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Review Paper

Advancing burn wound healing with artificial intelligence (AI): Innovative solutions in medical technology

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ABSTRACT

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Assessment of burn injuries, determining wound depth and total body surface area (TBSA), is a critical but also subjective and inaccurate process. These diagnostic errors can lead to unfortunate patient outcomes and the useless distribution of healthcare resources. Artificial intelligence (AI) has emerged as a promising technology to improve precision in burn care. Our review analyzes the current applications, foundational technologies, and significant challenges of AI in advancing burn wound healing. This review is based on a regulated analysis of key scientific literature. It also covers the range of AI applications, from initial diagnosis and assessment to final treatment. It examines the primary computational models and datasets that enable these novelties, as well as the practical and ethical barriers to their clinical implementation. The review reveals that deep learning (DL) models have significant potential to improve the precision of burn wound diagnosis. It also shows that AI is particularly effective at segmenting wound boundaries, grading burn depth, and approximating %TBSA. This review highlights AI's increasing role in predicting healing paths and personalizing treatment plans. The analysis identifies various barriers to widespread implementation, including the lack of diverse datasets, the risk of algorithmic bias, and the "black box" nature of some models, which can inhibit clinical trust. AI holds considerable potential to enhance the precision and objectivity of burn care by serving as a powerful decision support tool for clinicians. Realizing the full potential of these innovative solutions requires a mutual effort to address the known research gaps.

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1. Introduction

Burn injuries are a significant global health challenge, forming a major cause of mortality and disability worldwide [1,2]. These injuries impose considerable physical, psychological, and socioeconomic burdens on patients and on the healthcare systems, with an inconsistent impact on people in low and middle-income countries (LMICs) [3]. The accurate epidemiological gauge of burn injuries is often believed to be underestimated, mainly because of the limited availability of high-quality and standardized data from many districts [3,4]. Effective management of severe burns is a complex process that relies significantly on the expertise of specialized teams, which are often concentrated in regional centers and remain rare in remote areas [1,2].

An important challenge in burn care is the initial assessment of the wound, as accurate determination of burn depth and size is critical for guiding subsequent clinical decisions, such as fluid resuscitation protocols, the need for surgical intervention, and potential transfer to a specialized unit [5,6]. Nonetheless, traditional and visual assessment is infamously subjective and prone to inconsistency, with inaccuracies reported even among the most experienced specialists [7,8]. Studies indicate that visual evaluation of burn depth can be incorrect in 25-39% of cases [7], while total body surface area (TBSA) estimations by non-specialist referring physicians are commonly overestimated, as seen in some pediatric cases, by as much as 44% [6]. These types of mistakes can have significant effects. If the %TBSA is overestimated, too much fluid may be given, which can cause problems like pulmonary edema and compartment syndrome [5]. A misdiagnosis, on the other hand, can lead to patients being sent to expensive and unnecessary burn centers [5,6].

To tackle these challenges, researchers are increasingly turning to artificial intelligence (AI), machine learning (ML), and deep learning (DL) [4,9]. This growth is driven by the greater availability of digitized medical data, including vast archives of clinical images and electronic health records (EHRs) [4,10].

AI can analyze complex wound characteristics with a level of objectivity and consistency that is difficult for human observers to match [8]. These systems identify subtle patterns in tissue viability, wound boundaries, and depth from imaging data. Consequently, they provide a powerful decision support tool for clinicians [9,11].

In particular, advanced models such as deep Convolutional Neural Networks (CNNs) have become a significant focus of research in burn image analysis. Studies demonstrate that these models yield promising results in wound segmentation and severity classification [7,11,12].

Because the field of ML in burn care is changing so quickly, an updated review is needed [4,9]. This paper provides that update by summarizing new AI solutions based on both technical and clinical research. We aim to connect the AI applications, the technologies that power them, and the practical challenges of using them in a real clinical environment.

This review is organized as follows: First, we will cover AI's use in burn diagnosis and assessment (image segmentation, depth classification, and %TBSA estimation). Then, we will discuss AI's role in treatment and rehabilitation (such as predicting healing). Thereafter, we will describe the core technologies and datasets behind these applications. We will conclude the review by analyzing key problems, constraints, and ethical considerations, and by suggesting future research options. This entire AI-enhanced patient care pathway is schematically illustrated in Figure 1.

