limitations in medical specificity, advising users to “seek professional care for severe wounds” rather than providing granular therapeutic protocols. This integration demonstrates NLP's role in contextualising image-based diagnoses with patient-reported symptoms, particularly valuable in resource-limited settings.

Building on these core AI principles, this review will explore their adaptation in wound care – transforming documentation, predictive analytics, and personalised treatment strategies to address some of the critical challenges in modern wound management.

The current context of wound care

The delivery of wound care faces significant challenges within modern healthcare systems. An ageing population with increasing comorbidities contributes to growing patient complexity, while healthcare services struggle with resource constraints and workforce shortages. Chronic wounds cost the National Health Service (NHS) in England £5.6 billion (\$7.39 billion) annually for unhealed wounds, with total wound care expenditure reaching £8.3 billion (\$10.96 billion) in 2017/18, a figure projected to rise with increasing demographic pressures (Guest et al, 2020). The economic burden of chronic wounds extends beyond the

UK. In the US, chronic wound care is estimated to cost healthcare systems over \$28 billion annually, with diabetic foot ulcers alone contributing to approximately \$9 billion in expenditures (Sen, 2019). Similarly, European healthcare systems report increasing financial strain due to rising wound care demands, highlighting the universal nature of these challenges.

Current clinical challenges

Several critical challenges characterise modern wound care delivery:

- **Workforce limitations:** Healthcare systems face critical shortages of wound care specialists, exacerbating reliance on general practitioners for complex wound management (Barakat-Johnson et al, 2022). Studies highlight critical knowledge gaps in wound assessment and management among non-specialists (Mohammed et al, 2022).
- **Wound assessment variability:** Traditional ruler-based methods overestimate wound area by 44% and exhibit significant inter-clinician variability, impacting treatment decisions, care continuity, and patient outcomes (Wang et al, 2017).
- **Documentation constraints:** High documentation workload places significant time pressures on clinical teams, impacting efficiency and limiting time available for direct patient care. Traditional manual methods require multiple steps, increasing the administrative burden on clinicians (Mohammed et al, 2022).
- **Resource allocation:** Healthcare providers face increasing patient loads and workforce shortages, requiring efficient resource allocation to maintain high standards of wound care (Barakat-Johnson et al, 2022).

Impact on clinical practice

The challenges outlined in modern wound care delivery have direct consequences on quality of care, service delivery, and clinical outcomes, affecting both clinicians and patients:

- **Quality of care:** Time-consuming manual wound assessments strain clinical efficiency, limiting the time available for direct patient care. For example, evaluating 115 wounds manually requires 5 hours 31 minutes, creating significant administrative and clinical burden and reducing the capacity for patient interaction. This inefficiency delays assessment prevents national and local targets from being met and disrupts continuity of care (Mohammed et al, 2022).
- **Service delivery:** Traditional wound

assessment methods remain time-intensive and reliant on manual measurements, restricting the number of patients clinicians can effectively evaluate.

High patient loads combined with workforce shortages exacerbate delays in wound assessment, particularly in settings where non-specialists are required to manage complex wounds. The lack of standardised and objective assessment tools further contributes to inconsistencies in treatment planning.

- **Clinical outcomes:** Timely wound reassessment is crucial for preventing complications and ensuring effective treatment. However, delays in evaluation reduce opportunities for early intervention, increasing the risk of infection and hospitalisation. Workforce shortages further strain clinical capacity, limiting access to specialist care and making timely treatment in complex cases more challenging, ultimately leading to preventable complications (Barakat-Johnson et al, 2022).

Systemic healthcare pressures

Modern wound care is shaped not only by clinical challenges but also by broader systemic pressures that impact healthcare sustainability, workforce readiness, and administrative demands.

- **Economic burden:** The rising costs of chronic wound care pose a growing challenge to healthcare sustainability, requiring optimised resource allocation to meet increasing demand. Healthcare expenditure on wound management has surged in recent years, with a substantial proportion of costs driven by prolonged healing times and high dependency on community-based services. The financial strain on healthcare systems underscores the urgency of improving efficiency in care delivery and reducing the economic impact of chronic wounds (Guest et al, 2020).
- **Workforce development:** Advances in wound care protocols demand ongoing education and upskilling of healthcare professionals, placing additional strain on already limited training resources. As wound management becomes increasingly complex, the need grows for specialised knowledge in areas such as advanced dressings, infection control and technology-assisted assessment. However, healthcare providers often face constraints in accessing dedicated wound care education, leading to variability in clinical practice and potential disparities in patient

- outcomes (Barakat-Johnson et al, 2022).
- **Documentation requirements:** Increasing regulatory demands for evidence-based practice and clinical audits place a growing administrative burden on healthcare professionals. Documentation now extends beyond routine wound assessment to include detailed risk stratifications, treatment justifications, and multidisciplinary care coordination records. These expanding requirements contribute to clinician workload, reducing time available for direct patient care. Additionally, disparities in documentation practices across healthcare settings can lead to inconsistencies in wound management, further complicating efforts to standardise and improve patient outcomes.

