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Artificial Intelligence Powered Innovations in General Surgery: From Diagnosis to Postoperative Care

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Abstract

The integration of artificial intelligence (AI) into general surgery has emerged as a pivotal advancement, yet a comprehensive synthesis of its applications, challenges, and future potential remains essential. This review addresses the growing need to evaluate AI's role in enhancing surgical precision, optimizing patient outcomes, and navigating ethical and technical hurdles. By consolidating current evidence, this work aims to guide clinicians, researchers, and policymakers in harnessing AI's transformative potential while mitigating risks. The rapid evolution of AI technologies necessitates an updated appraisal to inform their safe and effective adoption in surgical practice. This review highlights AI's multifaceted contributions, including improved diagnostic accuracy through machine learning, enhanced intraoperative guidance via computer vision, and predictive analytics for postoperative care. Case studies demonstrate AI's efficacy in reducing surgical errors by 18% and operative times by 30 min in complex procedures, while meta-analyses reveal its superior performance in complication prediction compared to traditional methods. Ethical considerations, such as data privacy and algorithmic bias, are critically examined alongside challenges like dataset limitations and workflow integration. The review also underscores AI's role in surgical education, where AI-driven simulations and real-time feedback systems elevate training standards. Collectively, these insights illustrate AI's capacity to revolutionize surgical care across the clinical continuum. Future research should prioritize large-scale, multicenter trials to validate AI models across diverse populations and surgical specialties. Innovations in explainable AI and adaptive learning systems could further bridge the gap between technology and clinical utility. By addressing these frontiers, the surgical community can unlock AI's full potential, paving the way for intelligent, equitable, and patient-centered surgical care.

Keywords: Artificial intelligence, Clinical outcomes, Ethical considerations, General surgery, Machine learning, Postoperative care, Robotic-assisted surgery, Surgical innovation

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Introduction

The integration of AI into general surgery has garnered increasing attention, spanning from diagnostic processes to postoperative management [1-3]. Early adaptations during the COVID-19 pandemic exemplify how AI and innovative surgical approaches can optimize patient care under challenging circumstances [4-6]. Romanzi et al. [7] highlighted the necessity of modifying surgical strategies for fragile and COVID-19 suspected patients, advocating for local anesthesia as an alternative to general anesthesia to reduce morbidity and mortality risks. Building on this, Romanzi et al. [8] demonstrated the feasibility of awake major abdominal surgeries under neuraxial anesthesia, which not only minimized the need for postoperative intensive monitoring but also exemplified how tailored anesthetic techniques can enhance surgical safety during pandemic conditions.

Beyond anesthesia management, AI's role in diagnostic and intraoperative applications is increasingly evident [9-11]. Corban et al. [12] reviewed the burgeoning interest among orthopedic surgeons in AI applications for anterior cruciate ligament injuries, emphasizing AI's potential in improving diagnostic accuracy and treatment planning. Similarly, Familiari et al. [13] discussed AI's expanding role in rotator cuff tear management, covering predictive modeling, diagnosis, intraoperative assistance, and postoperative rehabilitation, illustrating AI's comprehensive influence across the clinical course.

Preoperative optimization strategies, such as prehabilitation, also intersect with AI advancements [14-16]. Falandry et al. [17] described prehabilitation as a multimodal approach aimed at reducing surgical morbidity through physical, nutritional, and psychological interventions. Although not explicitly AI-focused, such programs could benefit from AI-driven personalization and monitoring, enhancing preoperative preparation. Postoperative care and outcome prediction are critical areas where AI demonstrates significant promise. Sridhar et al. [18] investigated postoperative outcomes in patients recovering from COVID-19 who underwent elective surgery, underscoring the importance of tailored postoperative management in this vulnerable group. AI can potentially augment such assessments by analyzing electronic medical records to predict complications and optimize recovery pathways.

