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REVIEW **Open Access**

Artificial intelligence in emergency surgery: a scoping review within the artificial intelligence in emergency and trauma surgery (ARIES) project

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Abstract

Aim To map and critically appraise the current literature on Artificial Intelligence (AI) applications in emergency general surgery, with a focus on clinical decision-support tools for preoperative risk stratification and intraoperative assistance, and to identify ethical, structural, and regulatory barriers to implementation.

Methods A scoping review was conducted within the ARIES project, following established methodological frameworks. Relevant studies evaluating AI-based tools in emergency surgical settings were systematically identified and analyzed.

Results The literature describes AI applications mainly in two domains: preoperative decision support, including risk prediction and diagnostic or triage models for acute abdominal and traumatic conditions, and intraoperative assistance, largely focused on computer vision–based systems for anatomical recognition, safety guidance, and navigation in minimally invasive emergency procedures. Additional contributions address training and telementoring platforms, as well as cross-cutting ethical, legal, and regulatory considerations relevant to AI adoption in emergency surgical care.

Conclusions AI has the potential to complement emergency surgeons' clinical judgment, but its routine adoption in emergency surgical practice remains limited. Addressing methodological, ethical, and regulatory challenges, together with the development of robust data infrastructures and targeted training pathways, is essential to support safe, effective, and equitable implementation in acute care settings. In addition, the lack of dedicated investment and

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sustainable funding models for large-scale clinical implementation and prospective evaluation represents a critical barrier to the translation of AI from research into routine emergency surgical practice.

Keywords Artificial Intelligence, Decision-Making, Machine Learning, Deep Learning, Digital Surgery, Computer Vision, Robotic surgery, Ethics, Emergency Surgery, Technology, Training, Education, Cognitive Load, Fluorescence Imaging, Accountability, Reliability

Background

Advancements in medicine and surgery have supported the development of technologies aimed at improving clinical decision-making and patient outcomes [1–3]. Within this context, artificial intelligence (AI) has emerged as a promising tool to enhance diagnostic accuracy, support complex decision processes, and optimize surgical workflows [4].

Emergency surgery represents a distinct and particularly demanding clinical environment, characterized by time-critical decisions, high levels of uncertainty, and marked variability in patient presentation and available resources. Surgeons are frequently required to act rapidly with incomplete information in high-risk situations, where outcomes depend largely on clinical judgment, experience, and real-time intraoperative decision-making. These features differentiate emergency surgery from elective practice and limit the applicability of standardized pathways and controlled workflows.

While AI technologies are increasingly adopted in elective surgical settings, their integration into emergency surgery remains less mature [5]. In this setting, AI-based systems have primarily been explored as decision-support tools to assist surgeons in preoperative risk stratification and diagnostic triage, as well as in intraoperative guidance and surgical performance. A wide range of technologies, including machine learning (ML) models, computer vision (CV) algorithms, robotic platforms, fluorescence-guided surgery, virtual reality (VR) simulation, and connected digital systems, have been investigated for their potential to improve safety, training, and data integration in acute surgical environments [6, 7].

In surgical practice, AI-driven systems may enable varying levels of automation and decision support, always requiring appropriate human supervision. Within this framework, the Artificial Intelligence in Emergency and Trauma Surgery (ARIES) project was launched in 2021 to evaluate the engagement of emergency surgeons with AI-driven technologies. Findings from the ARIES initiative highlighted substantial gaps, including limited access to advanced technologies, insufficient training, particularly in robotics, and scarce institutional support for implementation in emergency settings [8, 9].

Despite increasing interest, the role of AI in emergency surgery remains incompletely defined. The existing literature is heterogeneous, spanning technical development, feasibility studies, training applications, and ethical, legal, and regulatory considerations, while real-world clinical implementation remains limited. A structured mapping of current evidence is therefore needed to clarify which AI applications are most relevant to emergency surgical practice and to identify the barriers that hinder translation into routine care.

The aim of this scoping review is to map and critically appraise the available literature on AI applications in emergency surgery, with a specific focus on preoperative decision-support tools, intraoperative assistance, training and education. In addition to describing the breadth of existing evidence, the review adopts an implementation-oriented perspective that reflects the highly complex, time-critical, and ethically sensitive nature of emergency surgical care. Ethical responsibilities, structural and regulatory constraints, and investment-related barriers are therefore examined as integral components influencing real-world adoption. This approach is intended to move beyond a purely descriptive overview of technologies and to provide a clinically meaningful framework to inform future research priorities, training strategies, and policy development in emergency surgery.

Methods

This scoping review was conducted in accordance with the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews) guidelines [10]. The objective of the review was to map and describe current applications of artificial intelligence in emergency surgery. Consistent with methodological guidance for scoping reviews, no formal risk of bias assessment was performed, and no quantitative synthesis or meta-analysis was planned due to the heterogeneity of the available literature.

Eligibility criteria

We included original peer-reviewed articles published in English that investigated or reported on the application of AI technologies to support decision-making or intraoperative guidance in emergency surgical contexts. Studies were included if they: (1)Addressed AI tools used in preoperative, intraoperative, or postoperative phases of emergency surgery; (2) Described AI applications that, while not exclusive to emergency settings, presented potential for adaptation to acute care surgery and (3) Reported clinical, technical, or feasibility outcomes relevant to emergency surgical practice.

We excluded: (1) Editorials, letters, opinion papers, conference abstracts, and non-peer-reviewed content; (2) Studies focusing exclusively on elective surgical settings without any relevance to emergency practice and (3) Articles not involving AI-based methods or tools.

Information sources and search strategy

A comprehensive literature search was performed across MEDLINE (via PubMed), IEEE Xplore, and EMBASE databases, covering all articles published up to March 31, 2024. The search strategy combined MeSH terms and free-text keywords, developed based on an initial exploratory scan of the literature. Boolean operators were applied to refine the search scope.

The following search terms were used in various combinations:

> *"emergency", "surgery", "surgeon", "artificial intelligence", "machine learning", "decision-making", "support", "prediction", "risk stratification", "preoperative", "intraoperative", "monitoring", "complication", "deep learning", "computer vision", "real-time", "navigation", "robotics", "fluorescence", "virtual reality", "training", "peritonitis", "appendicitis", "trauma", "cholecystitis", "acute abdomen".*

Selection of sources of evidence

Two reviewers independently screened titles and abstracts. Articles meeting the inclusion criteria were retrieved in full text and assessed for eligibility. Discrepancies were resolved through discussion or involvement of a third reviewer. Reference lists of included studies were hand-searched for additional relevant articles. The process is shown in figure S1.

Data extraction and charting process

Data were extracted for studies focusing on the implementation of AI-driven tools in the emergency setting using a standardized charting form as in Tables 1 and 2.

Critical appraisal and synthesis

As this is a scoping review, no formal risk of bias or quality assessment of the included studies was performed. Instead, studies were analyzed descriptively to identify trends, domains of application, validation methods, and translational potential in emergency surgery. The findings were organized into 6 thematic domains: (1) preoperative decision support tools; (2) intraoperative computer vision applications; (3) fluorescence-guided surgery; (4) robotic surgery platforms, (5) virtual training technologies, and (6) implementation challenges and legal/ethical issues.

The review emphasizes feasibility, interpretability, and potential clinical impact, rather than comparative effectiveness or outcome synthesis.

Results

Preoperative decision support tools

Preoperative risk prediction in emergency surgery: the POTTER and TOP calculators

Machine learning (ML) has emerged as a valuable approach for improving preoperative risk stratification in emergency surgery by capturing non-linear interactions within complex clinical datasets. Among the most extensively studied AI-based decision-support tools are the Predictive Optimal Trees in Emergency Surgery Risk (POTTER) calculator and the Trauma Outcome Predictor (TOP). Both models are built using Optimal Classification Trees (OCT) and provide real-time, interactive risk predictions through smartphone-accessible platforms, representing mature examples of AI-driven support in acute surgical care [11–15].

