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**Review Article**

# Mapping the use of artificial intelligence for skin injury assessment and care in hospitalized patients: A scoping review

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ABSTRACT

**Background & Aim:** Skin injuries are frequent hospital complications, and the role of artificial intelligence in management remains unclear. This review aimed to identify, map, and analyze the evidence on the use of artificial intelligence in the assessment, monitoring, and management of skin injuries in hospitalized patients worldwide.
**Methods & Materials:** A scoping review was conducted following the Joanna Briggs Institute guidance and the PRISMA Extension for Scoping Reviews (PRISMA-ScR). Searches were carried out in Embase, PubMed, Scopus, CINAHL, Cochrane Library, Web of Science, SciELO, BVS, LILACS, and the CAPES thesis and dissertation catalog. Eligible sources included primary studies, technical notes, dissertations, and theses. All references were organized in EndNote Web and transferred to Rayyan to support duplicate removal and facilitate screening by reviewers.
**Results:** The search resulted in the identification of 1,240 studies, of which eight were included and published in English. Most studies are technological development studies with samples ranging from 10 to 5,729 images or participants. Studies have shown that artificial intelligence techniques applied to pressure injuries, including Convolutional Neural Networks, Random Forest, Support Vector Machine, and Extreme Gradient Boosting, improve detection, measurement, classification, risk prediction, and clinical decision support, potentially reducing workload and enhancing care safety.
**Conclusion:** The application of artificial intelligence in the domain of skin injuries revealed a variety of uses. However, it was predominantly focused on the specific context of pressure injuries in hospitalized individuals. Consequently, a noticeable gap in the literature was identified regarding alternative categories of injuries affecting this population segment.

## Introduction

Healthcare-related problems, particularly adverse events, represent a significant public health issue, requiring rapid and effective actions for their mitigation (1). Among these events, skin injuries are frequent and clinically relevant in hospitalized patients. As the largest human organ, the skin is fundamental for maintaining physiological stability, and its damage can markedly affect patient safety and clinical outcomes (2).

Several intrinsic and extrinsic factors, such as changes in microclimate, tissue perfusion, nutritional status, and comorbidities, may reduce tissue tolerance and contribute to the development of skin injuries. These injuries include pressure ulcers, medical device–related injuries, skin tears, and incontinence-associated dermatitis (IAD), all of which require timely identification and management. (3-4).

Pressure ulcers exemplify the magnitude of this issue, with studies reporting varying incidence and prevalence across populations (5-8). Medical device–related injuries also present considerable risk, with estimated incidence and prevalence of 12% and 10% (9). Skin tears and IAD likewise affect vulnerable populations, particularly older adults and neonates, and have been reported with substantial frequency (10-15).

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Unlike pressure ulcers, medical device-related injuries are due to the use of devices designed and applied for diagnostic or therapeutic purposes. These injuries are generally associated with the pressure the device exerts on the skin and present a pattern or shape corresponding to the device used (5).

According to the International Skin Tear Advisory Panel, skin tears are injuries resulting from shear, friction, or blunt force trauma, causing separation of the skin layers. These injuries can be classified as partial- or full-thickness. In partial-thickness injuries, there is separation between the epidermis and dermis, while in full-thickness injuries, both the epidermis and dermis are separated (10). More prevalent in the elderly due to physiological changes in aging skin, skin tears have a combined prevalence and incidence of 6.0% and 11.0%, respectively (11).

Defined as a cutaneous inflammation characterized by erythema, exudation, and ulceration, affecting areas such as the perineum, gluteal region, lower abdomen, and thighs, IAD is also noteworthy among skin injuries. This condition is caused by prolonged exposure of the skin to urine and/or feces (12-13). These clinical challenges reinforce the need for improved strategies capable of supporting early detection, accurate assessment, and decision-making. Traditional methods rely heavily on subjective observation and manual measurements, which may increase variability and limit precision. (16). In this context, Artificial Intelligence has emerged as a promising tool for advancing the prevention, prediction, classification, and monitoring of skin injuries (16–18). Advances in machine learning, deep learning, and computer vision allow the analysis of complex clinical patterns and provide rapid, standardized outputs that complement clinical judgment.

Despite growing interest in this field, the literature remains dispersed and predominantly focused on pressure injuries. No review study was found that systematically maps how AI has been applied to different types of skin injuries acquired during hospitalization. Considering this gap, this scoping review aimed to identify, map, and analyze the evidence on the use of Artificial Intelligence in the assessment, monitoring, and management of skin injuries in hospitalized patients worldwide.

## Methods

### *Study design*

This is a scoping review, which aims at mapping the current evidence available in the literature, presenting the main concepts in the field, and identifying knowledge gaps, thereby facilitating new research (19). Scoping reviews are complex studies that require methodological rigor and should be conducted with independent evaluation by at least two reviewers, following specific protocols (20). This study was designed based on the recommendations set forth by the Joanna Briggs Institute (JBI) Review Manual and the PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation (21), through the following steps: protocol development and registration (22); consultation with stakeholders; formulation of the review objective and question; definition of eligibility criteria; planning of the search strategy; systematic search and selection of studies; data extraction; analysis of evidence; and presentation and discussion of results. The research protocol was registered with the Open Science Framework (OSF) (23) under doi.org/10.17605/OSF.IO/PT3RH.

### *Data sources and search strategy*

To conduct this review, nine databases were consulted using the Virtual Private Network (VPN) of the "Júlio de Mesquita Filho" São Paulo State University (*Universidade Estadual Paulista*, UNESP), namely: Excerpta Medica Database (Embase), PubMed, Scopus, Cumulative Index to Nursing and Allied Health Literature (CINAHL), Cochrane Library, Web of Science, SciELO via Web of Science, *Biblioteca Virtual em Saúde* (BVS), and *Literatura Latino-Americana e do Caribe em Ciências da Saúde* (LILACS) via BVS.

The review question was formulated according to the PCC acronym (Population, Concept, Context), where the Population (P) refers to hospitalized individuals, Concept (C) refers to Artificial Intelligence (AI), and Context (C) refers to skin injuries. The skin injuries included in this review are pressure injuries, medical device-related injuries, IADs, and skin tears. Thus, the research question was as follows: What are the applications of AI for skin injuries in the hospital environment?