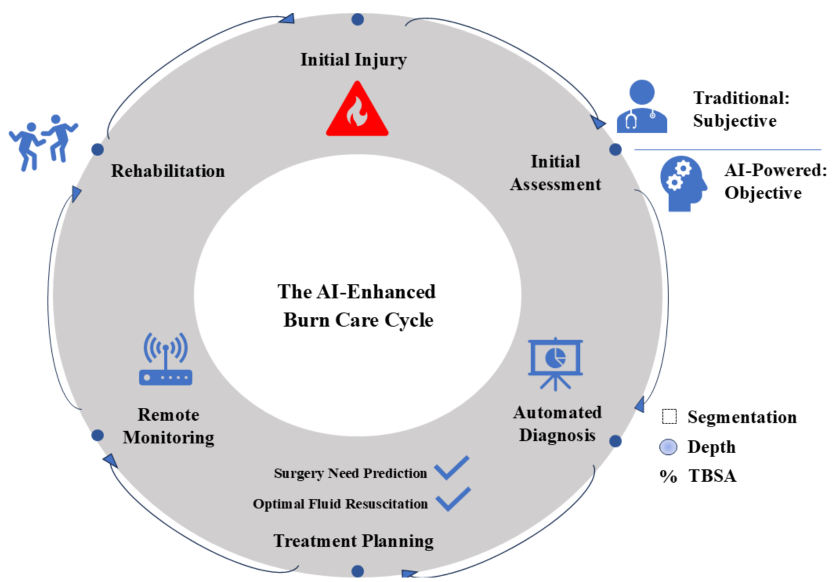

Figure 1. Schematic overview of the AI-enhanced burn care continuum, from initial assessment to treatment and rehabilitation.

2. Methods

2.1 Study Design and Review Framework

This review summarizes and analyzes the current state of AI in burn wound healing. We used a structured approach to identify and select relevant literature to ensure scientific rigor. Our approach covers each aspect, from the fundamental technology involved to the practical issues of using these tools in a clinical environment.

2.2 Search Strategy and Data Sources

By using major scientific databases such as PubMed, MEDLINE, and Embase. We conducted a systematic literature search to find relevant studies—our search strategy combined keywords and Medical Subject Headings (MeSH). We paired AI-related terms (e.g., "artificial intelligence," "machine learning," "deep learning") with burn-specific terms (e.g., "burn wound," "burn assessment," "wound healing"). To ensure our search was comprehensive, we reviewed the reference lists of key articles and systematic reviews to find additional studies.

2.3 Study Selection: Inclusion and Exclusion Criteria

To ensure we covered the most recent research, we limited our review to peer-reviewed, English-language articles published from 2015 through early 2025. If a study focused on developing, validating, or applying AI, ML, or DL technologies for burn wound diagnosis, management, or treatment, it was included. We accepted a range of article types, including original research, systematic reviews, and technical papers. Sources that were not peer-reviewed, not in English, or that did not include AI as a central part were excluded. We took this approach to ensure the review is built on high-quality, relevant scientific evidence.

2.4 Data Extraction and Synthesis

We began a qualitative data extraction process after selecting the articles. From each study, we systematically collected key information focusing on several themes. These items had specific supplementary pragmatics, including burn assessment, %TBSA, specific AI components such as CNNs and Support Vector Machines (SVMs), and the types of data used for training, such as digital photos and EHRs. From the literature, we also recorded the performance metrics reported, for example, accuracy, sensitivity, precision, and other parameters, along with any listed struggles or blind spots. Subsequently, we integrated the information by theme to formulate a cohesive story. This included cross-study comparisons to track the emergence of key technological vectors and to assess the existing research. This is so that the review is not just a book report but rather critical and analytical of the specific field.

3. AI in Burn Wound Diagnosis and Assessment

An accurate initial diagnosis of a burn wound is important for patient outcomes, but it remains a significant challenge in burn care. Traditional methods of assessing a burn's depth and size vary widely among clinicians. This reliance on personal judgment can lead to significant diagnostic errors, thereby reducing the effectiveness of treatment [1]. AI tools offer a solution by making burn assessment more objective, accurate, and consistent. These tools use advanced image analysis to help clinicians with important tasks, such as defining the wound's borders (segmentation), classifying its depth, and accurately measuring its surface area [9]. This automated diagnostic process is illustrated step by step in Figure 2.