The POTTER tool was developed to estimate 30-day mortality and morbidity in patients undergoing emergency surgery. Trained on more than 380,000 cases from the ACS-NSQIP database, it consistently outperformed conventional risk scores, including the American Society of Anesthesiologists physical status classification system (ASA) and the Emergency Surgery Score (ESS), achieving a c-statistic of 0.92 for mortality and 0.84 for morbidity prediction [16, 17]. A distinctive feature of POTTER is its use of OCT logic, which generates transparent, patient-specific decision pathways rather than opaque probability outputs.

Multiple validation studies have confirmed the generalizability of the model across different emergency surgical populations. In a large cohort of emergency laparotomy patients (n = 59,955), POTTER demonstrated high discrimination for major postoperative complications, including septic shock (0.93), respiratory failure (0.92), and acute renal failure (0.92) [18]. External validation in a middle-income country further supported its robustness, with a prospective Brazilian study (n = 194) reporting satisfactory predictive performance [19]. However, predictive accuracy declined with increasing age, decreasing from a c-statistic of 0.84 in patients aged 65–74 years to 0.71 in those aged ≥ 85 years, highlighting the challenges of risk prediction in elderly and frail populations [20].

To address perioperative resource allocation, a dedicated POTTER-ICU module was subsequently developed to predict the need for intensive care unit admission. Validated on more than 460,000 patients, this model achieved c-statistics of 0.89 in training and 0.88 in testing cohorts, suggesting potential utility in emergency surgical planning [21].

Table 1 AI algorithms and tools for preoperative decision-making in the emergency setting

References	AI system	Tool	Aim	Setting	Type of study	Numb of patients enrolled
Bertsimas et al. [16]	ML-based Predictive OpTimal Trees in Emergency Surgery Risk (POTTER) calculator	Smartphone	To predict 30 days-mortality and morbidity in emergency surgical patients	Emergency	Derivation and retrospective validation study	382,960 (ACS-NSQIP database)
El Hechi et al., [18]	ML-based POTTER Calculator	Smartphone	To predict 30 days-mortality and morbidity in emergency surgical patients undergone laparotomy	Emergency	Retrospective Validation study	59,955 (ACS NSQIP database)
Ribeiro Junior et al., [19]	ML-based POTTER calculator/smartphone	Smartphone	To predict 30 days- mortality and morbidity in emergency surgical patients	Emergency	Prospective Validation study (external)	194
Maurer et al. [20]	ML based POTTER calculator	Smartphone	To predict 30 days-mortality and morbidity in emergency surgical patients aged ≥ 56 years old	Emergency	Retrospective Validation study	29,366 (ACS NSQIP database)
Gebran et al. [21]	ML-based POTTER-Intensive Care Unit (ICU)	Smartphone	To predict the need to be admitted to ICU in emergency surgical patients	Emergency	Retrospective Validation study	464,861(ACS NSQIP database)
El Moheb et al. [22]	ML-based POTTER vs Surgeon evaluation	Smartphone/traditional decision making	to predict postoperative outcomes in emergency surgical patients	Emergency	Retrospective comparative study	150 patients + 15 surgeons
Maurer et al. [23]	ML-based Trauma outcome predictor (TOP) calculator	Smartphone	To predict outcomes in adult trauma patients	Trauma	Derivation and retrospective validation study	934,053 (ACS NSQIP database)
El Hechi et al. [24]	ML-based TOP calculator	Smartphone	To predict outcomes in geriatric trauma patients (aged ≥ 65 years old)	Trauma	Retrospective Validation study	260,505 (ACS NSQIP database)
Akbulut et al. [27]	ML-based AI algorithm	N/A	To predict perforated appendicitis	Emergency	Derivation and retrospective validation study	1797
Eickhoff et al. [28]	ML-based AI algorithm	N/A	To predict postoperative outcomes in perforated appendicitis	Emergency	Derivation and retrospective validation	163
Marcinkevics et al. [29]	ML-based AI algorithm	N/A	To diagnose, manage and severity of acute appendicitis in pediatric and adolescent patients	Emergency	Derivation and validation study	430
Marcinkevičs et al. [30]	ML-based AI algorithm	N/A	To predict acute appendicitis in pediatric patients	Emergency	Derivation and retrospective validation	579 pediatric patients/1709 US images
Park et al. [32]	CNN-based AI imaging classification	N/A	to diagnose acute appendicitis analysing CT imaging	Emergency	Derivation and internal and external validation	215 patients/667 CT images sets for derivation and internal validation; 26 patients/60 CT images for external validation
Cheng et al. [33]	CNN-based AI imaging classification	N/A	To detect SBO on abdominal X-Ray imaging	Emergency	Pilot study	Different stages of training and sets
Cheng et al. [34]	CNN-based AI imaging classification	N/A	To detect SBO on abdominal X-Ray imaging	Emergency	Pilot study	Different stages of training and sets
Kim et al. [35]	DL-based AI imaging classification	N/A	To detect SBO on X-Ray imaging	Emergency	Pilot study	900 abdominal X-Ray images

Table 1 (continued)

References	AI system	Tool	Aim	Setting	Type of study	Numb of patients enrolled
Kim et al. [36]	DL-based AI algorithm and imaging classification (YOLOv3)	N/A	ileocolic intussusception X-Ray in pediatric patients	Emergency	Pilot study	681
Su CY et al. [37]	CNN-based AI imaging classification (Inception-ResNet v2; Inception v4; DenseNet 121)	N/A	To detect subphrenic free air on chest-X-Ray	Emergency	Pilot study	Training set: 587 chest-Xray; Test set: 80
Kim M et al. [38]	ANN- based AI imaging classification (Res-Net50)	N/A	To detect pneumoperitoneum on abdomen X-Ray	Emergency	Pilot study	Different stages of training and sets
Cheng et al. [39]	DL-based AI imaging classification (ResNet50-V2)	N/A	To detect abdominal free fluid in Morrison's pouch with Focused Assessment with US in trauma patients (FAST)	Trauma	Pilot study	324 records for the training model; 36 + 36 for validation and testing
van Grinsven Et al [68]	CNN-based AI imaging classification	N/A	To detect hemorrage	Emergency /trauma	Pilot study	Different stages of training and sets

ML: machine learning; DL: deep learning; CNN: convolutional neural network is a type of DL method suited to analysing visual data and solving Computer Vision (CV) tasks; ANN: Artificial Neural Network; it is a type of DL method that teaches computers to process data in a way that is inspired by human brain. CT: computed tomography; SBO: small bowel obstruction; US: ultrasound/sonography; ACS NSQIP: American College of Surgeons (ACS) National Surgical Quality Improvement Program (NSQIP); it is a nationally validated, risk-adjusted, outcomes-based program designed to measure and improve the quality of surgical care

Beyond statistical performance, POTTER has also been compared with surgeon judgment. In a comparative study, its use improved clinicians' ability to predict mortality (AUC 0.88 vs. 0.84) and pneumonia (AUC 0.84 vs. 0.75), indicating that AI-based tools may enhance, rather than replace, clinical decision-making in emergency settings [22]. Nevertheless, despite its availability and accuracy, POTTER has not been widely implemented in routine clinical workflows, and no prospective studies have yet evaluated its impact on decision-making timelines, patient outcomes, or resource utilization.

The TOP calculator applies the same OCT framework to trauma care, where rapid risk stratification is essential. Trained on more than 930,000 cases from the National Trauma Data Bank, TOP achieved excellent discrimination for mortality prediction, with c-statistics of 0.95 for penetrating trauma and 0.89 for blunt injuries [23]. Validation in a large geriatric trauma cohort (n = 260,505) confirmed stable performance, particularly for critical complications such as acute respiratory distress syndrome and cardiac arrest, with discrimination ranging from 0.75 to 0.92 [24]. As with POTTER, however, the use of TOP in everyday trauma care remains largely theoretical, with no formal studies assessing its effect on triage accuracy, surgeon confidence, or patient outcomes.

