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Machine learning predictive models for intraoperatively acquired pressure ulcers: a scoping review protocol

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ABSTRACT

Introduction: Intraoperatively acquired pressure ulcers (IAPUs) are a frequent, costly and largely preventable complication of surgery. Traditional tools such as the Braden Scale ignore intraoperative risk factors, and surgical-specific scales capture only a small part of the data routinely recorded during surgery. Machine learning (ML) models can integrate these data, but the evidence on ML models developed specifically for IAPUs has not yet been mapped.
Objectives: To map and analyze the literature on ML predictive models for IAPUs in adult surgical patients: algorithms, input variables, outcome definitions, validation strategies, performance and calibration metrics, explainability methods, comparisons with traditional scales and barriers to clinical implementation.
Methodology: Scoping review following the Joanna Briggs Institute methodology and the Population–Concept–Context framework, reported according to PRISMA-ScR. PubMed, CINAHL Complete, Scopus, Web of Science, the Cochrane Library, IEEE Xplore and grey literature will be searched for sources published between 2000 and 2026 in English, French, Italian, Portuguese or Spanish. Two reviewers will independently screen and select sources, with a third reviewer resolving disagreements. The protocol is registered on the Open Science Framework [blinded for peer review].
Results: Data will be extracted by two independent reviewers with a piloted charting tool and presented in tables, charts and an evidence map of predictors, accompanied by a narrative synthesis.
Conclusion: This review will map the landscape of ML-based IAPU prediction, identify gaps in the literature and inform the development of an explainable, clinically deployable risk index for the operating room.

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RESUMO

Introdução: As úlceras por pressão adquiridas no intraoperatório (UPAI) são uma complicação cirúrgica frequente e evitável, com custos elevados para os sistemas de saúde. As ferramentas tradicionais de avaliação de risco de úlceras por pressão, como a Escala de Braden, ignoram os fatores de risco intraoperatórios, e as escalas adaptadas à população cirúrgica captam apenas parte dos dados registados durante a cirurgia. Os modelos de aprendizagem automática (AA) permitem integrar estes dados, mas a evidência sobre modelos de AA específicos para UPAI ainda não foi mapeada.
Objetivos: Mapear e analisar a literatura sobre modelos preditivos de AA para UPAI em doentes cirúrgicos adultos: algoritmos, variáveis de entrada, definições de resultado, estratégias de validação, métricas de desempenho e calibração, métodos de explicabilidade, comparações com escalas tradicionais e barreiras à implementação clínica.
Metodologia: Scoping review segundo a metodologia do Joanna Briggs Institute e o quadro População–Conceito–Contexto, reportada de acordo com a PRISMA-ScR. Serão pesquisadas as bases PubMed, CINAHL Complete, Scopus, Web of Science, Cochrane Library, IEEE Xplore e literatura cinzenta, para fontes publicadas entre 2000 e 2026 em inglês, francês, italiano, português ou espanhol. Dois revisores selecionarão as fontes de forma independente e um terceiro resolverá os desacordos. O protocolo está registado na Open Science Framework [ocultado para revisão cega].
Resultados: Os dados serão extraídos por dois revisores independentes com um instrumento previamente testado e apresentados em tabelas, gráficos e num mapa de evidência dos preditores, acompanhados de síntese narrativa.
Conclusões: Esta revisão mapeará o panorama da predição de UPAI baseada em AA, identificará lacunas na literatura e informará o desenvolvimento de um índice de risco explicável e clinicamente aplicável para o bloco operatório.

Introduction

Despite technological advances in healthcare, pressure ulcers (PU) remain one of the most frequent and preventable adverse events among hospitalized patients and a major patient safety concern.[1-3] A PU is localized damage to the skin and/or underlying tissue, usually over a bony prominence or related to a medical device, caused by pressure or by pressure combined with shear.[1] In hospitalized adults, the pooled prevalence is 12.8% and 8.4% of patients develop a PU during admission,[2] with pain, infection, longer hospital stays and higher costs as consequences.[3]