Need for innovation

These mounting challenges highlight the urgent need for innovative approaches to wound care delivery. Traditional methods of assessment, documentation, and monitoring struggle to meet current healthcare demands. The sector requires solutions that can enhance diagnostic precision, automate documentation processes and optimise resource allocation. Artificial intelligence presents a promising avenue to address these systemic issues through standardisation of assessment procedures, improvement in measurement accuracy, and support for clinical decision-making (Mohammed et al, 2022).

AI applications and impact in wound care

The translation of AI capabilities into clinical wound care practice represents a significant advancement in healthcare delivery. While the fundamental technologies of machine learning, deep learning, and natural language processing provide the technical foundation, their practical implementation has emerged as a direct response to the pressing challenges in modern wound care. These implementations address critical needs in assessment standardisation, resource optimisation, and clinical decision support, transforming how healthcare providers deliver and monitor wound care across various clinical settings.

Clinical assessment and diagnostic applications

AI has transformed clinical assessment in wound care through multiple complementary applications. These implementations build upon proven healthcare technologies to address specific clinical needs in measurement accuracy, tissue classification, and healing trajectory prediction. For instance, AI systems

classify chronic wounds (diabetic, pressure injury, lymphovascular, surgical) with 83% precision, using explainable heatmaps to highlight decision-critical tissue features. For diabetic wounds, the system achieves 72% precision, effectively supporting automated assessment and classification (Sarp et al, 2021).

The integration of AI-enhanced wound monitoring technologies into clinical workflows has improved the ability to detect subtle changes in wound healing. Smart dressings with integrated pH and temperature sensors enable early infection detection by identifying shifts in wound acidity and inflammatory temperature changes. These systems correlate increased temperature with bacterial proliferation and monitor acidosis trends indicative of infection progression (Su et al, 2024).

Hyperspectral imaging technologies have significantly advanced wound classification by distinguishing between healthy and wounded tissue based on spectral characteristics. This imaging modality, when integrated with 3D convolutional neural networks, has achieved high accuracy in identifying wound severity, independent of skin colour, making it a valuable tool for clinical assessment (Cihan and Ceylan, 2023).

Implementation of AI systems in clinical practice

The practical implementation of AI in wound care has demonstrated measurable improvements in clinical efficiency and accuracy. Mobile applications utilising deep learning algorithms have significantly enhanced wound measurement, reducing assessment time by 54% while improving first-attempt imaging accuracy to 92.2%. AI-driven platforms streamline workflows, enabling faster and more consistent wound documentation compared to manual methods (Mohammed et al, 2022).

Multispectral imaging combined with deep learning improved intraoperative decision-making in burn excision surgery. The AI system achieved 87% accuracy in distinguishing viable from non-viable burn tissue, enhancing surgeon precision and reducing unnecessary excision. When using AI guidance, surgeons improved their specificity in stopping excision from 42% to 67%, demonstrating its potential to optimise tissue preservation and debridement accuracy (Yu et al, 2023).

Smart dressing technologies integrate biosensing capabilities with real-time wound monitoring, enhancing diagnostic precision. pH-sensitive hydrogels utilising polyaniline polymers detect acidosis, indicating bacterial

proliferation, while near-infrared spectroscopy (NIRS) serves as a non-invasive tool for measuring tissue oxygenation levels, facilitating early detection of wound complications [19].

Advanced applications and care delivery systems

The integration of AI technologies into wound care has catalysed significant advancements in service delivery, enabling healthcare providers to extend specialist expertise beyond traditional clinical settings whilst improving care standardisation and resource utilisation. These developments demonstrate how AI applications can transform multiple aspects of wound care delivery, from remote monitoring to clinical decision support.