Implementation barriers and future directions Despite robust technical performance and ease of access through mobile platforms, the translation of POTTER and TOP into routine emergency surgical practice remains limited. Key barriers include the absence of integration with electronic health records, the lack of structured implementation and impact studies, limited clinician training in interpreting and trusting ML-based predictions, and persistent ethical concerns related to the use of AI in high-risk, time-critical clinical scenarios. These tools exemplify how technical readiness alone does not ensure clinical adoption, particularly in emergency settings where workflow compatibility, trust, and accountability are central to decision-making.

AI-based diagnostic support for acute abdomen and trauma

AI has also been widely investigated for diagnostic support and clinical triage in patients presenting with acute abdominal pain and traumatic injuries—two scenarios in which time-sensitive decision-making is critical. Numerous ML and deep learning (DL) models have demonstrated high diagnostic accuracy in retrospective studies for conditions such as acute appendicitis, bowel obstruction, intussusception, pneumoperitoneum, and intra-abdominal bleeding. However, despite encouraging performance metrics, clinical implementation remains limited, and real-world impact studies are largely lacking. Common methodological concerns include overfitting to development datasets and underfitting due to small or unrepresentative sample sizes, which limit reproducibility and generalizability.

Diagnosis and risk stratification in acute appendicitis

Acute appendicitis remains one of the most frequent indications for emergency surgery, yet diagnosis can be challenging in atypical presentations and specific

Table 2 Intraoperative real-time AI guidance for safe surgery in difficult cholecystectomies

References	AI system	Tool	Aim	Setting	Type of study	Numb of videos analysed
Tokuyasu et al. [48]	Algorithm of real-time object detection based on DL	YOLOv3 learning model	To detect 4 anatomical landmarks for CVS: cystic duct; Hepatic Segment 4; Common bile duct, Rouviere's sulcus	Laparoscopic cholecystectomy	Pilot study	76
Nakanuma et al. [49]	Algorithm of real-time object detection based on DL	Smart Endoscopic Surgery	To achieve a CVS in hepatocystic dissection	Laparoscopic cholecystectomy	Single center prospective feasibility trial	10
Liu et al. [50]	Algorithm of real-time object detection based on DL	SurgSmart based on YOLOv3 algorithm	To detect 4 anatomic landmarks for CVS: cystic duct, cystic artery, and common bile duct, cystic plate	Laparoscopic cholecystectomy	Pilot study	41
Laplante et al. [51]	Semantic segmentation in CV model	GoNoGoNet	To identify Go and No-Go zones in dissection for cholecystectomy	Laparoscopic cholecystectomy	Pilot study with consensus of SAGES experts	25
Mascagni et al. [52]	Algorithm based on CV models (DL)	EndoDigest platform	To detect critical events during surgery	Laparoscopic cholecystectomy	Pilot study	155
Fujinaga et al. [53]	Algorithm based on DL	Cross AI-system for landmarks detection and phase recognition	To detect simultaneously anatomical landmarks such as common bile duct, cystic duct, lower edge of the left medial hepatic segment (S4), Rouviere's sulcus	Laparoscopic cholecystectomy	Clinical feasibility study	20
Endo et al. [54]	Algorithm of real-time object detection based on DL	YOLOv3 learning model	To detect 4 anatomical landmarks for CVS: the extrahepatic bile duct (EHBD), cystic duct (CD), inferior border of liver S4 (S4), and Rouviere sulcus	Laparoscopic cholecystectomy	Pilot study	95
Madani et al. [55]	Algorithm of real-time object detection and classification based on DL (semantic segmentation)	GoNoGoNet and CholeNet	To identify the safe zone of dissection (Go zone) and the dangerous zone of dissection (No-Go zone), and target anatomy, including the gallbladder, liver, and hepatocystic triangle	Laparoscopic cholecystectomy	Pilot study	Different large datasets (Development set: Cholec80 dataset; validation set: M2CAI16-workflow Challenge dataset)
Mascagni et al. [56]	Deep neural network comprising a segmentation model (CV)	–	To achieve a CVS in real time	Laparoscopic cholecystectomy	Pilot study	201
Kawamura Et al [57]	algorithm for image classification based on a deep convolutional neural network	–	To achieve a CVS for hepatocystic triangle dissection	Laparoscopic cholecystectomy	Pilot study	52

YOLO: You Look Only Once; CVS: Critical View of Safety; SAGES: Society of American Gastrointestinal and Endoscopic Surgeons; CV: computer vision; DL: deep learning

populations, including pediatric and elderly patients. AI-based models have been developed to support diagnostic classification and severity prediction. A systematic review by Bhandarkar et al. [25] analyzed 39 studies and reported a mean diagnostic accuracy of 86%, with pooled AUROCs around 0.82. Similar findings were reported by Issaiy et al. [26], who showed that artificial neural networks and logistic regression models often achieved performance metrics exceeding 80% in both diagnosis and prediction of postoperative complications such as ICU admission and sepsis.

More advanced approaches incorporating explainable AI have also been proposed. Akbulut et al. [27] developed a CatBoost-based model combined with Shapley Additive Explanations (SHAP) to differentiate perforated from non-perforated appendicitis. In a cohort of 1,797 appendectomy patients, the model achieved accuracies of up to 92% and identified clinically relevant predictors, including C-reactive protein, bilirubin, and neutrophil-to-lymphocyte ratio. However, none of these tools have yet demonstrated a reduction in negative appendectomy rates, diagnostic delays, or improved clinical outcomes.

Imaging-based diagnosis of acute abdominal conditions

AI-based interpretation of medical imaging represents another active area of research in acute care. DL algorithms, particularly convolutional neural networks, have been applied to abdominal radiographs and CT scans with high diagnostic performance [28–31]. For example, Park et al. [32] reported an overall accuracy of 91.5% for appendicitis detection on CT imaging, although performance declined in early or perforated disease, necessitating radiologist oversight. Similarly, CNN-based models for bowel obstruction detection on plain radiographs achieved AUCs of up to 0.97 [33–35].

In pediatric settings, a YOLOv3-based model for intussusception detection demonstrated higher sensitivity than human radiologists (0.76 vs. 0.46) while maintaining comparable specificity (0.96 vs. 0.92), suggesting potential utility as a decision-support tool [36]. DL models have also shown promise in detecting pneumoperitoneum on chest and abdominal radiographs, achieving sensitivities of approximately 88% [37, 38]. Despite these advances, prospective evaluation and workflow integration remain largely absent.

AI for trauma and bedside ultrasound interpretation

In trauma care, focused assessment with sonography in trauma (FAST) is a rapid bedside examination used to identify free intraperitoneal fluid. Cheng et al. [39] developed a DL model based on a ResNet50-V2 architecture to assist FAST interpretation, achieving accuracies exceeding 97%. The system was integrated into an automated feedback platform to support image acquisition and interpretation by less experienced operators. While promising, this approach has not yet been implemented in real-time clinical practice.

Key considerations and implementation gaps

Across diagnostic domains, AI models consistently demonstrate high retrospective accuracy, yet substantial gaps remain. External validation and prospective trials are scarce, integration with emergency department and radiology workflows is limited, and interpretability challenges—particularly with DL models—continue to hinder clinician trust. To date, no robust evidence demonstrates improved patient outcomes, shorter diagnostic times, or more efficient resource utilization attributable to these tools.

Overall, AI-based diagnostic models show considerable potential to support triage and early decision-making in emergency surgery. However, further research is required to evaluate their safety, usability, and clinical impact before widespread implementation can be recommended.

Intraoperative computer vision applications

Intraoperative image-guided tools

Intraoperative decision-making represents one of the most cognitively demanding phases of emergency surgery, requiring rapid interpretation of complex visual information under conditions of uncertainty. In this context, machine learning (ML), computer vision (CV), and augmented reality (AR) have been increasingly explored to support surgeons during urgent procedures by enabling real-time image interpretation, anatomical recognition, and spatial navigation. CV-based systems can extract and process information from intraoperative images and videos, providing feedback that may reduce cognitive load, enhance precision, and help prevent avoidable errors.