The search strategy to conduct the database searches was based on Health Sciences Descriptors (*Descritores em Ciência da Saúde*, DeCS), Medical Subject Headings (MeSH), and Emtree, with the aim of using a structured vocabulary in Portuguese, English, and Spanish. "AND" and "OR" Boolean operators were also employed. To find evidence of AI applications specifically related to the assessment, monitoring, and management of skin lesions in hospitalized patients, terms related to text processing and communication with patients were not included. The search strategy for each database is described in Table 1.

**Table 1.** Search strategy developed for each database

| Database | Search strategy | Number |
|---|---|---|
| SciELO | (Pele OR Skin OR Piel) AND ("Inteligência Artificial" OR "Artificial Intelligence" OR "Inteligencia Artificial" OR "Aquisição de Conhecimento (Computador)" OR "Aquisição de Conhecimentos (Informática)" OR "IA (Inteligência Artificial)" OR "Inteligência de Máquina" OR "Raciocínio Automático" OR "Raciocínio Computacional" OR "Representação de Conhecimento (Computador)" OR "Representação do Conhecimento (Computador)" OR "Sistemas de Visão Artificial" OR "Sistemas de Visão Computacional" OR "Aprendizado de Máquina" OR "Machine Learning" OR "Aprendizaje Automático" OR "Aprendizado Automático" OR "Aprendizado de Transferência" OR "Aprendizagem Automática" OR "Aprendizagem de Máquina" OR "Aprendizagem de Transferência") | 18 |
| BVS | (Pele OR Skin OR Piel) AND ("Ferimentos e Lesões" OR "Wounds and Injuries" OR "Heridas y Lesiones" OR Ferida OR Feridas OR Ferimento OR Ferimentos OR "Ferimentos e Traumatismos" OR Lesão OR Lesões OR Trauma OR Traumas OR Traumatismo OR Traumatismos) AND (("Inteligência Artificial" OR "Artificial Intelligence" OR "Inteligencia Artificial" OR "Aquisição de Conhecimento (Computador)" OR "Aquisição de Conhecimentos (Informática)" OR "IA (Inteligência Artificial)" OR "Inteligência de Máquina" OR "Raciocínio Automático" OR "Raciocínio Computacional" OR "Representação de Conhecimento (Computador)" OR "Representação do Conhecimento (Computador)" OR "Sistemas de Visão Artificial" OR "Sistemas de Visão Computacional") OR ("Aprendizado de Máquina" OR "Machine Learning" OR "Aprendizaje Automático" OR "Aprendizado Automático" OR "Aprendizado de Transferência" OR "Aprendizagem Automática" OR "Aprendizagem de Máquina" OR "Aprendizagem de Transferência")) | 19 |
| LILACS | (Pele OR Skin OR Piel) AND ("Ferimentos e Lesões" OR "Wounds and Injuries" OR "Heridas y Lesiones" OR Ferida OR Feridas OR Ferimento OR Ferimentos OR "Ferimentos e Traumatismos" OR Lesão OR Lesões OR Trauma OR Traumas OR Traumatismo OR Traumatismos) AND (("Inteligência Artificial" OR "Artificial Intelligence" OR "Inteligencia Artificial" OR "Aquisição de Conhecimento (Computador)" OR "Aquisição de Conhecimentos (Informática)" OR "IA (Inteligência Artificial)" OR "Inteligência de Máquina" OR "Raciocínio Automático" OR "Raciocínio Computacional" OR "Representação de Conhecimento (Computador)" OR "Representação do Conhecimento (Computador)" OR "Sistemas de Visão Artificial" OR "Sistemas de Visão Computacional") OR ("Aprendizado de Máquina" OR "Machine Learning" OR "Aprendizaje Automático" OR "Aprendizado Automático" OR "Aprendizado de Transferência" OR "Aprendizagem Automática" OR "Aprendizagem de Máquina" OR "Aprendizagem de Transferência")) | 8 |
| Scopus | (ABS (Skin OR cutis OR derma OR "human skin" OR "skin layer")) AND (ABS ("Wounds and Injuries" OR "Wounds, Injury" OR "Wounds and Injury" OR "Injury and Wounds" OR "Injuries and Wounds" OR "Injuries, Wounds" OR "Physical Trauma" OR "Physical Traumas" OR "Trauma, Physical" OR Trauma OR Traumas OR "Research-Related Injuries" OR "Injury, Research-Related" OR "Research Related Injuries" OR "Research-Related Injury" OR Injuries OR Injury OR Wounds OR Wound OR "back injuries" OR "back injury" OR "back trauma" OR "injuries, poisonings, and occupational diseases" OR "injury force" OR "injury pattern" OR "injury rate" OR "major trauma" OR reinjuries OR reinjury OR "sprains and strains" OR "trauma mechanism" OR "traumatic injury" OR "traumatic lesion")) AND (ABS ("Artificial Intelligence" OR "Intelligence, Artificial" OR "Computational Intelligence" OR "Intelligence, Computational" OR "Machine Intelligence" OR "Intelligence, Machine" OR "Computer Reasoning" OR "Reasoning, Computer" OR "AI (Artificial Intelligence)" OR "Computer Vision Systems" OR "Computer Vision System" OR "System, Computer Vision" OR "Systems, Computer Vision" OR "Vision System, Computer" OR "Vision Systems, Computer" OR "Knowledge Acquisition (Computer)" OR "Acquisition, Knowledge (Computer)" OR "Knowledge Representation (Computer)" OR "Knowledge Representations (Computer)" OR "Representation, Knowledge (Computer)" OR "Machine Learning" OR "Learning, Machine" OR "Transfer Learning" OR "Learning, Transfer" OR "learning machines")) | 196 |
| Web of Science | ((ALL = ((Skin OR cutis OR derma OR "human skin" OR "skin layer"))) AND ALL = (("Wounds and Injuries" OR "Wounds, Injury" OR "Wounds and Injury" OR "Injury and Wounds" OR "Injuries and Wounds" OR "Injuries, Wounds" OR "Physical Trauma" OR "Physical Traumas" OR "Trauma, Physical" OR Trauma OR Traumas OR "Research-Related Injuries" OR "Injury, Research-Related" OR "Research Related Injuries" OR "Research-Related Injury" OR Injuries OR Injury OR Wounds OR Wound OR "back injuries" OR "back injury" OR "back trauma" OR "injuries, poisonings, and occupational diseases" OR "injury force" OR "injury pattern" OR "injury rate" OR "major trauma" OR reinjuries OR reinjury OR "sprains and strains" OR "trauma mechanism" OR "traumatic injury" OR "traumatic lesion"))) AND ALL=(("Artificial Intelligence" OR "Intelligence, Artificial" OR "Computational Intelligence" OR "Intelligence, Computational" OR "Machine Intelligence" OR "Intelligence, Machine" OR "Computer Reasoning" OR "Reasoning, Computer" OR "AI (Artificial Intelligence)" OR "Computer Vision Systems" OR "Computer Vision System" OR "System, Computer Vision" OR "Systems, Computer Vision" OR "Vision System, | 409 |