Remote monitoring and telehealth solutions

Remote monitoring platforms integrating augmented reality (AR) and contactless wound measurement have enhanced community-based wound care delivery. These systems provide accurate assessments of wound morphology, improving clinician-patient communication and enabling more consistent monitoring outside traditional clinical settings. Early studies suggest these technologies may reduce the need for frequent in-person visits, facilitating remote tracking of wound healing progression (Mamone et al, 2022). Integration with existing telehealth infrastructure has facilitated real-time specialist guidance for complex dressing changes and early intervention protocols, particularly valuable in resource-limited settings where specialist access presents significant challenges.

Clinical decision support systems

AI-enhanced decision support systems are increasingly integrated into wound care to improve treatment planning and risk assessment. Predictive analytics leveraging patient comorbidities, wound characteristics, and historical treatment data have demonstrated strong potential in identifying hospital-acquired pressure injury (HAPI) risks before they become clinically apparent.

A comprehensive review by Toffaha et al. (2023) identified 39 relevant studies implementing AI and decision support systems for pressure injury prediction, with models achieving accuracy rates between 75% and 93% in identifying high-risk patients. Their analysis revealed that machine learning algorithms using electronic health records could detect potential pressure injuries up to 48–72 hours before clinical manifestation, substantially expanding the intervention window for preventive care. These AI models

frequently outperformed traditional risk assessment tools by incorporating more diverse data sources, including patient mobility patterns, nutrition status, and environmental factors that traditional scales often overlook.

While most implementations remain in developmental or retrospective phases, with limited real-world clinical deployment, the evidence suggests that AI-powered decision support tools could significantly enhance standardised care delivery and risk mitigation in wound management (Toffaha et al, 2023). To complement these decision-making tools, AI also offers promising solutions to improve the tracking and documentation of wound care quality.

Quality assurance and documentation

Quality assurance applications have emerged as crucial tools for maintaining care standards across healthcare settings. Advanced AI-driven systems analysing wound photography and clinical notes have demonstrated significant improvements in documentation completeness and adherence to clinical protocols. Studies evaluating AI-powered wound assessment tools indicate that these platforms enhance record accuracy, reduce variability in wound documentation, and support comprehensive clinical governance by automating care protocol tracking and identifying assessment gaps. This enables proactive quality improvement initiatives whilst reducing the administrative burden on clinical staff (Barakat-Johnson et al, 2022).

Workforce impact and workflow transformation

The integration of AI technologies into clinical workflows has contributed to significant transformations in workforce efficiency and task delegation. AI-powered decision-support systems, such as deep learning models trained for pressure ulcer classification, have demonstrated the ability to enhance diagnostic precision and reduce variability in assessments.

A Faster R-CNN model was implemented and evaluated in clinical trials to assist healthcare professionals in categorising multiple stages of pressure ulcers, with the aim of supporting standardised reporting and minimising inconsistencies in wound documentation (Katz and Gefen, 2025).

These advances enable clinicians to make more informed treatment decisions, reducing the burden of subjective assessment. While AI applications continue to evolve, their integration into triage and wound assessment workflows suggests promising opportunities for optimising specialist expertise allocation. Future

Table 1. AI technologies in wound care: Capabilities, benefits, and implementation challenges.