Intraoperatively acquired pressure ulcers (IAPU) are hospital-acquired PU caused by conditions specific to the operating room (OR). Under anesthesia, patients cannot move or perceive discomfort, surgical positioning concentrates pressure on a few bony prominences for hours, and hypotension, vasopressors, hypothermia and blood loss reduce tissue perfusion.[4,5] Lesions usually appear in the first postoperative days, although deep tissue injuries may become visible later.[1,4] Reported incidence ranges from 0.3% to 57.4%, with pooled or mean estimates of 15% to 17%,[6,7] and risk depends on the interaction of patient characteristics, surgical duration and positioning, and device-related pressure.[4,5,8-10]

Current risk assessment tools struggle to capture this multifactorial risk. The Braden Scale was designed for general inpatients and has limited predictive validity in surgical patients.[11,12] OR-specific instruments such as the Munro and 3S scales and the Risk Assessment Scale for the Development of Injuries due to Surgical Positioning (ELPO) (validated for Portuguese population) perform better,[12-15] but are performed manually and poorly integrated into electronic medical records (EMR).[13,14] The 2026 International Guideline now recognizes artificial intelligence (AI) and machine learning (ML) based risk assessment as a possible complement to clinical judgment.[1]

Perioperative EMR and anesthesia information systems already record the variables that drive IAPU risk, such as procedure times, positioning, hemodynamic trends and comorbidities. ML algorithms can integrate these data, reaching a pooled area under the curve (AUC) of 0.94 in hospitalized and critically ill patients,[16] and explainability methods such as SHapley Additive exPlanations (SHAP) can make their predictions interpretable.[17] In surgical patients, published models range from logistic regression risk scores[18] and comparisons of ML algorithms[19] to prospective nomograms[20] and externally validated ensemble models.[21]

This evidence has not yet been mapped for the OR. Syntheses of ML-based PU prediction have pooled hospital-wide cohorts dominated by intensive care and general wards[16,22,23] or focused on the intensive care unit,[24] and an umbrella review concluded that most available tools derive from retrospective, internally validated models and do not meet current standards for development and reporting.[25] Across the hospital-wide and ICU reviews, logistic regression and random forest were the most frequently used algorithms,[23] most models were at high risk of bias (16 of 18 studies in one meta-analysis)[16] and

showed deficiencies in data pre-processing and validation,[22] and, in intensive care, only 2 of 14 studies reported the clinical deployment of a model.[24] The only OR-specific review appraised three IAPU prediction models from 25 studies and found all at high risk of bias, with calibration rarely reported and 88% of the evidence coming from single centers.[26] That review asked whether the available models are methodologically sound; this review asks what the field contains and how it has been built, and complements that appraisal rather than repeating it. It remains unclear which ML approaches have been applied to IAPU, which data they rely on, how they have been validated and what limits their use in practice. The TRIPOD+AI statement provides a benchmark for judging the completeness of this reporting.[27] Because the aim is to map the extent, range and nature of the evidence, rather than to answer a specific effectiveness question, a scoping review is the appropriate design.[28,29]

A preliminary search of PROSPERO, the Open Science Framework, JBI Evidence Synthesis and the Cochrane Database of Systematic Reviews, conducted in June 2026 and to be repeated before submission of the final review, identified that systematic review[26] but no published or ongoing scoping review of ML predictive models for IAPU. This review is the first phase of a doctoral project aimed at developing and prospectively validating an explainable ML-based risk index for IAPU in the OR, and its results will inform the selection of candidate predictors, outcome definitions and validation strategies.

The objective of this scoping review is to map the evidence on ML predictive models for IAPU in adult patients undergoing surgery in the OR, namely the techniques applied, the input variables and data sources, the outcome definitions, the validation approaches and performance metrics, the explainability methods, the comparisons with traditional risk scales, and the barriers and facilitators to clinical implementation, complementing the existing critical appraisal of these models rather than repeating it.

Methodology

Scoping reviews are a form of evidence synthesis that systematically maps the available literature on a topic, clarifying key concepts and identifying gaps.[30] This scoping review will be conducted in accordance with the JBI methodology for scoping reviews[29,31] and this protocol was developed following the JBI guidance and reporting items for scoping review protocols.[32] The final review will be reported following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR)[33] and, for the search, the PRISMA-S extension.[34] The protocol was registered on the Open Science Framework on 14 June 2026 [DOI blinded for peer review]. Two refinements were introduced after registration and before screening began, and we report them here for transparency. The upper limit of the publication window was extended from 2025 to 2026, so that the search would be current when executed, and Italian was added to the eligible languages after confirming the language competencies of the review team. The context block of the search strategy was also expanded after pilot searching, as explained below. Any further deviation will be documented and justified in the final review, in line with the methodological challenges identified for this review type.[35]