| Database | Search strategy | Number |
|---|---|---|
| | Computer" OR "Vision Systems, Computer" OR "Knowledge Acquisition (Computer)" OR "Acquisition, Knowledge (Computer)" OR "Knowledge Representation (Computer)" OR "Knowledge Representations (Computer)" OR "Representation, Knowledge (Computer)" OR "Machine Learning" OR "Learning, Machine" OR "Transfer Learning" OR "Learning, Transfer" OR "learning machines")) | |
| **Cochrane** | (Skin OR cutis OR derma OR "human skin" OR "skin layer") AND ("Wounds and Injuries" OR "Wounds, Injury" OR "Wounds and Injury" OR "Injury and Wounds" OR "Injuries and Wounds" OR "Injuries, Wounds" OR "Physical Trauma" OR "Physical Traumas" OR "Trauma, Physical" OR Trauma OR Traumas OR "Research-Related Injuries" OR "Injury, Research-Related" OR "Research Related Injuries" OR "Research-Related Injury" OR Injuries OR Injury OR Wounds OR Wound OR "back injuries" OR "back injury" OR "back trauma" OR "injuries, poisonings, and occupational diseases" OR "injury force" OR "injury pattern" OR "injury rate" OR "major trauma" OR reinjuries OR reinjury OR "sprains and strains" OR "trauma mechanism" OR "traumatic injury" OR "traumatic lesion") AND ("Artificial Intelligence" OR "Intelligence, Artificial" OR "Computational Intelligence" OR "Intelligence, Computational" OR "Machine Intelligence" OR "Intelligence, Machine" OR "Computer Reasoning" OR "Reasoning, Computer" OR "AI (Artificial Intelligence)" OR "Computer Vision Systems" OR "Computer Vision System" OR "System, Computer Vision" OR "Systems, Computer Vision" OR "Vision System, Computer" OR "Vision Systems, Computer" OR "Knowledge Acquisition (Computer)" OR "Acquisition, Knowledge (Computer)" OR "Knowledge Representation (Computer)" OR "Knowledge Representations (Computer)" OR "Representation, Knowledge (Computer)" OR "Machine Learning" OR "Learning, Machine" OR "Transfer Learning" OR "Learning, Transfer" OR "learning machines") in Title Abstract Keyword | 18 |
| **Embase** | (skin OR cutis OR derma OR 'human skin' OR 'skin layer') AND ('wounds and injuries' OR 'wounds, injury' OR 'wounds and injury' OR 'injury and wounds' OR 'injuries and wounds' OR 'injuries, wounds' OR 'physical trauma' OR 'physical traumas' OR 'trauma, physical'' OR trauma OR traumas OR 'research-related injuries' OR 'injury, research-related' OR 'research related injuries' OR 'research-related injury' OR injuries OR injury OR wounds OR wound OR 'back injuries' OR 'back injury' OR 'back trauma' OR 'injuries, poisonings, and occupational diseases' OR 'injury force' OR 'injury pattern' OR 'injury rate' OR 'major trauma' OR reinjuries OR reinjury OR 'sprains and strains' OR 'trauma mechanism' OR 'traumatic injury' OR 'traumatic lesion') AND ('artificial intelligence' OR 'intelligence, artificial' OR 'computational intelligence' OR 'intelligence, computational' OR 'machine intelligence' OR 'intelligence, machine' OR 'computer reasoning' OR 'reasoning, computer' OR 'ai (artificial intelligence)' OR 'computer vision systems' OR 'computer vision system' OR 'system, computer vision' OR 'systems, computer vision' OR 'vision system, computer' OR 'vision systems, computer OR 'knowledge acquisition (computer)' OR 'acquisition, knowledge (computer)' OR 'knowledge representation (computer)' OR 'knowledge representations (computer)' OR 'representation, knowledge (computer) OR 'machine learning' OR 'learning, machine' OR 'transfer learning' OR 'learning, transfer' OR 'learning machines') AND ([embasel/lim OR [pubmed-not-medline//lim) | 398 |
| **PubMed** | (Skin[Title/Abstract] OR cutis[Title/Abstract] OR derma[Title/Abstract] OR "human skin"[Title/Abstract] OR "skin layer") AND ("Wounds and Injuries"[Title/Abstract] OR "Wounds, Injury"[Title/Abstract] OR "Wounds and Injury"[Title/Abstract] OR "Injury and Wounds"[Title/Abstract] OR "Injuries and Wounds"[Title/Abstract] OR "Injuries, Wounds"[Title/Abstract] OR "Physical Trauma"[Title/Abstract] OR "Physical Traumas"[Title/Abstract] OR "Trauma, Physical"[Title/Abstract] OR Trauma[Title/Abstract] OR Traumas[Title/Abstract] OR "Research-Related Injuries"[Title/Abstract] OR "Injury, Research-Related"[Title/Abstract] OR "Research Related Injuries"[Title/Abstract] OR "Research-Related Injury"[Title/Abstract] OR Injuries[Title/Abstract] OR Injury[Title/Abstract] OR Wounds[Title/Abstract] OR Wound[Title/Abstract] OR "back injuries"[Title/Abstract] OR "back injury"[Title/Abstract] OR "back trauma"[Title/Abstract] OR "injuries, poisonings, and occupational diseases"[Title/Abstract] OR "injury force"[Title/Abstract] OR "injury pattern"[Title/Abstract] OR "injury rate"[Title/Abstract] OR "major trauma"[Title/Abstract] OR reinjuries[Title/Abstract] OR reinjury[Title/Abstract] OR "sprains and strains"[Title/Abstract] OR "trauma mechanism"[Title/Abstract] OR "traumatic injury"[Title/Abstract] OR "traumatic lesion") AND ("Artificial Intelligence"[Title/Abstract] OR "Intelligence, Artificial"[Title/Abstract] OR "Computational Intelligence"[Title/Abstract] OR "Intelligence, Computational"[Title/Abstract] OR "Machine Intelligence"[Title/Abstract] OR "Intelligence, Machine"[Title/Abstract] OR "Computer Reasoning"[Title/Abstract] OR "Reasoning, Computer"[Title/Abstract] OR "AI (Artificial Intelligence)"[Title/Abstract] OR "Computer Vision Systems"[Title/Abstract] OR "Computer Vision System"[Title/Abstract] OR "System, Computer Vision"[Title/Abstract] OR "Systems, Computer Vision"[Title/Abstract] OR "Vision System, Computer"[Title/Abstract] OR "Vision Systems, Computer"[Title/Abstract] OR "Knowledge Acquisition (Computer)"[Title/Abstract] OR "Acquisition, Knowledge (Computer)"[Title/Abstract] OR "Knowledge Representation (Computer)"[Title/Abstract] OR "Knowledge Representations (Computer)"[Title/Abstract] OR "Representation, Knowledge (Computer)"[Title/Abstract] OR "Machine Learning"[Title/Abstract] OR "Learning, Machine"[Title/Abstract] OR "Transfer Learning"[Title/Abstract] OR "Learning, Transfer"[Title/Abstract] OR "learning machines"[Title/Abstract]) | 144 |
| **CINHAL** | (Skin OR cutis OR derma OR "human skin" OR "skin layer") AND ("Wounds and Injuries" OR "Wounds, Injury" OR "Wounds and Injury" OR "Injury and Wounds" OR "Injuries and Wounds" OR "Injuries, Wounds" OR "Physical Trauma" OR "Physical Traumas" OR "Trauma, Physical" OR Trauma OR Traumas OR "Research-Related Injuries" OR "Injury, Research-Related" OR "Research Related Injuries" OR "Research-Related Injury" OR Injuries OR Injury OR Wounds OR Wound OR "back injuries" OR "back injury" OR "back trauma" OR "injuries, poisonings, and occupational diseases" OR "injury force" OR "injury pattern" OR "injury rate" OR "major trauma" OR reinjuries OR reinjury OR "sprains and strains" OR "trauma mechanism" OR "traumatic injury" OR "traumatic lesion") AND ("Artificial Intelligence" OR "Intelligence, Artificial" OR "Computational Intelligence" OR "Intelligence, Computational" OR "Machine Intelligence" OR "Intelligence, Machine" OR "Computer Reasoning" OR "Reasoning, Computer" OR "AI (Artificial Intelligence)" OR "Computer Vision Systems" OR "Computer Vision System" OR "System, Computer Vision" OR "Systems, Computer Vision" OR "Vision System, Computer" OR "Vision Systems, Computer" OR "Knowledge Acquisition (Computer)" OR "Acquisition, Knowledge (Computer)" OR "Knowledge Representation (Computer)" OR "Knowledge Representations (Computer)" OR "Representation, Knowledge (Computer)" OR "Machine Learning" OR "Learning, Machine" OR "Transfer Learning" OR "Learning, Transfer" OR "learning machines") | 30 |