AI technology	Description	Key capabilities	Benefits	Implementation challenges
Computer vision analysis	AI-powered imaging systems using deep learning algorithms to assess wound dimensions and tissue characteristics.	Reduces inter-observer variability, ensures consistent assessments, accurately measures wound dimensions, and identifies tissue characteristics with high precision.	Improves diagnostic accuracy, predicts healing trajectories, assists in treatment planning, and supports objective assessment of wound progression.	Infrastructure requirements, variability in wound images, skin tone bias affecting accuracy, need for diverse training datasets, and rigorous validation protocols.
Smart dressings and biosensors	Integrated sensors within wound dressings that monitor pH, temperature, and other biomarkers.	Detects changes in wound biochemistry, identifies early signs of infection through shifts in acidity and temperature, and monitors healing environment continuously.	Enables early detection of infection, reduces unnecessary dressing changes, and supports timely intervention for complications.	Cost barriers, materials integration challenges, data transmission issues, and clinical workflow integration.
Multispectral/hyperspectral imaging	Advanced imaging technologies that capture data across multiple spectral bands to assess wound characteristics.	Distinguishes between healthy and wounded tissue based on spectral characteristics, identifies viable vs non-viable tissue, and functions independent of skin colour.	Enhances intraoperative decision-making in burn excision, improves tissue classification accuracy, and provides objective assessment of wound severity.	Specialised equipment costs, technical expertise requirements, and integration with existing imaging workflows.
Natural language processing	AI systems that understand and process wound documentation and clinical notes.	Automates extraction of key information from clinical narratives, standardises documentation, and generates structured wound assessments.	Reduces documentation time, improves consistency in reporting, and enhances communication between care providers.	Training requirements for diverse clinical vocabularies, integration with EHR systems, and maintenance of medical accuracy.
Decision-support systems	AI platforms analysing wound data to provide evidence-based treatment recommendations.	Identifies hospital-acquired pressure injury risks, guides treatment selection, and supports standardised care protocols.	Enhances treatment decisions, supports less experienced clinicians, and improves risk assessment accuracy.	Clinical workflow integration, clinician acceptance challenges, and need for regular updates with evolving evidence.
Remote monitoring and telehealth	AI-enhanced platforms enabling assessment and specialist consultation outside traditional clinical settings.	Facilitates accurate remote wound assessment using augmented reality and contactless measurement technologies.	Extends specialist expertise to remote settings, reduces unnecessary clinic visits, and improves access to care.	Connectivity requirements, image quality variability, and patient technology access issues.
Predictive analytics	AI models analysing patient histories and wound characteristics to anticipate complications and healing trajectories.	Identifies high-risk patients, detects early warning signs, and predicts treatment responses based on multiple data streams.	Enables proactive intervention, improves resource allocation, and supports personalised treatment planning.	Data quality dependencies, model transparency issues, and need for continuous validation and refinement.
Quality assurance systems	AI tools for monitoring wound care protocol adherence and documentation completeness.	Supports best practice adherence through automated auditing and performance tracking.	Ensures consistent care quality, identifies improvement opportunities, and enhances clinical governance.	Implementation complexity, integration with existing quality frameworks, and change management requirements.

research will be crucial in further evaluating AI's direct impact on staff confidence, training outcomes, and workforce satisfaction (Fergus et al, 2022).

Table 1 summarises the key AI technologies used in wound care, outlining their capabilities, benefits, and implementation challenges.

Challenges and limitations of AI in wound care

Despite AI's transformative potential in wound care, its successful implementation is contingent upon overcoming significant challenges related to bias, costs, regulatory frameworks, interoperability, and workforce integration. Addressing these barriers is critical to ensuring safe, effective, and equitable AI adoption in clinical practice.

Bias in AI imaging and skin tone challenges

AI-powered wound imaging tools may exhibit bias in diagnostic accuracy across different skin tones, particularly for patients with darker skin. This issue arises from the underrepresentation of diverse skin tones in AI training datasets, leading to higher misclassification rates and potential delays in diagnosis.

The Fitzpatrick scale, widely used in AI model development, has some minor limitations in representing global skin diversity, as it was originally designed for UV sensitivity classification in light-skinned individuals (Fitzpatrick, 1988). As AI use increases, a potential switch to a more inclusive skin tone scales, such as the Monk Skin Tone scale [Figure 1] – a 10-shade gradient developed to better capture global skin diversity – offer enhanced classification of skin tones and undertones, improving AI fairness in wound assessment contexts (Monk, 2022; Montoya et al, 2024; Google AI, 2025).

Recent evidence underscores the importance of recognising skin tone as a crucial factor in wound care. A study by Katz and Gefen (2025) demonstrated that skin tolerance to shear forces varies considerably across different skin tones, with darker skin

exhibiting lower water content and higher transepidermal water loss, leading to increased pressure injury risk. These biomechanical differences highlight the need for AI-driven wound assessment systems to incorporate diverse patient datasets to improve diagnostic precision and equity in wound care.

Current research indicates several essential approaches to mitigate bias in AI-driven wound imaging. These include expanding training datasets to include a wider spectrum of skin tones (Groh et al, 2021; Groh, 2021), developing AI models that adjust for skin reflectance variations using multispectral imaging (Lee and Chen, 2023), and utilising alternative classification scales beyond the Fitzpatrick scale (Monk, 2022; Montoya et al, 2024).

Economic barriers to implementation

Although AI-powered wound care solutions offer long-term benefits, high initial costs remain a significant barrier to adoption. AI-integrated smart dressings require advanced biosensing technology and specialised materials, making them more expensive than conventional dressings.

Additionally, AI-powered imaging systems necessitate specialised hardware, such as hyperspectral cameras, which can be costly for resource-limited healthcare settings.