Review question

Using the Population, Concept, Context (PCC) framework recommended by JBI,[31] the primary review question is: *what is the extent, range and nature of the evidence on machine learning predictive models (Concept) for intraoperatively acquired pressure ulcers in adult surgical patients (Population) in operating room and perioperative settings (Context)?*

The following sub-questions will guide data extraction and synthesis:

- *Which ML techniques (e.g., regression-based models, tree-based ensembles, support vector machines, neural networks and deep learning, hybrid or stacked approaches) have been used to predict IAPUs, and in which surgical populations and specialties?*
- *Which preoperative and intraoperative variables have been used as predictors, from which data sources (e.g., EMR, anesthesia records, monitoring devices, pressure mapping, nursing assessments), and how were temporal or time-series data handled?*
- *How is the IAPU outcome defined, staged and ascertained (timing of skin assessment, attribution to the surgical episode, staging system), and which event rates are reported?*
- *Which development and validation strategies are used (data splitting, cross-validation, internal, temporal or external validation, handling of class imbalance and missing data), and which discrimination, calibration and clinical utility metrics are reported?*
- *Which explainability or interpretability methods are applied, and have the models been compared with traditional risk assessment scales such as the Braden, Munro, 3S or ELPO scales?*
- *Which barriers, facilitators, implementation experiences and research gaps are reported regarding the translation of these models into clinical practice?*

Inclusion criteria

Participants

This review will consider studies involving adult patients (18 years or older) undergoing any surgical or interventional procedure in an OR, including hybrid ORs, under any type of anesthesia and in any surgical specialty. Procedures performed outside the OR, in other procedural settings such as endoscopy suites, interventional radiology rooms and cardiac catheterization laboratories, will be excluded, because positioning practices, procedure duration, staffing and postprocedural skin assessment differ from those of the OR. Studies conducted exclusively in pediatric or neonatal populations will be excluded, given

the distinct physiological characteristics, risk profiles, positioning practices and prevention strategies that limit comparability with adult surgical populations. Studies with mixed adult and pediatric samples will be included if adult data are reported separately or if at least 80% of the participants are adults, a threshold set a priori to keep the criterion reproducible.

Concept

The core concept is the development, validation, comparison or implementation of predictive models for IAPUs based on machine learning. For the purposes of this review, ML is defined broadly as any computational approach in which a model is learned from data to predict an outcome. This covers supervised learning (e.g., logistic and penalized regression developed and evaluated within a predictive modeling framework, decision trees, random forests, gradient boosting, support vector machines, naive Bayes, k-nearest neighbors, artificial neural networks and deep learning), unsupervised or semi-supervised approaches when used within a pipeline that predicts IAPU occurrence, and ensemble or hybrid methods. We deliberately include regression-based models: they are the most common baseline against which ML algorithms are compared, they are usually reported side-by-side with them and excluding them would leave the map incomplete. The algorithm family will be extracted so that both can be told apart in the synthesis.

Eligible studies must describe the input variables used by the model and must predict the occurrence (or severity) of a PU attributable to the surgical episode. Both validated models using patient data (retrospective or prospective datasets) and early-phase or prototype models will be considered, since the latter may still offer useful insight into model development, input features or algorithm architecture. Reporting of performance metrics is desirable but not required for inclusion. We will exclude studies whose only ML application is image-based wound detection, classification or healing assessment, models that predict PUs in non-surgical populations (e.g., general wards, intensive care without a surgical exposure, long-term care), and studies that evaluate traditional risk scales without any learned model.

Context

This review will consider studies in which the exposure of interest is the intraoperative period, in any hospital or ambulatory surgical setting, in any country and any healthcare system. The outcome may be ascertained intraoperatively or in the postoperative period, provided that the primary study attributes the injury to the surgical episode; the timing of ascertainment used by each study will be extracted. Studies in which surgical patients form an identifiable subgroup of a broader hospital cohort will be included if results for the surgical subgroup, or predictors specific to the surgical exposure, are reported.