The widespread adoption of high-definition, magnified, and increasingly standardized laparoscopic imaging in emergency procedures, such as cholecystectomy and appendectomy, has generated large volumes of visual data suitable for training deep learning–based CV algorithms [40]. Within this technological evolution, the concept of the Surgeon–Machine Interface (SMI) was introduced to describe the dynamic collaboration between surgeons and digital tools, enabling context-aware intraoperative assistance [41]. This concept underpins the broader framework of Digital Surgery, which integrates advanced visualization, data analytics, robotic platforms, and AI into the surgical workflow [42].

From a functional perspective, CV applications in emergency surgery have focused on three main domains: surgical process understanding, detection of relevant anatomical or procedural features, and support for intraoperative navigation [44]. These applications rely primarily on two core computational tasks. The first is recognition, whereby ML algorithms identify anatomical structures, instruments, or tissues within surgical images. Although bounding-box object detection has demonstrated feasibility, its accuracy is often limited by the complex morphology and variable boundaries of soft tissues encountered in surgery [45, 46]. The second task involves tracking and segmentation, which enable pixel-level identification of anatomical structures or instruments. While segmentation of rigid surgical tools has shown encouraging performance, accurate segmentation of deformable anatomical structures remains challenging due to intraoperative variability [46, 47].

Despite promising technical results, most CV-based intraoperative guidance systems remain in early phases of validation and are predominantly evaluated in elective laparoscopic procedures, particularly cholecystectomy. Evidence from real-time emergency settings is still limited. Key challenges to broader implementation include validation across diverse patient populations and operative conditions, seamless integration of CV guidance into existing surgical platforms, and evaluation of clinically meaningful outcomes such as complication rates, operative time, and conversion to open surgery. Overall, AI-driven CV tools hold substantial potential to transform intraoperative guidance in emergency surgery, but translation into routine practice will require stronger clinical validation, regulatory clarity, and user-centered integration.

Intraoperative landmark guidance in laparoscopic cholecystectomy

In emergency general surgery, laparoscopic cholecystectomy (LC) remains one of the most frequently performed and technically demanding procedures. Achieving clear anatomical identification is essential to prevent complications, particularly bile duct injuries. In this setting, CV approaches based on artificial neural networks have been increasingly investigated to support intraoperative anatomical recognition and enhance surgical safety.

Several AI-based systems have been developed to provide real-time landmark identification during LC, most commonly using deep learning object-detection frameworks such as the "You Only Look Once" (YOLOv3) algorithm. Tokuyasu et al. [48] trained a YOLOv3 model on approximately 2,000 endoscopic images extracted from 76 LC videos to identify key anatomical landmarks, including the cystic duct, common bile duct, lower edge of the left medial liver segment, and Rouvière's sulcus. Although the model achieved modest precision values (0.07–0.32), it demonstrated the potential to increase surgeons' anatomical awareness during intraoperative verification phases. Subsequent feasibility studies confirmed the applicability of YOLO-based systems in real-time settings. Nakanuma et al. [49] reported successful intraoperative landmark recognition in a single-center clinical study, while Liu et al. [50] showed that AI-assisted landmark identification could outperform both surgical trainees and senior surgeons in controlled comparisons.

Beyond landmark detection, AI has also been applied to support surgical safety through real-time guidance of dissection planes and verification of the Critical View of Safety (CVS). Two representative systems, GoNoGoNet and CVSNet, were specifically designed to assist surgeons during LC by identifying safe and unsafe operative zones and by objectively confirming CVS achievement. GoNoGoNet delineates "Go" and "No-Go" zones within Calot's triangle, highlighting areas suitable for safe dissection and regions associated with a high risk of bile duct injury, such as the hepatoduodenal ligament and liver hilum [51]. CVSNet focuses on automated recognition of CVS criteria from laparoscopic video feeds, providing objective feedback on anatomical exposure and potentially reducing human error during critical dissection steps [52–57].

More recently, automated video analysis platforms have been introduced to integrate CV-based guidance with intraoperative documentation and quality assessment. Mascagni et al. [52] developed EndoDigest, a CV-driven system capable of analyzing laparoscopic videos, identifying key procedural phases, and detecting CVS achievement during LC. In addition to supporting intraoperative safety, such platforms may facilitate postoperative audit, structured video review, and performance assessment, contributing to broader quality-improvement strategies in emergency minimally invasive surgery.

Robotic surgery platforms in emergency settings

The integration of robotic platforms into surgical practice has introduced significant advances in precision, dexterity, and visualization (Fig. 1). While conventional systems such as the da Vinci® platform operate under a master–slave paradigm, recent developments have incorporated AI-driven functionalities, including motion tracking, tissue recognition, and trajectory planning [58–61]. These features support the concepts of the "augmented hand," "augmented eye," and "augmented brain," reflecting enhanced dexterity, improved visualization, and AI-assisted decision-making within progressively evolving levels of surgical autonomy (Fig. 2; Table S1) [5, 46, 61].

Despite these technological advancements, most robotic systems currently used in emergency surgery remain non-autonomous (autonomy levels 0–1), with partial autonomous functions largely confined to elective settings [61, 62]. In hemodynamically stable emergency patients, robotic-assisted surgery has demonstrated feasibility and safety comparable to conventional minimally invasive approaches. A 2021 consensus statement by the World Society of Emergency Surgery concluded that robotic emergency surgery can be safely performed in selected patients when adequate expertise and institutional resources are available [63].

Evidence supporting robotic surgery in emergency settings is primarily derived from retrospective studies and single-center experiences. A systematic review by Reinisch et al. [64], including 52 studies on robotic approaches for appendicitis, cholecystitis, hernias, and

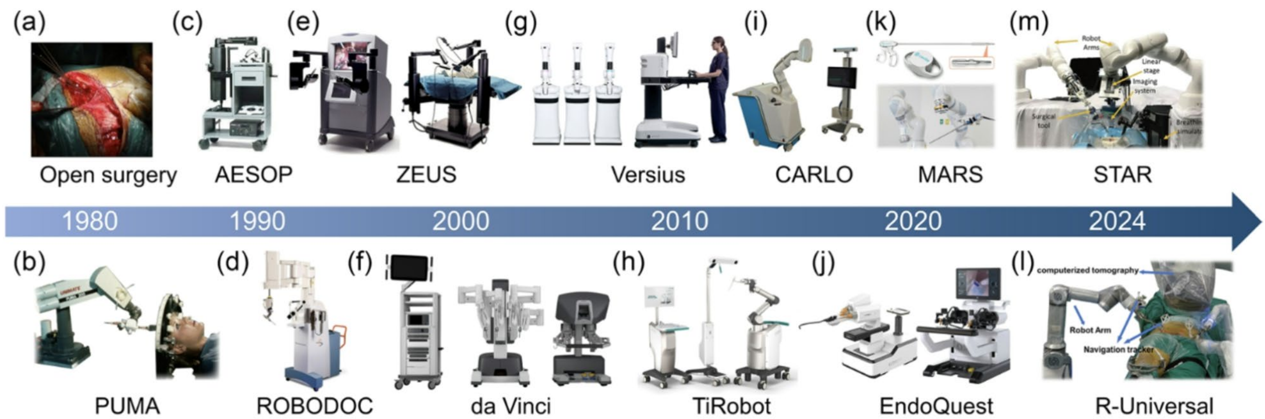

Fig. 1 Graphical representation of robotic platforms development and evolution [59]

other emergencies, confirmed feasibility across indications but highlighted low overall evidence quality and the absence of autonomous systems. Similarly, selected cohort studies have reported potential benefits of robotic approaches in specific scenarios, such as reduced conversion rates or postoperative complications in acute diverticulitis and other complex cases [65–67]. However, these findings remain heterogeneous and context-dependent.