Implementation expenses, including staff training and software integration, further delay widespread adoption. Research efforts must focus on developing cost-effectiveness studies to justify AI adoption in wound care pathways, creating scalable, low-cost AI solutions tailored for community healthcare settings, and establishing financial incentives or reimbursement models for AI-integrated care (Su et al, 2024).

Regulatory considerations and validation challenges

In addition to financial constraints, AI tools in wound care must also navigate complex validation and regulatory approval processes to ensure safety, accuracy and clinical efficacy.

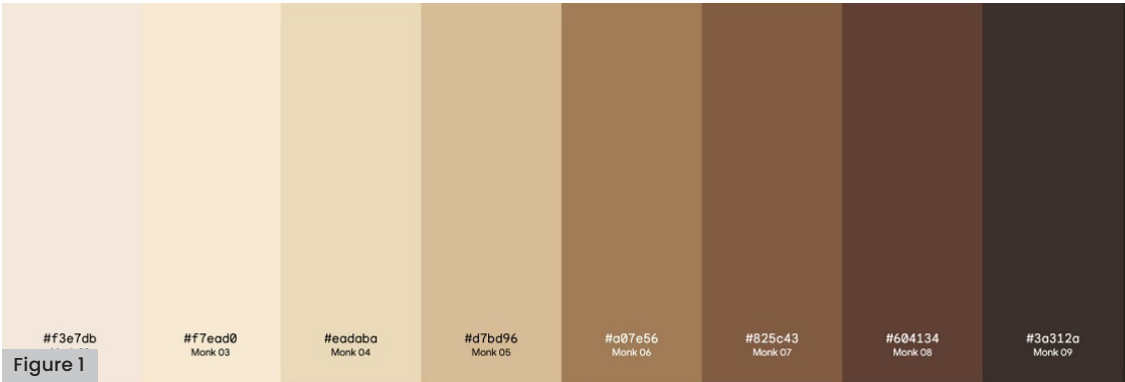


Figure 1. The Monk Skin Tone (MST) scale showing ten gradations of skin tones (A-J) from lightest to darkest with corresponding hex colour codes. The MST Scale was developed to provide more inclusive representation of human skin tone diversity compared to previously used scales. (Source: Monk, 2019).

International regulatory bodies set strict compliance standards:

- **ISO 13485:** Establishes quality management systems for medical device development. Compliance with ISO 13485 ensures that organisations maintain effective processes throughout the product lifecycle, emphasising risk management and design control activities (ISO, 2016).
- **Food and Drug Administration (FDA, US):** Requires pre-market approval for AI-powered imaging systems used in clinical practice. The FDA provides guidance on regulatory considerations for AI/ML-based medical devices, emphasising transparency, validation and real-world performance data to support regulatory submissions.
- **CE Mark (Europe):** Ensures compliance with European medical device regulations. All medical devices, including those incorporating machine learning, must comply with the CE marking requirements under the relevant EU regulatory frameworks to be lawfully marketed within Europe.
- **General Data Protection Regulation (Europe) and Health Insurance Portability and Accountability Act (US):** Regulate patient data privacy and AI compliance.

Ensuring compliance with these standards is critical for the safe deployment of AI in clinical settings. However, the dynamic nature of AI models, which continuously learn from new data, poses challenges for traditional regulatory approval frameworks.

Future regulatory efforts must address adaptive AI approval processes to accommodate self-learning models, harmonisation of AI medical device regulations across jurisdictions, and transparent reporting requirements for AI-based clinical decision-support tools.

Interoperability and technical integration

For AI to be effective in wound care, it must seamlessly integrate with existing electronic health records (EHRs) and hospital workflows. Interoperability remains a major challenge due to inconsistent data formats that hinder AI-EHR communication, variability in AI model outputs making standardisation difficult, and security concerns as AI-driven wound assessment tools must adhere to data-sharing regulations.

Healthcare organisations must focus on developing standardised AI frameworks that can interface with multiple EHR systems, ensuring secure AI-EHR integration to protect patient data privacy and facilitating clinician adoption through intuitive AI interfaces within

EHR platforms (Mohammed et al, 2022).

Infrastructure and model optimisation requirements

Successful AI deployment in wound care settings depends on robust infrastructure to support image capture, data processing, and clinical integration. Clinical areas must be equipped with adequate lighting, space for image capture, and reliable network connectivity for AI-driven wound assessment (Barakat-Johnson et al, 2022). Technical architecture must seamlessly integrate with existing EHRs and hospital IT frameworks to ensure smooth data interoperability.