Types of sources

This scoping review will consider primary studies of any design: retrospective and prospective cohort studies, case-control and cross-sectional studies, model development, validation and updating studies, randomized and non-randomized studies evaluating ML-guided prevention, implementation or quality improvement studies, and qualitative or mixed-methods studies reporting on the development, implementation or evaluation of an ML model for IAPUs, these being the designs most likely to document barriers and facilitators. Systematic reviews, scoping reviews and meta-analyses on ML prediction of PUs will be retrieved and their reference lists screened for eligible primary studies; reviews that specifically address the surgical population will themselves be extracted. When a primary study is eligible in its own right and is also included in an extracted review, data will be charted from the primary study only, and the review will be charted for its synthesis-level characteristics, so that no study is counted twice. Full papers published in peer-reviewed conference proceedings (e.g., IEEE and ACM), doctoral and master's theses and preprints will be eligible, because much of the relevant technical work first appears in these venues. When a preprint and its peer-reviewed version are both retrieved, they will be treated as a single source, and the published version will be charted. Conference abstracts without full text, opinion papers, editorials, letters and protocols will be excluded, as will sources whose full text cannot be obtained after contacting the authors.

Sources published from January 2000 to the date of the search will be considered. This window covers the period in which ML methods were adopted in clinical prediction research and EMRs became widespread in perioperative care. Sources in English, French, Italian, Portuguese and Spanish will be included, which are the languages in which the review team can assess full texts without translation; sources in other languages will be recorded and listed as excluded for language in the final review.

Search strategy

The search strategy aims to locate both published and unpublished sources and follows the three-step approach recommended by JBI.[31] First, an initial limited search of PubMed and CINAHL was undertaken between January and February 2026 to identify articles on the topic; the words in the titles and abstracts of relevant records, and the index terms used to describe them, were used to develop a full search strategy. The sensitivity of the draft strategy was then tested against a set of known eligible studies,[18-21] and this showed that records indexed only as "surgical" or "surgery-related" pressure injury were missed by a context block restricted to intraoperative and operating room terms. The context block was therefore expanded. Second, the full strategy, structured in three concept blocks combined with AND (pressure ulcer or injury; perioperative or operating room context; artificial intelligence, machine learning or predictive modeling), each combining controlled vocabulary with title and abstract free-text terms, will be adapted for each database. The complete PubMed strategy, which combines MeSH terms with title and abstract free-text terms, truncation and the Boolean operators OR and AND, is presented in Appendix 1. It will be translated to the controlled vocabulary and syntax of each database (e.g., CINAHL

Subject Headings), and the strategies for all other sources will be reported in full in the final review. Third, the reference lists of all included sources will be screened and forward citation searching will be performed to identify additional studies.

The following databases will be searched: PubMed (National Library of Medicine), CINAHL Complete (EBSCOhost), Scopus (Elsevier), Web of Science Core Collection (Clarivate), the Cochrane Library (Cochrane Database of Systematic Reviews and Cochrane Central Register of Controlled Trials), IEEE Xplore and the ACM Digital Library. In IEEE Xplore and the ACM Digital Library, where clinical context is poorly indexed and the yield is small, the strategy will be run with the pressure ulcer and ML blocks only, and the perioperative context will be applied at screening; this database-specific adaptation will be documented. Grey literature and additional sources will include ProQuest Dissertations and Theses Global, the Open Access Theses and Dissertations portal, the Portuguese open access repository RCAAP, the preprint servers medRxiv and arXiv, and the recent proceedings of the European Pressure Ulcer Advisory Panel, the European Wound Management Association, the National Pressure Injury Advisory Panel and the Association of periOperative Registered Nurses. Grey literature sources that do not support complex search syntax, such as RCAAP, will be searched with simplified combinations of the key terms of the three concept blocks.

All searches will be executed within the same calendar week, and the date, platform, exact string, limits and yield of each search will be recorded in a search log, in accordance with PRISMA-S.[34] Publication date (2000 to the search date) and language limits will be applied where the platform allows it and otherwise applied at screening. The searches will be re-run immediately before submission of the final review to capture recently published sources.