Wound segmentation is a key first step in analyzing burn images. This means accurately outlining the burn area to separate it from healthy skin and the background. This step is crucial because other automated measurements, like calculating the burn's size and depth, depend on it. Deep learning models, especially CNNs, are very effective for this task. For example, one study using a Mask R-CNN model achieved a Dice coefficient of 84.51% for burn segmentation in photos [4]. In another study, a framework using models such as HRNetV2 achieved an Intersection over Union (IoU) of 0.8467 to distinguish between burn and non-burn areas [11].

Researchers have developed specialized models to define the irregular edges of wounds better. For example, one study proposed a Global Convolutional Network (GCN) that included a boundary-refinement module. This model achieved a high Dice coefficient of approximately 0.90 for deep burn segmentation by using a boundary-focused labeling approach [8]. Another study created a DL model that correctly identified an average of 87.2% of the wound area across a diverse set of skin types. However, the second study also highlighted a significant challenge. The model was more accurate on patients with darker skin. This suggests that the model's performance is affected by the visual contrast between burned and unburned skin. The model also had a problem with false positives: it incorrectly identified minor burns in up to 20% of images that had none. This is an important consideration when designing fully automated systems [7].

After identifying a wound, the most critical task is to classify its depth, as this determines whether the patient needs surgery. Even expert clinicians are only 64% to 76% accurate in this area, underscoring the need for objective tools to support them (Figure 3) [12]. AI models have been trained to classify burn depth, most commonly using digital color photos. Deep learning models perform much better than traditional ML methods. For example, one study found that a deep CNN was 96% accurate in classifying burns into three grades.

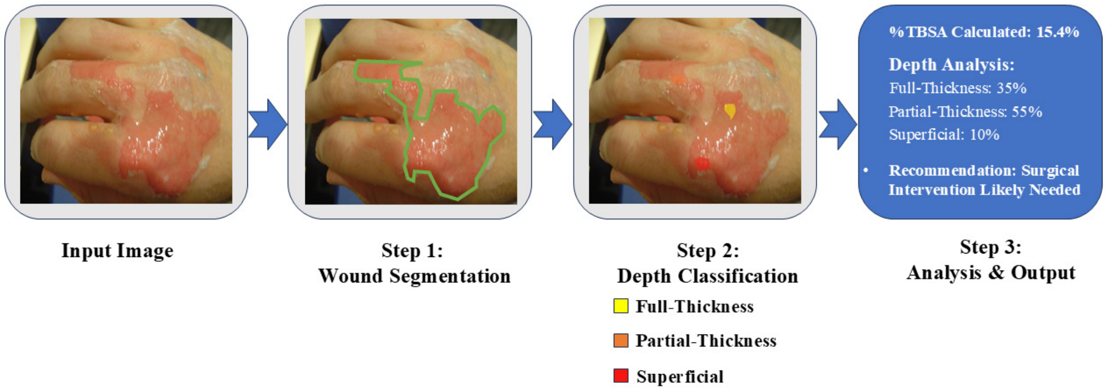

Figure 2. Step-by-step AI-driven diagnostic pipeline for burn wound assessment, including segmentation, depth classification, and %TBSA estimation.

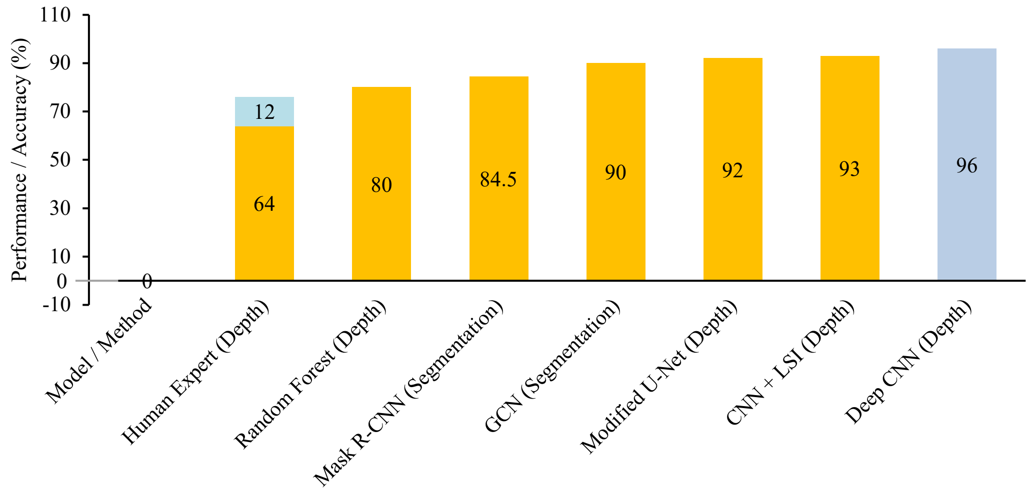

Figure 3. Comparison of diagnostic accuracy between artificial intelligence models and human clinicians in burn wound assessment.