Additionally, a search was conducted in the Gray Literature through the thesis and dissertation catalog of the Coordination for the Improvement of Higher Education Personnel (Coordenação de Aperfeiçoamento de Pessoal de Nível Superior, CAPES), using the following combinations: (Pele OR Skin) AND ("Inteligência Artificial" OR "Artificial Intelligence" OR "IA (Inteligência Artificial") and (Pele) AND ("Inteligência Artificial" OR "IA (Inteligência Artificial"). No studies were included from this search based on the eligibility criteria.

***Study selection***

The eligibility criteria included the following: primary original articles, technical notes, dissertations, and theses addressing how AI is used in the identification, treatment, and monitoring of skin injuries developed in the hospital context. Both quantitative and qualitative studies were considered, including case studies, cohort studies, cross-sectional studies, and randomized clinical trials, published up to 2024. The study population encompassed the hospitalized population, without distinction in terms of gender, specific age group, or language. The exclusions were as follows: advertisements, editorials, opinion articles, papers published in conference proceedings, letters to the editor, studies related to skin neoplasms, and materials focused on chronic injuries, as well as those that, after full reading, did not address the research question. Duplicate studies were counted only once.

It is noted that skin neoplasms and chronic wounds prior to hospitalization were excluded from the analysis, as the focus of this review was to assess the use of AI in wounds acquired during hospitalization. Chronic injuries are defined as those lasting more than six weeks (24). From the development of the search strategy for the databases selected, all studies were organized in the EndNote Web reference manager (Clarivate Analytics, Pennsylvania, United States of America), easing visualization of the results. It is worth emphasizing that, as previously described in the protocol for this review, the Mendeley reference manager was intended to be used; however, it was replaced by EndNote Web due to technical issues.

After this stage, the papers were transferred to Rayyan (Professional version) with the aim of managing and automatically removing duplicate studies, as well as facilitating the screening of articles by titles and abstracts. This process was meticulously performed by two reviewers in a blinded manner, following the eligibility criteria. The screening was conducted by two reviewers, with involvement of a third one required to solve conflicts and minimize bias possibilities.

Subsequently, the articles selected were read in full to assess their eligibility for the review. Following the selection of studies, the bibliographic references were analyzed to identify other scientific papers that addressed the central question and met the eligibility criteria. The goal of this approach was to find studies that had not been identified in the databases.

***Data extraction and synthesis of the results***

The following data were extracted from the studies: title, authors, year of publication, journal, study locus or setting, study objective, study type and sample, participant age, type of injury, outcomes, AI model or application used, performance metrics, and an explanation of the algorithm applied. Data extraction and organization were facilitated using Microsoft Excel software to ensure consistency, accuracy, and traceability of the information.

Both qualitative and quantitative findings were critically examined. To manage heterogeneity across study designs, populations, and AI models, studies were analyzed according to key characteristics, and a narrative synthesis approach was applied. The main characteristics of the included studies were organized and presented in summary tables, highlighting the most relevant information to meet the objective of the review.

### *Ethical considerations*

This scoping review was conducted taking into account the ethical aspects related to authorship of the articles researched and selected, with all authors properly cited. As this research was conducted exclusively with scientific texts, approval from an Ethics Research Committee was not required.