Study/source of evidence selection

Following the search, all identified records will be exported in RIS format from each database and imported into Rayyan,[36] a web-based platform for screening in evidence synthesis, which will manage the entire selection process. Duplicates will be identified using Rayyan's built-in detection, confirmed by one reviewer before removal, and the number removed will be reported; Rayyan was chosen for this step because it was among the most accurate platforms in a comparative evaluation of de-duplication performance.[37] Before formal screening starts, the whole team will pilot the eligibility criteria on a random sample of approximately 25 records, and the criteria will be refined and re-piloted if agreement is unsatisfactory, as JBI recommends[31]; agreement below 75% on the pilot sample will trigger refinement and a further pilot. Titles and abstracts will then be screened independently by two reviewers against the inclusion criteria, with Rayyan's blinding function enabled so that reviewers cannot see each other's decisions until screening is complete. Potentially relevant sources will be retrieved in full and assessed in detail against the criteria by the same two reviewers; reasons for excluding full-text sources will be recorded in Rayyan and reported. Disagreements at any stage will be resolved by discussion or, when consensus is not reached, by a third reviewer. The results of the search and the selection process will be reported in full in the final review and presented in a PRISMA 2020 flow diagram,[38] as recommended by PRISMA-ScR.[33]

Data extraction

Data will be extracted from the included sources by two independent reviewers, working in parallel, using a standardized charting tool developed for this review from the JBI template[31] and adapted to the ML prediction model literature (Appendix 2). The extracted data will include, at minimum: study characteristics (author, year, country, publication type, study aim, study design, number of centers, setting and surgical specialty, data source, participant characteristics, sample size and IAPU event rate); outcome definition (staging system, timing and method of skin assessment, attribution window); input data variables (candidate and final predictors, grouped as demographic and anthropometric, comorbidity and laboratory, surgical, anesthetic, positioning and support surfaces or devices, hemodynamic and temperature, and nursing assessment and scale scores, together with the handling of time-series data); ML model details (time point of prediction: preoperative, intraoperative or end of surgery; prediction horizon; algorithm families, feature selection, handling of missing data and class imbalance, hyperparameter tuning, software); validation approach (data splitting, cross-validation, internal, temporal or external validation, size of the validation set); performance metrics (discrimination such as AUC, sensitivity, specificity, predictive values and F1-score; calibration such as calibration plots, slope, intercept or Brier score; decision curve or other clinical utility analyses); explainability methods (e.g., SHAP); comparators, when present, against traditional risk assessment tools or other ML algorithms; implementation challenges (integration into EMR or clinical decision support systems, prospective deployment, barriers and facilitators reported); and the authors' own limitations and recommendations. To make the completeness of reporting visible without turning this into a critical appraisal, the tool will also record, as present or absent, a small set of reporting elements drawn from the TRIPOD+AI statement,[27] such as whether calibration, the handling of missing data, external validation and code or model availability were reported.

The charting tool will be piloted by both reviewers on three to five included sources and refined iteratively; any modification will be detailed in the final review. Disagreements will be resolved through discussion or, if consensus is not reached, by a third reviewer. Authors of primary sources will be contacted when missing or additional data are needed. In line with JBI guidance for scoping reviews, no formal assessment of methodological quality or risk of bias will be performed, since the purpose of the review is to map the evidence rather than to evaluate it.[29]

Data analysis and presentation

The extracted data will be analyzed descriptively and mapped against the review questions, following the JBI recommendations for the extraction, analysis and presentation of results in scoping reviews.[39] A numerical summary will describe the sources by year, country, study design, surgical specialty, data source, sample size and event rate, ML algorithm family, validation type and reported metrics, using frequencies and percentages and, where appropriate, medians and ranges. Since scoping reviews do not pool effect estimates, model performance will not be meta-analyzed. Where a source reports several models or several datasets, the metrics charted will be those of the final or best-performing model as designated by the authors, separately for internal and for external validation, and every algorithm compared will be listed under modelling. Instead, the reported discrimination and calibration metrics will be tabulated by algorithm family and validation type and shown graphically, for example through a timeline of ML applications in IAPU risk assessment and the distribution of AUC values across ML model types. The purpose of these charts is to show patterns and the heterogeneity of reporting, not to rank models.