This was significantly better than the 80% accuracy of the best traditional model (a random forest classifier) in the same study [9]. Another model was explicitly trained to predict the need for surgery and performed well, achieving an AUC (area under the curve) of 0.885. However, this research also identified a critical problem: the model performed better on lighter skin tones. This finding highlights the significant risk of algorithmic bias, in which an AI system may not perform equally well across all groups of people [7].

To improve diagnostic accuracy, researchers are using advanced imaging methods that provide more detailed information than standard photos [9]. For example, one study used polarized-light photography of children's burn wounds to train a modified U-Net model. They achieved an average test accuracy of 92%. While this result is promising, the study had a key limitation: it used a minimal training set of only 17 images. To prevent overfitting (where the model memorizes the training data), the researchers heavily relied on data augmentation to create more training examples [12]. Other advanced methods have also shown acceptable results. Techniques such as multispectral imaging (MSI), laser speckle imaging (LSI), and optical coherence tomography (OCT) have been combined with ML models. Some early studies report accuracies over 90%. For instance, a study using a pig model and LSI data with a CNN achieved over 93% accuracy in classifying burn depth [9].

AI can also automate the estimation of burn size, known as %TBSA (Total Body Surface Area). This measurement is critical for guiding fluid replacement and making triage decisions, but manual methods are often inaccurate [5]. Typically, the AI calculates %TBSA after the wound has been accurately outlined (segmented). Mobile health (mHealth) apps are becoming a practical platform for this technology. For instance, a mobile tool for first responders used an AI model that was 92% accurate at defining burn boundaries, providing real-time support for patient management [6]. Another approach used ML to create a 3D body model from simple body measurements. Its %TBSA estimates were as accurate as the current "gold-standard" method, 3D scanning [4]. These tools have the potential to reduce the high rate of estimation errors made by other hospitals. This would improve the initial care patients receive before being transferred to a specialized burn center [5].

4. AI in Burn Wound Treatment and Management

Beyond initial diagnosis, AI is now being used to guide a burn patient's entire treatment process. This includes predicting wound healing, creating personalized treatment plans, and supporting long-term rehabilitation. AI can process large and diverse datasets. This allows care to shift from general guidelines to treatments tailored to each patient. The goal is to improve outcomes, reduce complications, and make care more efficient [10]. This section will explore the primary uses of AI in the treatment and management of burn wounds.

An essential use of AI in burn care is predicting how long a wound will take to heal. This prediction helps doctors decide if a patient needs surgery. An early, accurate prediction can separate burns that will heal on their own from those that require procedures such as skin grafting. This helps prevent prominent scarring and other long-term problems [1,9]. AI models have shown they can make these predictions with high accuracy. For instance, one model used reflectance spectrometry data with an artificial neural network. It predicted whether a burn would heal in fewer than 14 days with 86% accuracy. Another algorithm analyzed thermography data and correctly predicted the required treatment (such as a skin graft or natural healing) with 85% accuracy [4]. These predictive tools give clinicians objective, data-driven support to help them decide when and why to perform surgery. This could reduce treatment delays and improve final patient outcomes.

AI can also help create personalized treatment plans. It does this by combining many kinds of patient data, including genetics, other health conditions, and wound characteristics [10]. This allows doctors to move beyond "one-size-fits-all" treatments and provide care tailored to each patient. For example, AI can help optimize fluid replacement, a critical step in early burn care. By more accurately estimating burn size (%TBSA) and using other patient data, AI can guide fluid administration. This helps prevent "fluid creep," a harmful condition caused by excessive fluid intake [1,5]. While this field is still developing, AI has excellent future potential. It may one day recommend specific dressings or creams based on a patient's unique details and their wound [1].

AI is also changing patient care after the initial hospital stay, especially during rehabilitation, through telemedicine and remote monitoring systems [2]. These systems allow continuous wound monitoring without the need for frequent, difficult clinic visits, a significant benefit for patients living in remote areas. For example, AI-powered mobile apps can analyze photos of a wound taken by the patient or a caregiver. This helps to track healing progress, detect early signs of infection, and monitor for any complications [2,6].