Cost-effectiveness represents a major unresolved issue. Large population-based analyses have shown higher adjusted costs for robotic emergency procedures compared with laparoscopy, without consistent improvements in length of stay or morbidity [68]. Conversely, smaller series and narrative reviews suggest that cost efficiency may improve with increasing surgical volume, experience, and optimized institutional workflows, particularly in high-volume centers [69].

Overall, the widespread adoption of robotic surgery in emergency settings is limited by restricted access to platforms, especially during off-hours, prolonged operative times during the learning curve, high acquisition and maintenance costs, and the lack of structured robotic training programs for emergency surgeons [8, 9]. Proposed strategies to address these barriers include centralization of robotic resources in emergency surgery hubs, development of dedicated training pathways, prospective evaluation of cost-effectiveness based on clinical outcomes, and the emergence of more affordable or modular robotic systems [62, 70, 71]. Advances in AI integration may further support a more rational and equitable expansion of robotic surgery in acute care.

Fluorescence-guided emergency surgery

In emergency surgical settings, indocyanine green (ICG) fluorescence imaging has emerged as a valuable adjunct for intraoperative decision-making by enabling real-time visualization of anatomical structures and tissue perfusion [62, 68–75]. Its application in both open and minimally invasive procedures has been associated with improved operative guidance, reduced conversion rates, and enhanced surgeon confidence in complex and high-risk scenarios, provided that appropriate expertise and equipment are available [62, 68–75].

ICG fluorescence has demonstrated particular utility during emergency cholecystectomy, bowel resection, and anastomosis, especially in cases of acute intestinal ischemia, strangulated bowel, and complicated abdominal conditions. Clinical studies have shown that ICG-guided emergency cholecystectomy may reduce conversion to open surgery and allow safe extension beyond traditional timing thresholds for acute cholecystitis [76]. A randomized controlled trial comparing ICG-assisted and conventional laparoscopic cholecystectomy reported a trend toward fewer complications in the ICG group, although statistical significance was limited by sample size [77].

Assessment of intestinal perfusion during emergency surgery is often subjective and unreliable when based solely on macroscopic evaluation. ICG angiography offers a more objective approach to evaluating bowel viability and defining resection margins. Several studies have demonstrated discrepancies between visual assessment and actual tissue perfusion, with ICG imaging influencing intraoperative strategy in a substantial proportion of cases involving acute mesenteric ischemia or strangulated bowel obstruction [78–81]. In trauma settings, ICG has also been applied in hemodynamically stable patients to assess bowel perfusion, anastomotic viability, and mesenteric injuries, with potential reductions in postoperative complications and planned reoperations [78, 84–86].

Despite these advantages, ICG fluorescence imaging has important limitations. Interpretation of perfusion remains largely qualitative and operator-dependent, particularly among less experienced surgeons [82]. Image quality may be affected by hemodynamic instability, vasopressor use, obesity, inflammation, or scarring, and the limited tissue penetration of near-infrared fluorescence (approximately 5–10 mm) constrains its applicability in certain clinical scenarios [87–89]. These factors

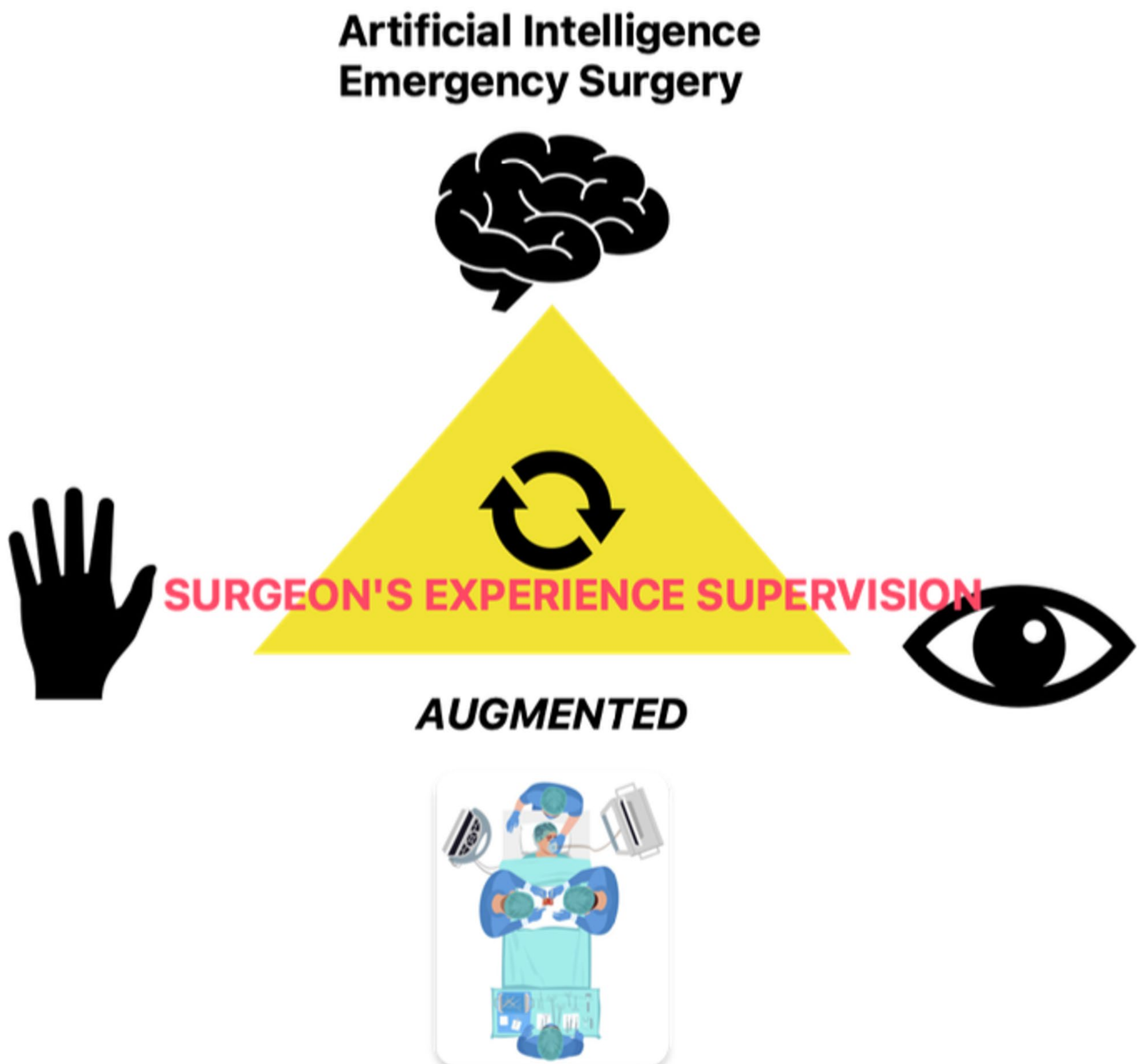

Fig. 2 Artificial Intelligence Emergency Surgery in the operating room: augmented hand, augmented eye, augmented brain. A graphical representation

underscore the need for standardized protocols, appropriate patient selection, and dedicated training.

Importantly, fluorescence quantification and objective image interpretation represent an emerging research frontier with direct relevance to AI-driven intraoperative support. Several software-based approaches have been proposed to quantify fluorescence intensity and perfusion dynamics, including the SPY imaging platform, Fluorescence-based Enhanced Reality (FLER), and Q-ICG algorithms, which analyze fluorescence intensity curves to improve reproducibility and reduce subjectivity [90]. While preliminary results are promising, further validation in human emergency surgery is required.

Current WSES consensus supports the selective use of ICG fluorescence-guided techniques in emergency surgery to enhance intraoperative decision-making and potentially improve outcomes, provided that adequate training, equipment availability, and standardized protocols are ensured [91]. Future research should focus on integrating fluorescence imaging with AI-based quantification and computer vision tools, as well as on evaluating cost-effectiveness and patient-centered outcomes in real-world emergency settings.