Predictor variables will be summarized in an evidence map that cross-tabulates variable categories against studies, indicating whether each variable was a candidate or a retained predictor and whether it is available preoperatively or only during surgery. This map is meant to inform the selection of candidate predictors in the next phase of the project. Outcome definitions, explainability methods, comparisons with traditional scales and implementation aspects will be summarized in tables. Barriers, facilitators and limitations reported by the authors will be categorized through basic qualitative content analysis, and the frequency of the TRIPOD+AI reporting elements will be presented to characterize gaps in reporting. A narrative summary will accompany all tabulated and charted results, describe how the findings relate to the review objective and questions, and identify gaps and implications for research and for the development of ML-based risk assessment in the OR. Additional material will be provided as supplementary files.

Limitations

This protocol has some limitations that we acknowledge from the outset. Restricting inclusion to five languages may leave out relevant work, particularly from China, where much of the recent ML literature on pressure ulcers originates; we chose this restriction because the team cannot appraise full texts in other languages reliably, and we will report every record excluded for language. The ML block of the search deliberately includes broad truncated terms (algorithm*, model*) to maximize sensitivity, which means that a large share of the retrieved records will be irrelevant and that screening will be labor-intensive; the pilot screening exercise is intended to keep the criteria consistent under that load. Definitions of the outcome vary across studies, in the timing of skin assessment, in the attribution window and in the staging used, and this will limit how directly models can be compared; we will extract these elements explicitly rather than force a single definition. In IEEE Xplore the perioperative context is applied at screening instead of in the search string, and grey literature coverage is pragmatic, so some technical work may still be missed. Finally, this is a fast-moving field; the searches will be refreshed before submission of the final review, but the map will inevitably represent a snapshot.

Conclusion

This protocol describes a scoping review that will provide the first systematic map of machine learning predictive models for intraoperatively acquired pressure ulcers, complementing the recent critical appraisal of their risk of bias. By mapping the algorithms, the input variables, the outcome definitions, the validation strategies, the performance and calibration metrics, the explainability methods and the implementation experiences reported in this literature, and by making the completeness of reporting visible against current standards, the review will clarify how far ML-based prediction has actually progressed in the OR and where the methodological and translational gaps and weaknesses lie.

The results will inform perioperative nurses, anesthesiologists, surgeons and healthcare data scientists about the current state of the field, and they will directly guide the next phases of the doctoral project in which this review is embedded: the expert-informed selection of candidate predictors, the development of an explainable ML-based risk index from routinely collected perioperative EMR data, and its prospective comparison with the Braden and ELPO-PT scales. More broadly, we expect this review to help design future prediction studies that are better aligned with the reality of intraoperative data and with the reporting and validation standards required for safe clinical use.

Ethical approval

Ethical approval was not required, as this study is a scoping review protocol based on published and publicly available sources.

Registration

This scoping review protocol is registered on the Open Science Framework (registered on 14 June 2026 with doi: 10.17605/OSF.IO/3TNFP).

Data availability

No new data were generated for this protocol. The search log, the charting tool and the dataset extracted from the included sources will be provided as supplementary material with the final review and on the Open Science Framework project page.

Declaration on the use of generative artificial intelligence

During the preparation of this study and manuscript, the author(s) used Claude Opus 5 (Anthropic), in September 2026, to assist with the structuring and language editing of the protocol text, formatting candidate references, and with checking the internal consistency of the citations. All references were verified by the authors against the primary sources. The authors declare that they have reviewed and edited the output and accept full responsibility for the content.

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Appendix 1. Complete PubMed search strategy.

Database: PubMed (National Library of Medicine); interface: PubMed.gov. Search date: 21 September 2026. The AI/ML block was expanded with named-algorithm terms after internal peer review of this protocol and all searches were re-executed with the final strategy; the yields below are those of that run. Filters applied to line #4: publication date 2000/01/01 to 2026/12/31; languages English, French, Italian, Portuguese, Spanish. The same three-block structure is translated for CINAHL Complete, Scopus, Web of Science, the Cochrane Library; in IEEE Xplore and the ACM Digital Library, only the pressure ulcer and ML blocks are used. All strategies will be reported in the final review.