AI is also making important advances in physical rehabilitation, a key part of long-term burn recovery. Structured exercise is essential to prevent problems such as muscle and skin tightening (contractures) that can occur after prolonged periods of inactivity [13]. AI systems with computer vision can monitor patients as they perform their prescribed exercises at home. Using a standard camera, these systems analyze a patient's movements in real time, measuring their range of motion (ROM) and detecting incorrect patterns that indicate the exercise is being performed incorrectly. By acting as "virtual coaches" and providing immediate, corrective feedback, these tools can improve how well patients stick to their program and the quality of their rehabilitation. This may lead to better functional recovery and reduce the need for constant in-person supervision [2,13].

5. Foundational Technologies and Datasets

The successful use of AI in burn care depends on two main factors: advanced technologies that can learn from complex data and large, high-quality datasets to train and test them. The data must be well-labeled (annotated) for the AI models to learn effectively. This section provides an overview of the key technologies behind AI in burn assessment. It also discusses the critical role of the datasets that power these technologies and the challenges involved in creating them.

The core technologies for modern AI in medical imaging are ML and, more specifically, DL [10]. Although older ML models such as SVMs and Random Forests were standard in early studies, DL models are now more widely used because they perform better on image analysis tasks [4,9]. Among DL models, CNNs are the most important, as they are explicitly designed for image data [7]. Various CNN architectures, such as ResNet, U-Net, and Mask R-CNN, are commonly used for image segmentation and classification. A significant advantage is that these models can automatically learn important features directly from images, thereby eliminating the need for humans to identify them first [8,11,12] manually. To further improve performance, researchers often use a technique called transfer learning. This involves taking a model already trained on a large, general dataset (such as ImageNet) and making minor adjustments using a smaller, specific medical dataset. This strategy is very useful in medical research where large datasets are often hard to find [7].

The performance of any AI model depends heavily on the quality and variety of its training data. In burn care, the primary data source is digital images of the wounds [9]. While standard color photos from cameras and smartphones are the easiest to obtain, their usefulness can be limited by issues such as inconsistent lighting, varying camera angles, and poor image quality [7]. To solve these issues, researchers are exploring advanced imaging techniques that provide more detailed, measurable data. These include multispectral and hyperspectral imaging, which use multiple wavelengths of light to understand tissue properties better. Other methods, such as LSI, Laser Doppler Imaging (LDI), and OCT, provide information on blood flow and tissue structure [9]. Although these advanced techniques show great promise for more accurate diagnoses, their high cost and complexity are significant barriers to their widespread use in clinics [7].

A significant challenge for developing effective AI models in burn care is the lack of large, publicly available, and standardized datasets [3]. Most studies have used small datasets from single hospitals, making it hard to know whether their results will generalize to other settings or can be replicated by other researchers [4]. Creating these datasets takes a lot of effort, as clinical experts must carefully label wound borders and classify burn depths, a process where even experts can disagree [7,11]. Furthermore, many current datasets are not diverse enough, especially in terms of different skin tones, which can lead to biased AI models that do not perform well for underrepresented groups [7]. To help address this, projects such as the World Health Organization (WHO) Global Burn Registry (GBR) were established to collect standardized global data, but participation has been inconsistent [3]. Therefore, creating large, ethically gathered datasets from multiple centers that are easy for researchers to access is a critical next step to ensure new AI tools are both practical and fair.

6. Challenges, Limitations, and Ethical Considerations

6.1 *Data Quality, Availability, and Standardization*

The performance of AI models is fundamentally constrained by the quality and availability of their training data. In burn care, a major limitation is the lack of large, high-quality, and standardized datasets [4]. Most existing studies rely on relatively small datasets collected from single institutions, which limits the generalizability of their findings and complicates comparisons across different AI models [9]. Developing high-quality datasets is a resource-intensive process that requires expert clinicians to annotate wound boundaries and classify burn depth—tasks that are inherently subjective and prone to interobserver variability [11]. Additionally, class imbalance is common, with certain burn types being underrepresented, further complicating model training. Although initiatives such as the World Health Organization Global Burn Registry (GBR) aim to promote standardized global data collection, their adoption has been inconsistent due to limited resources, insufficient institutional support, and the absence of unified protocols [3].