Beyond physical and technical infrastructure considerations, implementing smart dressing technologies presents practical challenges. Material incompatibilities between flexible electronics and biological tissues can lead to degradation in electrical performance and adhesion over time. To ensure stable conductivity and sensor functionality, advanced materials such as liquid metal interconnects and gold-based electrodes have been developed, improving stretchability and long-term adhesion in dynamic wound environments. These optimisations are essential for maintaining reliable wound monitoring and infection control, particularly in cases where wounds are subject to frequent mechanical strain (Su et al, 2024).

Workforce adaptation and training considerations

AI adoption in wound care requires clinicians to be equipped with the necessary digital literacy to interpret AI-generated recommendations (Car et al, 2025). Many healthcare professionals lack AI-specific training, particularly in decision-support tools, express concerns about AI replacing clinical judgement, and struggle with integrating AI outputs into routine patient care workflows (Heerschap, 2023; Sivaraman et al, 2023).

To ensure effective AI adoption, workforce development strategies should incorporate comprehensive clinician training programmes focused on AI literacy, transparent AI decision-support systems to improve trust, and clear guidelines on AI-human collaboration, reinforcing AI as an augmentative tool rather than a replacement (Heerschap, 2023; Sivaraman et al, 2023; Car et al, 2025).

Future developments and strategic recommendations

The evolution of AI in wound care continues to advance, shaped by both current challenges and emerging technological capabilities.

Looking ahead, many of the current limitations can be overcome by next-generation AI developments and strategic implementation. The next phase of development will be defined by enhanced predictive models, seamless clinical integration and automated data-driven decision-making. These advances hold the potential to revolutionise wound management by enabling earlier interventions, reducing hospitalisation rates, and improving patient outcomes.

Advanced clinical applications

Predictive analytics enhancement

Next-generation AI systems offer enhanced predictive capabilities for wound healing trajectories. These systems analyse multiple data streams—such as tissue characteristics, patient factors, and treatment responses—to support more proactive intervention. Emerging AI-powered wound prediction models leverage deep learning to detect early signs of infection, tissue deterioration, and delayed healing. These systems analyse historical wound data and real-time physiological markers to provide proactive treatment recommendations. In diabetic foot ulcer management, for example, predictive AI has been used to identify patients at high risk of amputation, allowing clinicians to intervene sooner and improve limb salvage outcomes. Research indicates that early identification of healing complications could significantly reduce hospital admissions and improve patient outcomes (Guest et al, 2020).

Integration of clinical data

Future systems will increasingly combine information from various sources to enhance personalised wound care. The integration of EHRs, wound imaging tools, and social determinants of health data is expected to refine predictive analytics, optimise treatment pathways, and improve patient outcomes. Platforms like DHIS2 have demonstrated the potential to aggregate clinical, demographic, and geographic data, supporting data-driven decision-making in wound care (Paddo et al, 2024).

Pattern recognition advances

Advanced machine learning algorithms are increasingly capable of identifying subtle changes in wound characteristics over time. These systems learn from clinical outcomes, continually refining their ability to detect early warning signs of complications. Recent deep learning models have demonstrated the ability to predict wound healing stages by analysing collagen fibre patterns in histological images, achieving an accuracy of 82% in classifying six

distinct healing phases (He et al, 2024). Such advancements provide valuable insights into wound progression and have the potential to enhance AI-driven wound care management.

Documentation automation

Future systems will further reduce administrative burden through advanced natural language processing (NLP) tools. AI-powered documentation platforms have demonstrated the ability to generate post-operative reports with greater accuracy than those manually written by surgeons, reducing errors and enabling clinical staff to dedicate more time to direct patient care (Lapid, 2025). Additionally, AI-driven clinical documentation tools are being adopted by healthcare systems worldwide to automate medical notetaking and streamline administrative workflows. Systems like Abridge have been integrated into more than 100 hospitals across the US, including rural and paediatric care settings, highlighting the growing role of NLP in reducing clinician workload (Reuters, 2025).

Strategic implementation recommendations

The successful integration of AI technologies in wound care requires careful consideration of implementation strategies. Healthcare organisations must develop clear objectives and implementation plans that align with clinical needs and service delivery goals (Barakat-Johnson et al, 2022).