Simulations and training systems in emergency surgery

Artificial intelligence–enhanced simulation systems represent an important application of AI in emergency surgery, supporting technical skill acquisition, decision-making, and preparedness for rare, high-risk clinical scenarios. By integrating AI models into virtual reality (VR)–based platforms, complex emergency situations can be recreated using real-world clinical data, enabling dynamic scenario generation, adaptive feedback, and objective performance assessment. This approach is particularly relevant in emergency surgery, where exposure to uncommon but critical situations is limited and time-pressured decision-making is essential [92, 93].

Experimental and clinical studies have demonstrated that VR-based training improves visuomotor coordination, hand–eye precision, and cognitive performance in complex surgical tasks. Trainees exposed to VR simulation show smoother movements, greater concentration, and reduced error rates, supported by real-time feedback mechanisms [94–96]. In a landmark randomized trial, Seymour et al. reported that residents trained with VR simulators during laparoscopic cholecystectomy were faster, committed fewer errors, and achieved greater procedural safety compared with those trained using conventional methods [97].

VR-based surgical training commonly relies on three-dimensional anatomical models reconstructed from computed tomography (CT) and magnetic resonance imaging (MRI) data, enabling realistic simulation of anatomy and surgical pathways. Training modules may range from basic psychomotor exercises to complete procedural simulations, allowing flexible skill development and continuous performance assessment [98, 99].

Technological advancements, including force-feedback devices, multisensory interfaces, and head-mounted displays (HMDs), have further enhanced immersion and realism. The availability of lower-cost commercial platforms has also improved accessibility, broadening the adoption of simulation-based education [100, 101]. Nevertheless, relevant limitations persist, including incomplete haptic fidelity, simulator-related discomfort, high costs for advanced systems, and the need for trained faculty, which may restrict widespread implementation [102, 103].

The integration of VR with augmented reality (AR), AI-driven analytics, and networked environments such as the metaverse expands its potential role in emergency surgery training and collaboration. These platforms enable remote interaction, procedural simulation, and real-time expert support. In emergency and disaster contexts, applications such as telementoring platforms and wearable smart glasses have demonstrated benefits in improving communication, triage accuracy, and situational awareness, particularly in time-sensitive and resource-limited environments [104–107].

Despite its promise, AI-enhanced simulation in emergency surgery faces challenges related to infrastructure requirements, cost sustainability, and unequal access across healthcare systems. Without targeted implementation strategies, these technologies risk widening existing educational disparities. Future research should therefore focus on validating the impact of AI-driven simulation on clinical performance and patient outcomes, integrating these tools into structured emergency surgery training pathways, and ensuring scalable and equitable deployment [108].

Data quality, ethics and regulatory barriers to AI adoption in emergency care

The rapid development and increasing use of AI in medical and surgical fields have been both transformative and controversial. In emergency surgery, in particular, AI raises complex questions regarding the balance between technological guidance and human decision-making. In an unplanned and highly variable clinical environment, the surgeon's autonomy and responsibility remain central during patient evaluation and operative management. While AI technologies may enhance decision support, the ultimate accountability for intraoperative choices and outcomes continues to rest with the surgeon.

Most ML–based tools are developed through the analysis of clinical data. Over recent years, healthcare systems have progressively transitioned toward large-scale data analytics, facilitated by the digitization of medical records, advanced electronic health records (EHRs), disease surveillance systems, and population-level data management strategies [109]. The development of AI algorithms relies on large and heterogeneous datasets ("Big Data"), which may include structured data (e.g., coded variables and numerical values), semi-structured data (e.g., clinical notes combining discrete elements and free text), and unstructured data such as operative reports, images, and videos. Owing to their volume and complexity, these datasets require ML-based approaches, including natural language processing, to extract clinically meaningful information and transform raw inputs into interpretable data representations [110].

Large clinical databases, including registries, data warehouses, and relational databases, represent a crucial resource for surgical AI research, as highlighted by the World Society of Emergency Surgery research task [111]. However, the quality and representativeness of input data directly influence algorithmic performance. Clinical data must be carefully curated, labeled, and validated to reflect real-world practice accurately. Errors or inconsistencies in data labeling can severely limit model reliability, regardless of algorithmic sophistication. Consequently, close collaboration between clinicians and data scientists is required to ensure data integrity prior to model development [112].

A major ethical challenge in surgical AI relates to the so-called "black box effect," whereby AI systems generate predictions or recommendations without transparent insight into their internal decision-making processes. When the reasoning behind outputs is not accessible, clinical interpretation and translation into practice become problematic [113]. To address this issue, the concept of explainability has emerged, although it remains variably defined from technical and legal perspectives, and is not explicitly codified in current legislation [114]. These limitations have driven the development of explainable artificial intelligence (XAI), which aims to improve transparency through either inherently interpretable ("white-box") models or post-hoc explanation techniques applied to complex architectures. XAI has gained particular relevance with the emergence of large language models and generative AI systems, which often achieve high performance at the expense of interpretability [115].

For AI tools to be safely adopted in emergency surgery, they must be explainable, validated, and clinically interpretable. Surgeons need to understand what a model predicts, why it generates a specific output, and how reliable that prediction is in a given context [116, 117]. Proposed approaches include interpretable-by-design models, explainability overlays for neural networks, and emerging trust frameworks such as blockchain-based architectures and smart contracts. However, these solutions remain largely experimental and have not yet been systematically validated in emergency surgical settings [118].

Another critical ethical concern is the under-representation of racial minorities, specific ethnic groups, and patients with rare or atypical conditions within training datasets, a phenomenon often described as "health data poverty." Historical exclusion or under-representation of certain populations in medical research can lead to data-driven biases, which may translate into inequitable clinical decision-making and worsen health disparities [119]. Addressing these biases requires not only technical solutions but also deliberate efforts to ensure diversity, inclusiveness, and external validation of AI models.

Digital surgery is increasingly emerging from the convergence of AI, virtual and augmented reality, and robotic technologies [42, 120]. Digital surgery has been defined as the use of technology to enhance preoperative planning, intraoperative performance, therapeutic decision-making, and surgical training, with the goal of improving outcomes and reducing harm [121]. Within this framework, the availability of high-quality annotated datasets, particularly surgical video data, is essential for advancing AI-assisted and semi-autonomous surgical systems. In this context, the Society of American Gastrointestinal and Endoscopic Surgeons (SAGES) issued expert recommendations in 2023 addressing surgical video data management across four key domains: data use, data structure, data exploration, and data governance [120]. These recommendations are summarized in Table 3.

Table 3 Surgical video data management according to SAGES guidelines [120]

Recommendation Area	Details
Data Collection	Establish standardized protocols for video data acquisition to ensure consistency and quality
	Utilize high-definition video formats to capture detailed visual information relevant to surgical procedures
Data Structure	Implement a structured format for video data storage, including metadata such as patient demographics, procedure types, and timestamps
	Encourage the use of file naming conventions that enhance data retrieval and organization
Data Accessibility	Ensure that video data is readily accessible to researchers while maintaining patient confidentiality and compliance with ethical guidelines
	Create centralized databases or repositories for video data sharing among institutions to promote collaboration and research
Research Applications	Support the use of video data in AI algorithm training, focusing on tasks such as image recognition and pattern analysis in surgical procedures
	Encourage studies that evaluate clinical outcomes based on video analysis, aiming for quality improvement in surgical techniques and patient care
Educational Use	Advocate for the integration of surgical video data into training programs for residents and fellows, providing opportunities for assessment and feedback
	Utilize video data for creating educational resources that highlight best practices and complex surgical techniques
Quality Improvement Initiatives	Promote the analysis of surgical videos as a means to identify areas for improvement in surgical performance and patient safety
	Encourage feedback mechanisms where surgical teams can review video data to reflect on performance and outcomes, fostering a culture of continuous improvement

Ethics and responsibility in AI-assisted surgery

The integration of AI into surgical practice raises complex ethical concerns, particularly in emergency and trauma surgery. Core issues include informed consent, data privacy, trust, and legal accountability [122]. These challenges must be addressed within the foundational ethical principles of beneficence, non-maleficence, autonomy, and justice [123].