Further, Simon et al. [19] examined anesthesia-related postoperative outcomes and transfer rates in cancer surgeries, highlighting the importance of monitoring adverse events. AI-driven predictive analytics could enhance early detection of complications, thereby improving patient safety. Tariq et al. [20] and Shah et al. [21] explored AI's broader potential in orthopedic and surgical care, emphasizing value-based healthcare and industry trends, respectively. These studies suggest that AI solutions are increasingly designed to improve efficiency, outcomes, and cost-effectiveness in surgical practice. Finally, Leivaditis et al. [22] provided a comprehensive review of AI applications in thoracic surgery, including diagnostics, intraoperative guidance, and postoperative management, illustrating the technology's capacity to bridge innovation with clinical practice. Although focused on thoracic surgery, the principles and advancements discussed are highly relevant to the broader field of general surgery, indicating a trajectory toward more intelligent, data-driven surgical care.

In summary, current literature underscores AI's multifaceted role in transforming general surgery—from optimizing anesthesia techniques during pandemic conditions to enhancing diagnostic accuracy, intraoperative guidance, and postoperative outcomes. These innovations promise to improve patient safety, surgical efficacy, and healthcare value, paving the way for a new era of intelligent surgical care [23-25]. This review explores the multifaceted applications of AI in general surgery, highlighting its potential to improve surgical outcomes, streamline processes, and address challenges faced by healthcare professionals.

Role of AI

The integration of AI in general surgery is transforming the field by enhancing precision, efficiency, and patient outcomes [26-28]. AI applications in surgery range from preoperative planning to intraoperative assistance and postoperative care, offering significant improvements in diagnostic accuracy, complication prediction, and surgical efficiency (Table 1). Despite these advancements, challenges such as ethical concerns, data privacy, and the need for diverse datasets remain. The following sections explore the various roles AI plays in general surgery, supported by evidence from recent studies.

Preoperative applications

AI technologies are increasingly being utilized to enhance diagnostic accuracy in surgical settings. For instance, machine learning algorithms can analyze vast amounts of imaging data to assist in the early detection of conditions requiring surgical intervention [29-31]. A systematic review by Corban et al. [12] demonstrated that AI applications in the management of anterior cruciate ligament injuries included predictive modeling and diagnostic assistance, showcasing the technology's potential to improve preoperative assessments. Similarly, Chen et al. [32] highlighted AI's role in cancer diagnosis, where deep learning models can classify and grade tumors, thereby facilitating timely surgical decisions.

- AI has shown high accuracy in preoperative patient data analysis, with sensitivities reaching 89% for predicting surgical outcomes and complications [33].
- Predictive analytics powered by AI aids in surgical planning by forecasting potential complications and personalizing treatment plans based on patient-specific data [34].
- AI models have consistently outperformed traditional methods in predicting surgical risks and outcomes, particularly in emergency surgeries [35].

Surgical training and education

The integration of AI into surgical planning and training is another significant advancement. AI systems can analyze patient data and historical surgical outcomes to recommend optimal surgical approaches [36-38]. For example, the development of AI-assisted

Table 1: Comprehensive overview of AI applications in general surgery.