Essential elements for successful implementation include:

- Comprehensive staff training programmes that build both confidence and competence
- Clear protocols for AI integration into existing clinical workflows
- Robust validation processes for AI-driven decision support
- Regular evaluation of clinical outcomes and system performance
- Mechanisms for ongoing feedback and system refinement

Staff development remains crucial to the successful integration of AI, and organisations must invest in comprehensive training programmes that enhance both confidence and competence (Ma et al, 2024).

Research priorities

Several key areas require further investigation to advance AI implementation in wound care

Clinical outcomes research

Long-term studies examining the impact of AI implementation on clinical outcomes remain essential. Research must address:

- **Comparative effectiveness of AI-augmented versus traditional care:** Assessing whether AI-enhanced wound care leads to superior clinical outcomes compared to standard care models.
- **Impact on healing rates and complications:** Investigating how AI-driven wound assessment tools influence healing time, infection rates, and overall wound progression.
- **Clinical safety and risk assessment:** Evaluating potential risks associated with AI-guided interventions, ensuring patient safety and adherence to clinical guidelines.
- **Integration with existing care pathways:** Understanding how AI can seamlessly integrate into multidisciplinary wound care teams and EHR systems for optimal workflow efficiency.

Emerging evidence underscores the importance of these investigations in shaping AI deployment in wound care. Recent research demonstrates that deep learning models can accurately predict wound healing trajectories based on image analysis and clinical parameters, thereby improving early intervention strategies (Schlereth et al, 2022). Furthermore, AI-driven risk stratification models have shown potential in identifying patients at higher risk of wound complications, enabling proactive management and resource allocation (Patel et al, 2023).

Economic impact analysis

Healthcare organisations require robust evidence regarding the economic impact of AI implementation. This encompasses both direct costs and potential savings through improved efficiency. Research should examine:

- **Implementation costs across different healthcare settings:** Evaluating the initial investment required for AI technologies, including hardware, software, and training, to understand financial barriers and scalability in various environments.
- **Long-term cost savings and return on investment:** Investigating how AI can reduce operational expenses, such as decreasing hospital readmissions and optimising resource allocation, thereby enhancing the financial sustainability of healthcare systems.
- **Healthcare resource utilisation optimisation:** Assessing AI's role in streamlining workflows, reducing clinician workload, and improving patient throughput, leading to more efficient use of medical resources. (Dennis, 2023).
- **Sustainability and scalability metrics:**

Determining the long-term viability of AI solutions, including their adaptability to evolving medical practices and their capacity to scale across different departments or institutions.

By addressing these areas, healthcare organisations can make informed decisions about integrating AI technologies, ensuring that such innovations lead to both improved patient outcomes and economic benefits.

Patient experience investigation

Understanding the patient perspective on AI-supported care delivery is increasingly important. Ensuring that AI tools align with patient needs is essential for acceptance and adoption. Research suggests that patient trust in AI-driven healthcare solutions depends on transparent implementation and clinician oversight (Barakat-Johnson et al, 2022).

Key areas for investigation include:

- **Patient acceptance and experience with AI-augmented care:** Assessing how AI influences patient comfort and engagement in wound care treatment.
- **Impact on patient-provider communication and relationships:** Examining whether AI-supported decision-making enhances or hinders communication between patients and healthcare providers.
- **Accessibility and equity considerations:** Evaluating how AI technologies impact different patient demographics and whether they introduce unintended disparities (Barakat-Johnson et al, 2022).
- **Patient-reported outcomes and satisfaction measures:** Investigating how AI-assisted wound care affects patient satisfaction and clinical engagement.

Realising the transformative potential of AI in wound care requires a delicate equilibrium between cutting-edge technological advancement and pragmatic clinical implementation. As these sophisticated systems continue to evolve across healthcare settings, their sustained success will increasingly depend on how thoughtfully innovations are integrated into existing care pathways and clinical practices. While AI applications offer promising solutions to longstanding challenges in wound assessment, treatment planning, and resource allocation, we must recognise that technological capability alone cannot guarantee improved patient outcomes.

The full potential of AI-augmented wound care can only be realised through

methodical strategic implementation that considers workflow integration, robust validation protocols, and ongoing performance evaluation. Furthermore, meaningful clinician engagement throughout development and deployment phases remains essential, ensuring that AI tools genuinely address real-world clinical needs rather than creating additional administrative burdens. Equally important is the establishment of comprehensive ethical oversight frameworks that address data privacy concerns, mitigate potential biases in imaging technologies, and maintain the primacy of patient-centred care values. It is through this balanced approach – embracing innovation while maintaining clinical rigour – that AI can truly transform wound care practice.