An emerging ethical challenge relates to the increasing autonomy of AI-enabled surgical devices. While most surgical robots still operate under a master–slave paradigm, some components already perform autonomous adjustments based on tissue feedback. As AI systems begin to support or influence intraoperative decisions, it remains unclear whether existing regulatory oversight is sufficient, even when the AI does not physically act on the patient [5, 60, 124]. The AIS Task Force and the AIS Editorial Board Study Group on Ethics have identified six key ethical domains: reliability of AI systems; data privacy; representativeness of training data; transparency and uncertainty management; equity in access to care; and technology as a potential equalizer in surgical education [5, 60, 124].

Ethical complexity is particularly heightened in emergency settings, where time pressure may limit informed consent and compromise data quality, further amplifying the risks associated with algorithmic decision-making [125].

Table 4 Key Regulations on AI in Surgery. CE: Conformité Européenne; CDSS: Clinical Decision Support System

Region	Regulation	Focus	Obligations
EU	GDPR (Art. 13, 22)	Explainability in automated decision-making	Ongoing – patients must be informed about AI decisions
EU	AI Act (2024–2027 rollout)	Risk classification, transparency, human oversight, and implementation phases	Effective 1 Aug 2024; full application by 2 Aug 2026; high-risk systems until 2027
EU	AI Act – Prohibited Uses	Bans on manipulative, emotion-detection, and social scoring systems in certain contexts	Emotion inference banned in work/education; exceptions for therapeutic use
EU	AI Act – High-Risk AI Systems	Medical AI (e.g., diagnostic tools, CDSS, triage systems, etc.) – strict requirements apply	Conformity assessment, CE marking, safety, robustness, and data quality required
EU	AI Act – Risk Categories & Responsibilities	Defines obligations for providers, deployers, distributors; outlines risk tiers (high, low, minimal)	Providers must ensure documentation, oversight, incident reporting; deployers must monitor, assess risk
US	FDA Oversight	Regulatory approval of AI/ML medical devices; focus on decision-support tools	Rapidly expanding approvals; no specific AI act yet; rising demand for adaptive oversight mechanisms
WHO	WHO AI Regulatory Guidance (2023)	Six pillars: documentation, transparency, collaboration, human oversight, data protection, equity	Guidance only – not legally binding

Legislation and global implementation of AI in surgery

The regulatory landscape for AI in healthcare and in surgery in particular, remains fragmented and heterogeneous across regions. While countries such as the United States and members of the European Union have made substantial progress in regulatory development, globally unified standards for ensuring AI safety, transparency, and accountability are still lacking.

In the European Union, the General Data Protection Regulation (GDPR) mandates transparency in automated decision-making (Art. 13(2)(f), Art. 22(2), and Art. 22(4)), requiring that patients be informed when clinical decisions involve AI-based systems [126]. Building on this framework, the EU AI Act, which entered into force in 2024, introduces a comprehensive risk-based classification system for AI applications, with phased implementation through 2027, as summarized in Tables 4, 5, 6 [127]. The AI Act emphasizes transparency, human oversight, data governance, and non-discrimination, and prohibits manipulative or exploitative AI practices, such as emotion inference in non-medical settings, while allowing their use in therapeutic contexts under specific legal safeguards (Recitals 29 and 44).

Under the AI Act, high-risk AI systems, including diagnostic tools, clinical decision support systems (CDSS), emergency triage algorithms, and public health resource allocation platforms, are subject to stringent regulatory obligations. These include conformity assessment, technical documentation, data quality requirements, human oversight protocols, and post-market monitoring. Responsibilities are explicitly assigned to both providers (e.g., developers and manufacturers) and deployers (e.g., hospitals and healthcare institutions), encompassing AI literacy, risk management, transparency, and evaluation of impacts on fundamental rights. In contrast, low-risk systems—such as AI chatbots for wellbeing, AI-generated medical image modifications, or wandering detectors in long-term care facilities—are subject to limited transparency obligations, while minimal-risk systems (e.g., administrative or pharmaceutical research tools) are largely exempt. General-purpose AI systems, including large language models, fall under provider obligations unless deployed in high-risk clinical scenarios. Importantly, third parties such as importers, distributors, or entities modifying existing systems may be legally recognized as AI providers and thus assume equivalent regulatory responsibilities (Recital 84, Art. 16 of Regulation 2017/745).

In the United States, the Food and Drug Administration (FDA) approved the first robotic surgical system in 2000 and has since authorized an increasing number of

Table 5 AI systems provider vs deployer responsibilities under the EU AI Act. **CE: Conformité Européenne**

Responsibility Area (EU AI Act)	Provider Obligations	Deployer Obligations
AI literacy	✓ Required (Art. 4)	✓ Required (Art. 4)
Risk management	✓ Required (Art. 9)	✕ Not required
Data governance	✓ Required (Art. 10)	✓ Required (Art. 26.3)
Technical documentation	✓ Required (Art. 11)	✕ Not required
Record keeping	✓ Required (Arts. 12, 18)	✓ Required (Art. 26.6)
Transparency duties	✓ Required (Art. 13)	✓ Required (Arts. 26.1, 26.5)
Human oversight	✓ Required (Art. 14)	✓ Assign qualified personnel (Art. 26.2)
Accuracy & cybersecurity	✓ Required (Art. 15)	✕ Not explicitly required
Quality management	✓ Required (Art. 17)	✕ Not required
Corrective actions	✓ Required (Art. 20)	✓ Required in case of misuse (Art. 26.5)
Conformity assessment & CE marking	✓ Required (Arts. 43–49)	✕ Not applicable
Fundamental rights impact assessment	✕ Not required	✓ Required (Art. 27)
Monitoring and incident reporting	✕ Not required	✓ Required (Arts. 26.5, 72)

Table 6 AI Risk Systems Classification under the EU AI Act. CDSS: Clinical Decision Support System

Risk Level	AI systems	Regulatory Requirements
High Risk	CDSS, diagnostic tools, triage systems, AI for insurance pricing, emergency call classification	Full compliance: documentation, conformity assessment, CE marking, human oversight, transparency, etc
Low Risk	Wellness chatbots, AI-generated medical deepfakes, wandering detectors in care homes	Basic requirements: transparency (Art. 50) and AI literacy (Art. 4)
Minimal Risk	Administrative tools, pharmaceutical research and development AI	No regulatory obligations

AI- and ML-enabled medical devices. Between 2019 and 2020 alone, AI-related approvals increased by 39% [128–131]. To date, most FDA-authorized systems function as clinical decision-support tools rather than autonomous agents. Nevertheless, their expanding use has prompted calls for more adaptive regulatory oversight to ensure patient safety, algorithmic transparency, and post-deployment monitoring [124, 132, 133].

At a global level, the World Health Organization (WHO) released regulatory guidance in October 2023, outlining six core principles for AI governance in healthcare: robust documentation, transparent risk management, human-centered oversight, collaboration between regulators and developers, protection of patient data, and prevention of inequities in access and outcomes [131].

Despite these regulatory advances, the literature consistently highlights persistent gaps in interoperability, accountability, and bias mitigation across jurisdictions. These challenges are particularly relevant for emergency and surgical settings, where time-critical decision-making and high-stakes clinical responsibility complicate the application of existing regulatory frameworks. Coordinated international efforts will therefore be essential to harmonize regulations and support the safe, equitable integration of AI into surgical care.