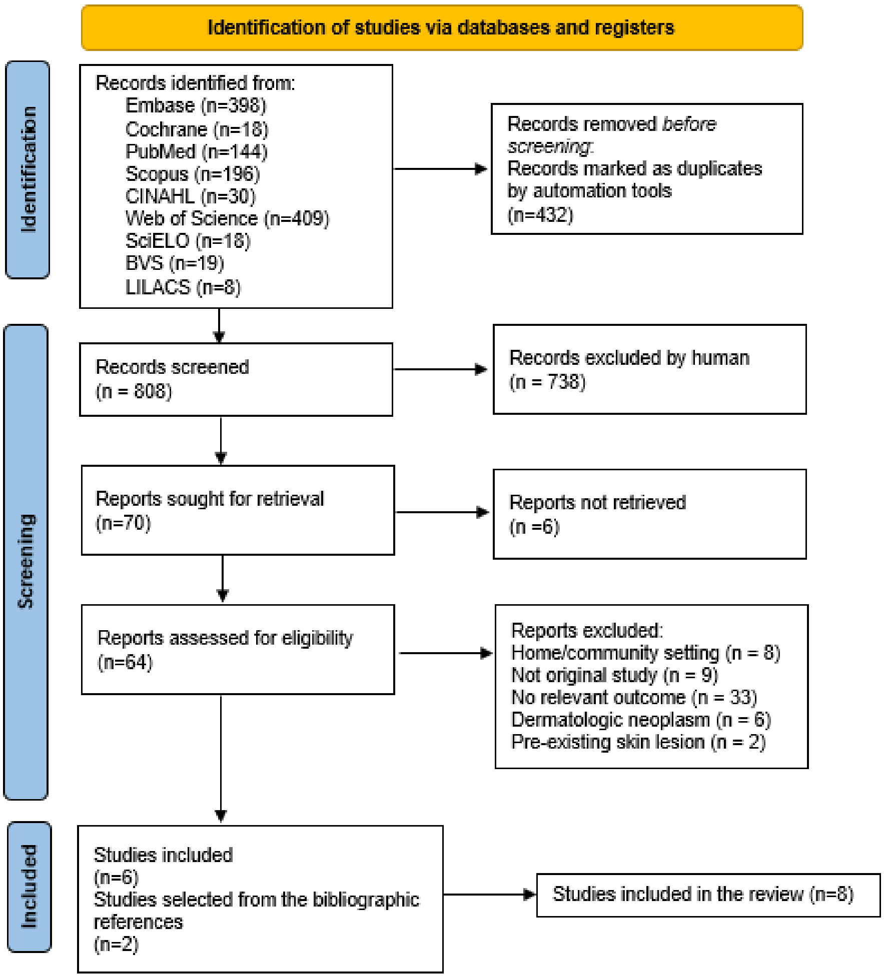


**Figure 1.** PRISMA-ScR flowchart showing the study selection and inclusion process in the scoping review

## Results

Through the strategies proposed, the search resulted in identifying 1,240 studies, which yielded six studies after applying the eligibility criteria. After a detailed analysis of the bibliographic references of the studies included, two additional studies were added to the sample, totaling eight materials in this review. Figure 1 presents the PRISMA-ScR flowchart, detailing the selection and screening process for the studies included in the review.

As shown in Table 2, the studies included were published in 2017 (n=1), 2018 (n=1), 2020 (n=1), 2021 (n=1), 2022 (n=2), 2023 (n=1) and 2024 (n=1) in various countries such as the United States (n=1), Spain (n=1), China (n=3), India (n=1) and Taiwan (n=2). All articles were published in English. Technological development studies (n=6), cohort studies (n=1), and cross-sectional studies (n=1) were identified, with the following objectives: measuring and segmenting pressure injuries (n=2), classifying (n=2), evaluating (n=1), preventing (n=2), and predicting outcomes (n=1).

**Table 2.** Characterization of the selected studies regarding identification, author, year, journal, study location/setting, objective, and type of publication

| Title | Authors | Year | Journal | Study locus/ Setting | Study objective | Study type |
|---|---|---|---|---|---|---|
| Automated measurement of pressure injury through image processing (25) | Dan Li and Carol Mathews | 2017 | Journal of Clinical Nursing | United States Western Pennsylvania Hospital | To develop an image processing algorithm for the automatic measurement of pressure injuries using images stored in Nursing records. | Cross-sectional algorithm development |
| Tissue classification and segmentation of pressure injuries using convolutional neural networks (26) | Sofia Zahia, Daniel Sierra-Sosa, Begonya Garcia-Zapirain, and Adel Elmaghraby | 2018 | Computer Methods and Programs in Biomedicine | Spain Hospital Igurko | To present a new approach for the automatic classification of tissues in pressure injuries. | Technological development |
| A model for predicting 7-day pressure injury outcomes in paediatric patients: A machine learning approach (27) | Xiao Chun, Liyan Pan, Yan Lin, Liyan Ye, Huiying Liang, Jianping Tao, and Yi Luo | 2020 | Journal of Advanced Nursing | China Tertiary specialized hospital in Guangdong Province | To identify predictors associated with pressure injury progression and establish a model to predict 7-day outcomes in pediatric patients with pressure injuries. | Retrospective cohort |
| Infrared Thermal Images Classification for Pressure Injury Prevention Incorporating the Convolutional Neural Networks (28) | Y Wang, Xiaoqiong Jiang, Kangyuan Yu, Fuqian Shi, Hui Zhou, and Fuman Cai | 2021 | IEEE Access | China Wenzhou Medical University | To integrate infrared thermal images and Convolutional Neural Networks (CNNs) to identify and prevent hospital-acquired pressure injuries. | Technological development |
| Deep learning approach based on superpixel segmentation-assisted labeling for automatic pressure ulcer diagnosis (29) | Che Wei Chang, Mesakh Christian, Dun Hao Chang, Feipei Lai, Tom J. Liu, Yo Shen Chen, and Wei Jen Chen | 2022 | PLOS ONE | Taiwan Far Eastern Memorial Hospital | To propose a region-assisted superpixel-based method for image labeling to classify tissues. | Technological development |
| A Deep Learning Approach for Automated Detection and Segmentation of Pressure Ulcers Using Infrared-Based Thermal Imaging (30) | Bhaskar Pandey, Deepak Joshi e Ajat Shatru Arora, Nekram Upadhyay, and H. S. Chhabra | 2022 | IEEE Sensors Journal | India Indian Spinal Injuries Center | To develop a tool for the automated segmentation of pressure injuries using thermal imaging and deep learning. | Technological development |
| The Application of Hyperspectral Imaging to the Measurement of Pressure Injury Area (31) | Lin-Lin Lee and Shu-Ling Chen | 2023 | International Journal of Environmental Research and Public Health | Taiwan Rehabilitation Ward of a Teaching Hospital | To analyze the use of Hyperspectral Imaging (HSI) and Machine Learning for evaluating pressure injuries and to compare HSI accuracy with injury measurements (length × width) obtained by Nursing teams. | Cross-sectional and prospective |
| A Predictive Model of Pressure Injury in Children Undergoing Living Donor Liver Transplantation Based on Machine Learning Algorithm (32) | Xiaomei Chen, Shi Tang, Yanwen Qin, Sui Zhou, Lina Zhang, Yile Huang, and Zheying Chen | 2024 | Journal of Advanced Nursing | China Renji Hospital, School of Medicine, Shanghai Jiaotong University | To formulate and validate a predictive model using Machine Learning algorithms to predict the pressure injury risk in children subjected to living donor liver transplantation. | Retrospective and predictive |