Line	Search string	Records
#1	"Pressure Ulcer"[Mesh] OR "pressure ulcer*"[tiab] OR "pressure injur*"[tiab] OR "pressure sore*"[tiab] OR "decubitus ulcer*"[tiab] OR bedsore*[tiab] OR "bed sore*"[tiab]	22,844
#2	"Perioperative Care"[Mesh] OR "Perioperative Period"[Mesh] OR "Operating Rooms"[Mesh] OR "Intraoperative Complications"[Mesh] OR "Surgical Procedures, Operative"[Mesh] OR "Anesthesia"[Mesh] OR "Patient Positioning"[Mesh] OR intraoperative*[tiab] OR "intra operative"[tiab] OR perioperative*[tiab] OR "peri operative"[tiab] OR postoperative*[tiab] OR "post operative"[tiab] OR surger*[tiab] OR surgical*[tiab] OR operative*[tiab] OR "operating room*"[tiab] OR "operating theatre*"[tiab] OR "operating theater*"[tiab] OR "operating table*"[tiab] OR anesthes*[tiab] OR anaesthes*[tiab] OR "patient positioning"[tiab] OR "surgical positioning"[tiab] OR "prone position*"[tiab] OR "supine position*"[tiab] OR "lateral position*"[tiab] OR lithotomy[tiab]	5,675,235
#3	"Artificial Intelligence"[Mesh] OR "Data Mining"[Mesh] OR "artificial intelligence"[tiab] OR "machine learning"[tiab] OR "deep learning"[tiab] OR "neural network*"[tiab] OR "multilayer perceptron"[tiab] OR "decision tree*"[tiab] OR "random forest*"[tiab] OR "gradient boosting"[tiab] OR xgboost[tiab] OR "support vector*"[tiab] OR "data mining"[tiab] OR "predictive model*"[tiab] OR "prediction model*"[tiab] OR "risk prediction"[tiab] OR "risk score*"[tiab] OR nomogram*[tiab] OR ensemble[tiab] OR boosting[tiab] OR lightgbm[tiab] OR "naive Bayes"[tiab] OR "k-nearest"[tiab] OR "logistic regression"[tiab] OR algorithm*[tiab] OR model*[tiab]	5,895,223
#4	#1 AND #2 AND #3, with date and language filters	742

Appendix 2. Data charting instrument

Items to be charted from each included source. The instrument will be piloted on three to five sources and refined; the final version will be appended to the review.

Domain	Items
Source characteristics	First author; year; country; publication type (journal article, conference paper, thesis, preprint); study aim; study design; number of centers (single-center or multicenter); setting and surgical specialty; data source (EMR, anesthesia record, monitoring device, pressure mapping, nursing records, registry); participant characteristics (age, sex, body mass index, ASA physical status, comorbidity burden); sample size (development/validation); IAPU event rate; funding.
Outcome definition	Term used (IAPU, surgery-related PI, perioperative PI); staging system (NPIAP/EPUAP, other); timing and method of skin assessment; attribution window after surgery; stages included; anatomical sites.
Predictors	Candidate and final variables by category: demographic and anthropometric; comorbidity and laboratory; surgical (procedure, duration, urgency, approach); anesthetic (type, drugs, fluids, blood loss); positioning and support surfaces or devices; hemodynamic and temperature (summary vs time-series); nursing assessment and scale scores (Braden, Munro, ELPO, other); timing of availability (preoperative vs intraoperative).
Modelling	Time point of prediction (preoperative, intraoperative, end of surgery) and prediction horizon; algorithm family or families; feature selection; handling of missing data; handling of class imbalance; hyperparameter tuning; software or libraries.
Validation	Data splitting; cross-validation; internal, temporal or external validation; validation sample size; events per variable.
Performance	Discrimination (AUC/C-statistic, sensitivity, specificity, PPV, NPV, accuracy, F1); calibration (plot, slope, intercept, Brier score, Hosmer–Lemeshow); clinical utility (decision-curve analysis, net benefit); threshold selection. Metrics will be charted for the final (or best-performing) model as reported by the authors, separately for internal and external validation; all algorithms compared will be listed in Modelling.
Explainability and comparison	Explainability or interpretability method (SHAP, LIME, feature importance, nomogram, other); comparison with conventional scales or clinician judgment and its result.
Implementation	Integration into EMR or clinical decision support; prospective deployment; user evaluation; reported barriers and facilitators; ethical, legal or data-governance considerations.
Reporting elements (present/absent)	Selected TRIPOD+AI items: calibration reported; missing-data handling reported; any external validation; model or code availability; sample-size justification; fairness or subgroup analysis.
Authors' conclusions	Stated limitations; recommendations; identified gaps.

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