6.2 *Model Generalization and Algorithmic Bias*

Limited and homogeneous datasets directly contribute to poor model generalization and increase the risk of algorithmic bias. AI models trained on specific patient populations may perform inadequately when applied to different demographic groups, a critical concern for a global health condition such as burn injury [7]. Much of the existing burn research has historically focused on lighter skin tones, raising concerns that AI systems trained on such data may be less accurate for patients with darker skin [4,7]. Evidence from Boissin et al. highlights the complexity of this issue: while their wound segmentation model performed better on darker skin, their surgical decision model showed higher accuracy in lighter skin types. If such disparities are not identified and addressed during development and validation, AI systems may unintentionally exacerbate existing health inequities [10].

6.3 *Model-Level Challenges*

6.3.1 *Transparency and the "Black Box" Problem*

Many high-performing deep learning models, particularly complex convolutional neural networks, function as "black boxes," meaning their internal decision-making processes are not easily interpretable by humans [4]. This lack of transparency represents a major barrier to clinical adoption. Clinicians must understand how and why an AI system arrives at a particular recommendation—especially for high-stakes decisions such as surgical intervention—to trust and responsibly use these tools. When AI reasoning cannot be explained, clinical confidence diminishes, and concerns arise regarding accountability in cases of error or adverse outcomes [10]. Addressing the black box problem is therefore essential to ensure that AI systems function as supportive decision-making tools rather than opaque authorities.

6.4 *Clinical Implementation Challenges*

6.4.1 *Integration into Clinical Workflows*

Even highly accurate AI models offer limited value if they cannot be seamlessly integrated into existing clinical workflows [10]. Burn units and emergency departments operate under time constraints that leave little room for complex or slow technologies. Consequently, AI tools must be intuitive, efficient, and compatible with existing systems such as electronic health records (EHRs). Successful integration also requires a thorough understanding of clinicians' practical needs and workflows [2]. The effectiveness of AI-powered mobile applications for first responders underscores the importance of user-centered design [6]. Additionally, adequate clinician training is essential to ensure correct interpretation of AI outputs and to prevent misuse or overreliance on automated systems [2].

6.5 *Ethical, Legal, and Regulatory Issues*

6.5.1 *Ethical and Privacy Concerns*

The development and deployment of AI in burn care necessitate the collection of sensitive patient data, including identifiable clinical images. This raises significant ethical concerns related to data privacy, security, and informed consent [2]. Protecting patient confidentiality is essential for maintaining trust and complying with ethical and legal standards [10]. Robust data governance frameworks are required to prevent unauthorized access or data breaches. Furthermore, transparent consent processes must ensure that patients clearly understand how their data will be used for AI development and clinical decision support [4]. Uncertainty regarding data ownership—whether it belongs to patients, healthcare institutions, or AI developers—further complicates ethical oversight.

6.5.2 *Regulatory and Validation Hurdles*

Before AI tools can be safely deployed in clinical practice, they must undergo rigorous validation to demonstrate safety, effectiveness, and reliability. However, burn care currently lacks standardized frameworks for evaluating and validating AI models [4,9]. Variability in datasets, performance metrics, and validation methods makes it difficult to compare studies or establish minimum performance standards. High-quality evidence from multicenter studies and prospective trials, including randomized controlled trials where appropriate, is urgently needed to assess the real-world impact of AI on patient outcomes and healthcare costs [4]. Establishing clear regulatory pathways and evidence-based guidelines is essential to ensure that only safe, effective, and equitable AI tools are introduced into clinical burn care. These interconnected challenges are summarized in Figure 4.

7. Future Directions

7.1 *Emerging Innovations in AI-Driven Burn Care*

The role of AI in burn care is rapidly expanding beyond diagnostic support toward a more integrated role across the entire patient care pathway. Future developments are likely to involve combining AI with real-time data sources, such as wearable biosensors, robotics, and immersive technologies, enabling adaptive, patient-centered treatment strategies. Continuous data analysis may allow earlier detection of complications such as sepsis or dehydration, facilitating timely clinical interventions [2].

In surgical settings, AI-assisted robotic systems may enhance the precision of procedures such as debridement and skin grafting [10]. AI is also expected to play an increasingly important role in rehabilitation and long-term recovery. Virtual reality (VR) technologies are already being used to reduce pain during procedures such as dressing changes [4]. At the same time, AI-based motion analysis systems can support personalized, home-based rehabilitation programs to improve mobility and prevent contractures [13]. Augmented reality (AR) may further enhance telemedicine by enabling remote expert guidance during complex procedures in resource-limited settings [4]. Additionally, AI-powered voice assistants have the potential to improve patient adherence to remote care plans and follow-up protocols [2].