Addressing ethical and regulatory challenges in emergency surgery

The use of AI in emergency surgery presents unique challenges due to the urgent nature of clinical decisions and limited time for informed consent or comprehensive data validation. Key concerns include [125, 133]: (1) accountability and explainability of AI-generated decisions; (2) algorithmic bias affecting accuracy across diverse populations; (3) privacy and data protection, particularly for electronic health records (EHRs) (e.g., HIPAA compliance in the U.S.) and (4) security vulnerabilities, including the potential for AI system hacking.

To address these risks, frameworks like the FAIR principles (Findability, Accessibility, Interoperability, and Reusability) have been promoted to improve data transparency and scientific reproducibility in medical AI [134].

The use of AI in emergency surgery presents specific challenges related to accountability, explainability, algorithmic bias, data protection, and cybersecurity [125, 133]. To mitigate these risks, frameworks such as the FAIR principles have been proposed to improve data transparency and reproducibility [134].

Biases related to race, sex, ethnicity, and comorbidities remain a major limitation in AI systems trained on non-representative datasets. These must be actively mitigated through diverse training cohorts, validation studies, and real-world monitoring [135, 136]. Emerging technologies such as blockchain-based architectures, including smart contracts and trust oracles, have also been proposed to improve system reliability, data integrity, and security [137].Ultimately, ethical and legal integration of AI into emergency surgery will require not only technological innovation but also robust implementation science, including multicenter prospective studies and context-sensitive governance models.

Interpretability and explainability in surgical AI

The interpretability of AI models, often referred to as "explainability", is fundamental for their safe and ethical implementation in surgical care. Interpretability refers to the ability of human users (surgeons, regulators, or patients) to understand how an AI system arrives at its outputs. This is especially crucial in emergency surgery, where decisions carry high stakes, time is limited, and trust in machine recommendations must be immediate and well-founded [116, 123]. Interpretability methods fall broadly into two categories [139, 140]: (1) Model-intrinsic interpretability, where the architecture (e.g., decision trees or rule-based models) is inherently understandable; (2) Post-hoc interpretability, which applies algorithms like SHAP (Shapley Additive Explanations) or LIME (Local Interpretable Model-Agnostic Explanations) to explain the predictions of complex models such as deep neural networks.

These tools can clarify which features most influenced a model's prediction, e.g., in risk stratification models like POTTER or TOP, SHAP values may reveal whether lactate, leukocytosis, or operative timing were driving the predicted mortality risk. However, interpretability in surgical AI poses unique challenges because clinical decisions often involve nonlinear interactions and contextual cues not captured by model features. Surgeons may misinterpret algorithmic outputs if explainability tools oversimplify or present misleading certainty.

There is a lack of standardized benchmarks to assess whether explanations are clinically meaningful. Recent efforts in XAI aim to bridge this gap by visualizing intraoperative decision points in real time (e.g., highlighting perfusion zones during ICG-guided surgery); providing uncertainty estimates to communicate model confidence and incorporating human-in-the-loop systems, where AI suggestions are paired with interactive interfaces allowing surgeon input, override, or confirmation.

In neural network–based systems, techniques such as Monte Carlo dropout can be employed during inference to estimate epistemic uncertainty, providing clinicians with confidence intervals rather than single-point predictions [140]. Similarly, in LLM–based tools, sample consistency, the reproducibility of outputs across multiple runs, can serve as a proxy for uncertainty, highlighting areas where human oversight may be required [141]. Furthermore, new measures, metrics and standards are required to mitigate clinical "hallucinations" (confident but factually incorrect or misleading outputs) associated with the use of Generative AI. Best practices must include rigorous data curation and validation with proper benchmarking, transparency and traceability and ethical and regulatory considerations.

Despite these advancements, interpretability remains an open research frontier. In emergency surgery, the challenge is amplified by dynamic clinical contexts, inconsistent data availability, and the urgency of action. Ensuring that AI systems provide not just accurate but interpretable recommendations will be critical to gain trust, meet regulatory standards, and support safe deployment at scale. Transparent model behavior, aligned with clinical reasoning, will be essential to ensure that AI tools augment rather than obscure human judgment [122].

Perspectives on AI, cognitive load and surgeons' well-being

Beyond regulatory, ethical, and technical considerations, the impact of AI in emergency surgery must also be examined through the lens of human factors and surgeon well-being. Beyond measurable patient outcomes, several expert-driven studies highlight the potential of AI and cognitive support systems (CSTs) to mitigate mental workload, stress, and decision fatigue among emergency surgeons and operational responders.

Evidence from telementoring trials involving military medics suggests that remote expert guidance, while not consistently improving technical performance metrics, can significantly enhance procedural confidence in high-stakes scenarios such as hemorrhage control and damage-control surgery [142, 143]. Similarly, the integration of neurotechnological systems that monitor real-time cognitive workload through EEG and eye-tracking has shown potential to optimize collaboration between surgeons and semi-autonomous robotic assistants, contributing to improved intraoperative performance and reduced cognitive burden [144]. A recent systematic review of CSTs further supports their ability to improve surgical accuracy and reduce error rates, although ergonomic constraints and the lack of robust clinical validation remain important barriers to widespread adoption [145].

Collectively, these findings support a growing expert consensus that AI in emergency surgery should not be viewed solely as a diagnostic or technical adjunct, but also as a strategic asset to enhance surgeon resilience, situational awareness, and workflow efficiency. Future implementation studies should therefore evaluate not only patient-centered outcomes, but also human factors such as cognitive stress, confidence, and team dynamics in high-pressure surgical environments.

Conclusions

Artificial Intelligence holds significant potential to enhance emergency surgical care by supporting high-quality, consistent decision-making in time-critical, high-risk scenarios. Early applications suggest that AI is feasible and potentially beneficial across key phases of acute surgical care, particularly in preoperative risk stratification, diagnostic support, and intraoperative guidance. Despite growing public attention, real-world adoption of AI in emergency surgery remains limited, with most tools still confined to early validation phases rather than routine clinical use.

When appropriately developed and implemented, AI can complement—rather than replace—the clinical judgment, experience, and technical skills of emergency surgeons. However, the integration of AI in emergency surgery continues to face substantial barriers, including limited availability of high-quality real-world data, lack of context-specific tools, unequal access to technology, insufficient training pathways, and constrained investment in large-scale clinical implementation. Although the literature continues to evolve rapidly, the structural, ethical, and implementation challenges identified in this review remain largely unchanged and continue to limit real-world adoption.

Advancing toward an "intelligent emergency surgery system" will require robust data infrastructures, inclusive and affordable technologies (e.g., low-cost robotic platforms and consumables), and the formation of trained, multidisciplinary teams. Ethical, legal, and regulatory issues must also be addressed proactively through coordinated collaboration between emergency surgeons, engineers, policymakers, and healthcare administrators.

This scoping review emphasizes that emergency surgery represents one of the most challenging frontiers in modern medicine, characterized by unpredictable variables that cannot be fully controlled by protocols alone. In this setting, AI has the potential to become a valuable ally when supervised and guided by the surgeon's expertise, intuition, and responsibility at the bedside and in the operating room.

Abbreviations

AI	Artificial intelligence
ML	Machine learning
DL	Deep learning
CV	Computer vision
VR	Virtual reality

Supplementary Information

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Supplementary Material 1

Author contributions

BDS conceived and designed the study. BDS carried out a systematic review of the literature. BDS selected articles and wrote the manuscript. All the authors critically read, revised the manuscript and approved the final manuscript.

Availability of data and materials

Data sharing is not applicable to this article as no datasets were generated or analysed during the current study.

Declarations

Conflict of interest

The authors declare that there are no conflicts of interest. AW Kirkpatrick has no direct conflicts with any aspects of this manuscript, but has consulted for the Zoll Medical, 3M Acelity, and Innovative Trauma Care Corporations, and is the Principle Investigator of the he COOL trial; Closed or Open after Laparotomy for Source Control Laparotomy in Severe Complicated Intra-Abdominal Sepsis (https://clinicaltrials.gov/ct2/show/NCT03163095.

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