Table 3 presents the studied population, age, type of injury, and outcomes obtained. It is important to highlight that all the articles analyzed addressed pressure injuries, focusing on this type of lesion in different parts of the human body.

In addition, presents a compelling overview of recent advances in AI and imaging for pressure injury assessment and prediction. The studies highlight automated wound measurement, precise tissue classification, and predictive modeling across pediatric and adult populations. Non-invasive, contactless methods improve accuracy, reduce nurses' workload, and support timely, personalized interventions. While the results are promising, several studies emphasize the need for larger datasets and broader validation to ensure these tools can be reliably integrated into everyday clinical practice. The studies analyzed demonstrate that artificial intelligence has been employed across a range of clinical applications for pressure injuries, including automated wound measurement, tissue classification, prediction of injury progression, and early detection (Chart 4).

Machine learning techniques – such as Support Vector Machines (SVM), Random Forests, Extreme Gradient Boosting, Decision Trees, and K-Means clustering – were used to classify pressure injuries, measure wound dimensions, and forecast clinical outcomes. These models consistently achieved high levels of accuracy, sensitivity, specificity, and concordance with expert clinical evaluations.

**Table 3.** Distribution of the articles selected according to the studied population, age, type of injury, and outcomes.

| Study | Study sample | Age | Type of injury | Outcome |
|---|---|---|---|---|
| 25 | 239 images | - | Pressure injury | An automated image-processing system accurately measured pressure injury dimensions, reducing nurses' workload and potential infection risk by avoiding direct wound contact. |
| 26 | 22 images | - | Pressure injury | Convolutional neural networks accurately classified tissue types, highlighting the need for larger datasets to improve model accuracy and clinical reliability. |
| 27 | 152 patients | Between >28 days and <18 years | Pressure injury | Predictive model accurately forecasted 7-day outcomes in pediatric pressure injury patients, suggesting that combining clinical indicators enhances early prediction and care quality. |
| 28 | 349 participants | - | Pressure injury | Infrared thermal imaging with convolutional neural networks enabled early detection of pressure injuries, identifying high-risk areas before visible skin damage occurred. |
| 29 | 5,729 images | - | Pressure injury | Deep learning model integrating superpixel segmentation and labeling enabled automatic pressure injury diagnosis, effectively segmenting wounds, classifying tissues, and supporting clinical decision-making |
| 30 | 10 participants | Between: 19–47 years | Pressure injury | Deep learning approach using thermal imaging enabled fully contactless, non-invasive pressure injury detection, accurately assessing wound size and depth with high precision and cost-efficiency. |
| 31 | 30 participants | Mean: 71.7 ± 15.97 years | Pressure injury | Hyperspectral imaging provided a rapid, consistent, and highly accurate assessment of pressure injury areas, outperforming traditional evaluation methods through a non-invasive process. |
| 32 | 438 children | < 1 year: 270 participants<br>1–3 years: 91 participants<br>> 3 years: 77 participants | Pressure injury | Machine learning model predicted pressure injury risk in pediatric liver transplant recipients, supporting nurses in tailoring preventive interventions and improving postoperative care. |

In parallel, deep learning architectures demonstrated notable advantages in image-based applications. Convolutional Neural Networks (CNNs) and advanced segmentation models– including U-Net, DeeplabV3, Pyramid Scene Parsing Network (PsPNet), Feature Pyramid Network (FPN), and Mask R-CNN – proved especially effective in tasks such as automatic tissue recognition, wound border detection, and re-epithelialization monitoring. These systems frequently achieved optimal performance metrics, particularly in accuracy and recall. Additionally, the studies provided methodological descriptions of the algorithms implemented, enabling a deeper understanding of their operational mechanisms and clinical relevance. Collectively, the evidence summarized in Table 3 underscores the increasing feasibility of integrating AI tools into clinical workflows to support rapid, non-invasive, and reliable assessment of pressure injuries, while enhancing predictive capacity and decision-making in patient care.

**Table 3.** Distribution of selected articles according to AI and its application, metrics, and explanation of the algorithm