Conclusions: Shaping the future of AI in wound care

Artificial intelligence is revolutionising wound care by addressing critical challenges in assessment variability, resource allocation, and early intervention. With chronic wounds creating both significant economic burden and clinical challenges across healthcare systems, AI-driven solutions are emerging as indispensable tools for clinicians. These solutions have already demonstrated their ability to improve diagnostic accuracy, optimise resource allocation, and support less experienced healthcare professionals, creating a more resilient and responsive healthcare system.

The evidence for AI's transformative potential in wound care is compelling. Automated assessment systems have achieved sub-millimetre precision (mean error: 0.3 mm) in wound measurement, significantly outperforming traditional manual methods (Mohammed et al, 2022).

AI-powered decision support systems have enabled nurses to manage complex cases with specialist-level accuracy, achieving concordance rates of 92% in pressure ulcer assessment (Fergus et al, 2024). These achievements underscore AI's capacity to enhance clinical practice while addressing workforce challenges.

Despite this immense potential, AI's full integration into wound care requires careful planning and alignment with clinical priorities. The successful adoption of AI must be underpinned by key principles:

- **Augmenting, not replacing, clinical expertise:** AI must function as a decision-support tool, reinforcing rather than substituting professional judgement. The technology should enhance clinical decision-making while maintaining the

essential human elements of wound care (Sezgin, 2023).

- **Ensuring seamless workflow integration:** AI applications should be incorporated into existing clinical pathways with minimal disruption, ensuring smooth adaptation for clinicians and patients alike. This integration must consider the varied settings where wound care is delivered, from acute hospitals to community care.
- **Comprehensive training and workforce development:** Healthcare professionals must be adequately trained in the interpretation and utilisation of AI outputs to enhance confidence in decision-making. This includes developing digital literacy and understanding AI's capabilities and limitations (Guest et al, 2020).
- **Regulatory compliance and ethical considerations:** Robust validation studies and adherence to ethical AI governance are paramount to ensuring patient safety and trust in AI-driven interventions. This includes addressing potential biases in AI systems, particularly regarding diverse patient populations (Montoya et al, 2024)).
- **Continuous evaluation and iterative improvement:** AI models should be routinely assessed for accuracy, efficiency, and bias mitigation, allowing ongoing refinements to enhance their clinical utility. This process must be data-driven and responsive to real-world clinical outcomes.

The path forward requires strong interdisciplinary collaboration among clinicians, AI researchers, and policymakers to ensure that AI-driven wound care solutions remain clinically relevant, ethically sound, and seamlessly integrated into healthcare systems. This collaboration must address current challenges, including cost barriers, infrastructure requirements, and interoperability issues, while maintaining focus on improved patient outcomes.

Looking ahead, AI's role in wound care will continue to evolve, driven by advancements in predictive analytics, deep learning, and wearable health technologies. The future promises more sophisticated AI systems capable of detecting subtle wound changes, predicting healing trajectories, and delivering personalised treatment recommendations. These systems will increasingly integrate multiple data streams, combining clinical observations with patient-specific factors to optimise care delivery (Mohammed et al, 2022).

Equally important is the human element in AI adoption. Engaging healthcare professionals throughout the implementation process fosters

acceptance and trust, ensuring that AI solutions align with real-world clinical needs. Additionally, understanding the patient perspective is vital, as AI-supported wound care must prioritise individualised treatment approaches, improved accessibility, and enhanced quality of life. This patient-centred approach must consider diverse populations and healthcare settings to ensure equitable access to AI-enhanced care.

The economic implications of AI adoption in wound care are significant. While initial implementation costs may be substantial, the potential for reduced hospital admissions, improved healing outcomes, and optimised resource utilisation suggests long-term cost-effectiveness [19]. Healthcare organisations must carefully balance these factors while maintaining focus on quality care delivery.

Conclusion

As AI continues to evolve, its success in wound care will be defined not just by its ability to streamline workflows, but by its capacity to enhance patient outcomes, support clinical expertise, and uphold the highest standards of care. By embracing AI's potential while prioritising ethical implementation and clinician engagement, healthcare organisations can ensure that AI-driven wound care remains both innovative and patient-centred, shaping a future where technology and human expertise work in harmony to deliver optimal wound care outcomes. ●

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