7.2 *Key Research Gaps and Priorities*

Despite encouraging progress, several critical research gaps must be addressed before AI can be widely and equitably adopted in burn care.

Priority areas include developing large, ethnically diverse, multicenter datasets to reduce algorithmic bias and improve model generalizability [4,7]. Greater support for standardized data collection initiatives, such as the WHO GBR, is essential to overcome current limitations in participation and data consistency [3].

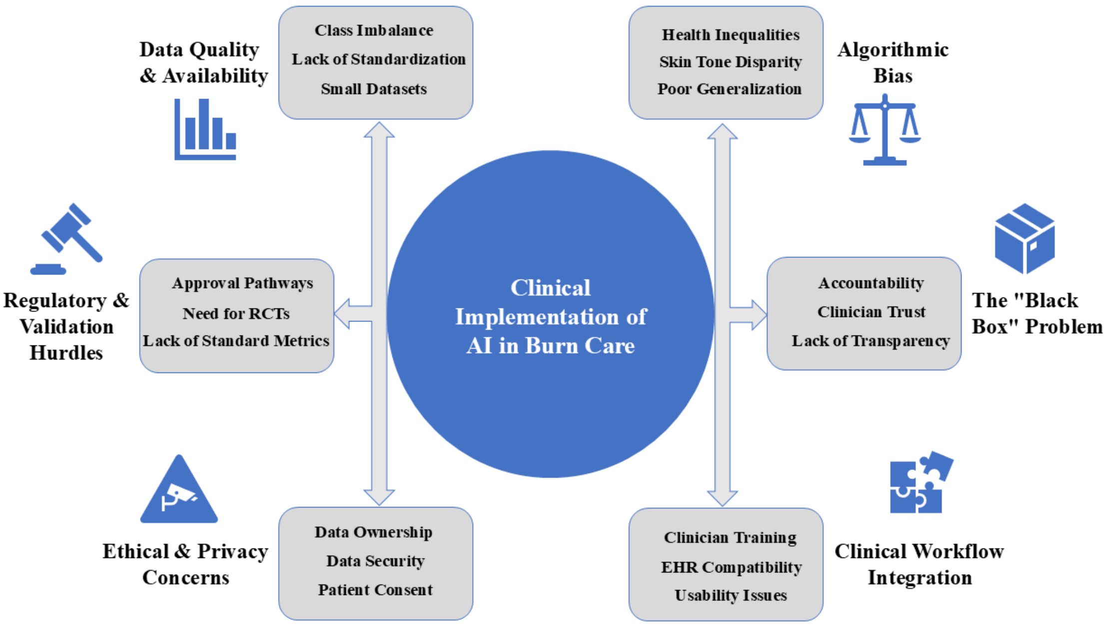

Figure 4. Major technical, clinical, and ethical barriers to the implementation of AI in burn care.

Equally important is the need for rigorous clinical validation through prospective, multicenter studies designed to assess not only technical performance but also clinical outcomes and cost-effectiveness [4,9]. Establishing standardized reporting frameworks would improve transparency, reproducibility, and comparability across AI studies in burn care [4]. Finally, future research must place greater emphasis on usability, clinical integration, and ethical governance to ensure that AI tools are trustworthy, interpretable, and aligned with real-world clinical needs [2,10].

8. Conclusion

Artificial intelligence holds substantial promise for improving the accuracy, objectivity, and efficiency of burn care across diagnosis, treatment, and rehabilitation. Current evidence suggests that AI-powered systems can meaningfully support clinical decision-making; however, these tools should be viewed as complements—not replacements—for clinical expertise. Addressing persistent challenges related to data quality, algorithmic bias, interpretability, clinical integration, and regulatory validation is essential for responsible implementation. With coordinated efforts in data standardization, rigorous validation, and ethical oversight, AI-driven technologies have the potential to transform the future of burn care.

Authors' contributions

MM and AF: contributed to the study conception and design. MMo and PA: Literature search and collected data. MMo and PA: wrote the first draft of the manuscript. All authors discussed the results and contributed to the final version. All authors read and approved the final version of manuscript.

Conflict of interest

No potential conflict of interest was reported by the authors.

Ethical declarations

Not applicable.

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