| Study | AI/Application | Metrics | Algorithm explanation |
|---|---|---|---|
| **25** | Machine Learning<br>Support Vector Machine<br>Segmentation of pressure injuries. | Intra-rater reliability = 0.89<br>Inter-rater reliability = 0.89 /0.84/0.86 | Support Vector Machine – A supervised machine learning algorithm that identifies the optimal hyperplane to separate data into distinct classes. |
| **26** | Deep Learning:<br>Convolutional Neural Network (CNN)<br>Automatic classification of tissues in pressure injuries. | Dice Similarity Coefficient = 91.38%<br>Accuracy = 92.01% | Convolutional Neural Network – Deep learning architecture specialized in image analysis, capable of automatically extracting and learning spatial and visual features from input data. |
| **27** | Machine Learning<br>Random forests<br>Extreme gradient boosting<br>Predicting 7-day progression of pressure injuries. | 21 variables:<br>Accuracy = 0.80/0.77<br>Sensitivity = 0.78/0.82<br>Specificity = 0.83/0.71<br>AUC = 0.89/0.82<br>19 variables:<br>Accuracy = 0.82/0.77<br>Sensitivity = 0.78/0.82<br>Specificity = 0.85/0.71<br>AUC = 0.90/0.82<br>10 variables:<br>Accuracy = 0.82/0.66<br>Sensitivity = 0.80/0.75<br>Specificity = 0.84/0.57<br>AUC = 0.89/0.73 | Random Forests – An Ensemble learning method that constructs multiple decision trees and integrates their outputs to enhance predictive accuracy and robustness.<br><br>Extreme Gradient Boosting – Optimized gradient boosting technique that builds sequential decision trees, iteratively minimizing errors to improve overall model performance. |
| **28** | Deep Learning:<br>Convolutional Neural Network<br>Monitoring through skin image classification and early identification of pressure injuries. | Specificity = 93.58%<br>Sensitivity = 96.67%<br>Accuracy = 95.2%<br>AUC = 0.98 | Convolutional Neural Network – A deep learning architecture optimized for image analysis, capable of autonomously extracting spatial and visual features from input data. |
| **29** | Deep Learning:<br>Convolutional Networks for Biomedical Image Segmentation (U-Net)<br>Atrous Spatial Pyramid Pooling for Semantic Image Segmentation (DeeplabV3)<br>Pyramid Scene Parsing Network (PsPNet)<br>Feature Pyramid Network for Object Detection (FPN)<br>Mask Region-based Convolutional Neural Network (Mask R-CNN)<br>Automating pressure injury diagnosis through tissue classification and injury segmentation. | Wound segmentation and re-epithelialization detection task<br>Precision/Recall/Accuracy:<br>U-Net (0.9868/0.9867/0.9911)<br>DeepLabV3 (0.9888/0.9887/0.9925)<br>PsPNet (0.9317/0.9494/0.9780)<br>FPN (0.8556/0.9492/0.9346)<br>Mask R-CNN (0.8345/0.8542/0.8533)<br><br>Tissue classification inside ulcerations<br><br>Precision/Recall/Accuracy:<br>U-Net (0.9913/0.9897/0.9899)<br>DeepLabV3 (0.9915/0.9915/0.9957)<br>PsPnet (0.9614/0.9897/0.9899)<br>FPN (0.8615/0.9507/0.9508)<br>Mask R-CNN (0.9191/0.7871/0.8903) | Convolutional Networks for Biomedical Image Segmentation – A deep convolutional architecture developed for accurate pixel-level segmentation in biomedical images, particularly effective in medical imaging tasks.<br><br>Atrous Spatial Pyramid Pooling for Semantic Image Segmentation (DeepLabV3)– A deep learning model that captures multi-scale contextual information through dilated convolutions, enabling precise semantic segmentation.<br>Pyramid Scene Parsing Network (PsPNet) – A CNN-based architecture that leverages pyramid pooling to integrate both global and local contextual information for improved scene understanding.<br>Feature Pyramid Network (FPN) – A deep neural architecture that enhances object detection performance by merging feature maps at different spatial resolutions.<br>Mask Region-Based Convolutional Neural Network (Mask R-CNN) – An advanced CNN framework that performs simultaneous object detection and instance segmentation, generating both bounding boxes and pixel-wise masks. |
| **30** | Deep Learning<br>Automating detection and segmentation of pressure injuries. | Confidence = 96–100%<br>Learning rate stabilized at ~0.8<br>Mean Average Precision = 0.7593<br>Average Recall (AR@100) = 0.475–0.5 | Deep Learning – A subset of machine learning that autonomously learns hierarchical and complex patterns from large datasets through multilayered neural networks. |
| **31** | Machine Learning<br>K-Means algorithm<br>Evaluation of pressure injuries and automated classification of injury areas and injury assessment. | 1. Staff Length×Width vs. Machine Learning Length×Width<br>2. Staff Length×Width vs. Machine Learning Combined with Morphology<br>3. Machine Learning Length×Width vs. Machine Learning Combined with Morphology<br>Statistical parameters: | K-Means Algorithm – An unsupervised clustering technique that partitions data into distinct groups by minimizing the variance within each cluster based on feature similarity. |

| Study | AI/Application | Metrics | Algorithm explanation |
|---|---|---|---|
| | | Pearson r = 0.80/0.44/0.69<br>Spearman ρ = 0.82/0.44/0.70<br>Intraclass correlation coefficient = 0.81/0.54/0.81<br>Unweighted κ = 0.03/0.01/0.01<br>Weighted κ = 0.76/0.42/0.71 | |
| **32** | Machine Learning<br>Decision trees<br>Random forests<br>Gradient boosting decision tree<br>Extreme gradient boosting<br>Predicting pressure injuries. | Precision/Sensitivity/Specificity/ AUC:<br>Decision Tree (0.876/0.724/0.892/0.893)<br>Random Forest (0.696/0.897/0.675/0.852)<br>Gradient Boosting Decision Tree (0.938/0.759/0.957/0.892)<br>Extreme gradient boosting (0.526/0.828/0.495/0.699) | Decision Trees – A supervised learning method that iteratively splits data into branches using feature values, forming a tree-like model for classification or regression.<br><br>Random Forests – An ensemble learning approach that builds multiple decision trees and combines their outputs to increase predictive accuracy.<br><br>Gradient Boosting Decision Tree (GBDT) – An ensemble learning method that sequentially constructs decision trees, with each tree correcting the errors of its predecessors to progressively reduce prediction error.<br><br>Extreme Gradient Boosting (XGBoost) – An optimized implementation of gradient boosting that builds sequential decision trees with advanced regularization and computational efficiency to improve model performance and reduce overfitting. |

## Discussion

This scoping review revealed diverse AI applications aimed at supporting prevention, assessment, monitoring, and treatment planning for skin injuries within hospital environments. However, the evidence was consistently centered on pressure injuries, a pattern that likely stems from their high prevalence and significant clinical consequences. This concentration also highlights the need for broader exploration of AI solutions across other skin injury categories.

Among the AI models identified, CNNs were the most frequently employed (26,28). These architectures have advanced medical image analysis by enabling the interpretation of complex visual information (33), improving accuracy, speed, and accessibility (34). Through convolutional operations, CNNs detect patterns and anomalies across millions of pixels, surpassing human perceptual abilities (33). Their ability to match or surpass expert performance, streamline clinical workflows, and extend diagnostic capacity to resource-limited settings underscores their relevance for advancing pressure injury assessment (33).

Beyond CNNs, several advanced architectures such as U Net, Mask R CNN, DeepLabV3, PSPNet, and FPN were also identified as supporting automated tissue classification and wound segmentation. U-Net demonstrated strong segmentation performance even when trained on limited datasets (35), while Mask R-CNN enabled precise instance-level segmentation (36). DeepLabV3 further enhanced multi-scale feature extraction through atrous convolutions (37-38), and both PSPNet and FPN contributed to strengthened contextual and multi-resolution analysis(39-41). PSPNet integrates ResNet with Spatial Pyramid Pooling to capture features across multiple scales, and FPN refines visual representations by extracting multi-scale information from single-scale images (39-41). In combination, these architectures were applied in one included study to automate segmentation tasks and tissue characterization, with the shared goal of streamlining the analysis process and improving the precision of injury mapping (29). By optimizing clinical workflows, these advanced models provide meaningful support for clinical decision-making in pressure injury assessment.

Classical Machine Learning methods also played an important role in the studies. K-means clustering improved consistency in wound area calculations by minimizing human error during hyperspectral image analysis (31, 42). In parallel, tree-based algorithms such as decision trees, random forests, gradient boosting, and extreme gradient boosting demonstrated strong predictive capacity through rule-based or ensemble learning (27, 32). These models provided interpretable outputs and reinforced the feasibility of integrating traditional ML approaches into pressure injury evaluation workflows (43-46).

Support Vector Machines (SVMs) were also employed to automate pressure injury monitoring, reducing manual workload and limiting direct wound contact (47). Additionally, deep learning methods demonstrated strong potential for fully automated detection, diagnosis, and segmentation, strengthening their relevance for clinical image analysis (48). Collectively, these techniques illustrate the breadth of AI strategies available for enhancing accuracy and efficiency in pressure injury care.

Overall, the findings confirm that AI applications, ranging from classical Machine Learning to advanced deep learning models, provide promising support for preventing, detecting, and monitoring pressure injuries. Yet, these advances remain narrowly focused on a single injury type. The absence of studies addressing medical device–related injuries, incontinence-associated dermatitis, or skin tears underscores the need for expanding research efforts to capture the full spectrum of skin integrity challenges in hospitalized populations.

### *Implications for practice and research*

The findings indicate that the application of AI in healthcare is still at an early stage of integration. While AI holds potential to enhance diagnostic accuracy and optimize workflows, structural and organizational challenges, such as limited infrastructure, insufficient data interoperability, and the need for specialized training, may impede its implementation in complex hospital environments (49).

These limitations have strengthened the call for more robust evaluation strategies capable of ensuring that AI tools are not only innovative but also safe, reliable, and contextually appropriate for clinical use. Recent evidence underscores the need for rigorous assessment frameworks. In a recent study, an AI-based fall-risk prediction model outperformed traditional assessment tools by integrating large volumes of patient data and identifying complex patterns associated with inpatient falls. However, despite its superior predictive performance, successful implementation requires robust validation procedures and continuous monitoring to ensure reliability, clinical usability, and the safe incorporation of AI into nursing practice (50).

Regulatory and validation processes are essential for safe and effective adoption. Experiences with AI tools in other healthcare contexts show that rigorous validation protocols and continuous performance monitoring are crucial to ensure reliability and clinical trust (50). In the context of skin lesions, high-quality, diverse datasets are needed to support algorithmic precision and generalizability.

Ethical and governance considerations also remain central. Issues such as data privacy, algorithmic bias, and accountability require transparent management (51). In skin integrity care, where patient images are highly sensitive, safeguarding confidentiality and fairness is critical. Enhancing digital literacy and ethical awareness among nursing professionals will be essential to ensure responsible, equitable, and safe AI use.

Specific gaps were observed in pediatric populations, preventive applications, and less common skin injuries (27,32,33,37). AI-driven tools have the potential to support early detection, prevention, and clinical decision-making, particularly in populations vulnerable to skin injuries. Prolonged hospitalizations, use of therapeutic devices, sedation, and restricted mobility can further increase susceptibility to skin complications in children (52). Future research should focus on predictive modeling across lesion types, validation in multicenter and international studies, and the integration of AI into real-world workflows (53).

Despite technological advances, human judgment remains indispensable. Nurses' critical thinking, ethical discernment, and individualized care cannot be replicated by machines. AI should be viewed as an ally, supporting decision-making and reducing workload, but human oversight and compassion remain essential, particularly in complex or ethically sensitive situations (54).

By addressing these gaps and challenges, AI applications have the potential to enhance preventive care, improve patient safety, streamline workflows, and ultimately support high-quality, evidence-based nursing practice.

### *Limitations*

A key limitation of this review is that, although multiple AI models were identified, only a small proportion have been applied or evaluated in real-world clinical environments, which restricts the assessment of their practical effectiveness. Furthermore, most studies were conducted using small or homogeneous datasets, limiting the generalizability of their findings. Robust validation in clinical settings requires the inclusion of large and diverse patient samples, a condition that remains challenging to achieve in routine healthcare contexts. These constraints underscore the persistent gap between AI development and clinical implementation, emphasizing the need for future research focused on usability, clinical outcomes, and performance in real-world scenarios.

Additionally, this review did not include studies involving chatbot-based tools for patient communication, which may have constrained the exploration of AI's role in direct patient engagement. This exclusion was intentional and aligned with the scope and objectives of the study. Nonetheless, we recommend that future research address this emerging area to capture its potential contribution to patient-centered care.

## Conclusion

AI use in the healthcare field is rapidly expanding. Mapping the evidence regarding the various AI applications in the management of pressure injuries in hospitalized patients has broadened knowledge and demonstrated the transformative potential of this technology for clinical practice. The studies included revealed that pressure injuries have been the subject of various AI applications; however, robust evidence is still lacking for other common types of skin injuries common in hospital settings, such as medical device-related injuries, skin tears, and IADs, indicating a field that requires further exploration through targeted research studies and solutions.

There is potential for enhancing existing AI techniques, and we suggest future research focused on the prevention, diagnosis, monitoring, and management of the aforementioned clinical conditions. Developing AI models tailored to these injuries might contribute to a more effective and personalized approach to skin care, extending the benefits of this technology in the healthcare field.

## Conflict of interest

We declare that there is no conflict of interest of any kind on the part of the authors involved in the preparation of this manuscript.

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