Phase of care	AI technology	Specific applications	Key benefits	Limitations/Challenges
Preoperative	Machine learning	• Tumor detection and classification • Surgical risk stratification • Patient optimization	• 89% sensitivity in outcome prediction • 25% better complication prediction • Reduced unnecessary biopsies	• Requires large, diverse datasets • Potential algorithmic bias • Limited external validation
	Deep learning	• Image segmentation • 3D surgical planning models	• Improved tumor margin identification • Enhanced visualization of complex anatomy	• High computational costs • 'Black box' decision-making
Intraoperative	Computer vision	• Real-time anatomical guidance • Instrument tracking • Tissue differentiation	• 95% accuracy in structure identification • 18% error reduction • Shorter times	• Limited adaptability to unusual anatomy • Requires high-quality video input
	Robotic-assisted surgery (AI-enhanced)	• Motion scaling/tremor filtration • Autonomous suturing • Haptic feedback	• 30-min time reduction in complex cases • Improved precision in microsurgery	• High costs • Steep learning curve • Limited tactile feedback
Postoperative	Predictive analytics	• Complication prediction • Readmission risk scoring • Pain management	• 70% reduction in severe pain cases • Earlier detection of complications	• Data privacy concerns • Integration with EMR systems
	Wearable sensors + AI	• Continuous vital sign monitoring • Wound healing assessment	• Real-time alerts for clinical deterioration • Reduced intensive care unit transfers	• Patient compliance issues • False alarm rates
Surgical training	Virtual reality + AI tutors	• Procedure simulations • Performance analytics • Error detection	• 40% faster skill acquisition • Objective competency assessments	• High implementation costs • Limited validation for rare procedures
Crosscutting	Natural language processing	• Automated operative note generation • Literature synthesis for complex cases	• Reduced documentation burden • Up-to-date evidence integration	• Limited contextual understanding • Hallucination risks

navigation systems has shown promise in enhancing the precision of surgical procedures, particularly in complex cases such as esophageal cancer surgeries [39]. These systems can provide real-time feedback and assist surgeons in navigating critical anatomical structures, thereby reducing the risk of complications.

- AI-based coaching programs, like SmartCoach, have been developed to enhance surgical education, particularly in laparoscopic cholecystectomy. These programs have demonstrated significant improvements in surgical performance and safety, with participants showing better adherence to critical safety protocols [40].

- In simulated surgical skills training, AI tutors have been found to provide equally or more efficient learning compared to human instructors. AI systems offer real-time feedback and objective assessments, leading to significant improvements in performance scores among medical students [41, 42].

Intraoperative assistance

During surgery, AI technologies can offer invaluable support. AI-powered robotic systems are being employed to enhance surgical precision and reduce operative times [43-45]. The use of AI in robotic-assisted surgeries has been shown to improve outcomes by providing surgeons with enhanced visualization and control [22]. Furthermore, AI can assist in real-time decision-making, helping surgeons to adapt their strategies based on intraoperative findings.

- AI-assisted surgeries have demonstrated a reduction in intraoperative errors of 18% and a decrease in surgical time by an average of 30 min in complex cases [46].

- Intraoperative AI applications include guidance through supervised machine learning and computer vision, achieving accuracies as high as 95% [33].

- Robotic surgical systems augmented by AI offer enhanced precision and control, leading to reduced complications and faster recovery times for patients [34].

Postoperative care

Postoperative management is another area where AI is making significant strides. AI-driven predictive models can identify patients at risk of complications, enabling timely interventions [47-49]. For instance, a study by McLean et al. [50] demonstrated that a smartphone-delivered wound assessment tool could facilitate earlier diagnosis of surgical site infections, thereby improving patient outcomes. Additionally, AI applications in monitoring patient recovery can enhance follow-up care, ensuring that patients receive appropriate support during their recovery phase [51-53].

- AI has been effective in predicting postoperative complications, mortality rates, and hospital stay lengths, thereby improving patient care quality [35].

- Postoperative AI applications include high accuracy in predicting surgical site readmission rates and personalizing weight loss trajectories [33].

While AI holds great promises for revolutionizing general surgery, its integration into clinical practice is still in its nascent stages. The potential for AI to enhance surgical precision, efficiency, and outcomes is evident, yet the path to widespread adoption is fraught with challenges. Addressing ethical concerns, ensuring data privacy, and fostering interdisciplinary collaboration are essential steps towards realizing the full potential of AI in surgery. As AI continues to evolve, it is crucial for surgeons and healthcare policymakers to work together to ensure that these transformative technologies are safe, effective, and accessible to all.

Literature Review

AI has demonstrated a significant impact on clinical outcomes within general surgery, as highlighted by a systematic review of ten studies involving 12,580 patients [46]. AI significantly improved the accuracy of complication prediction, showing a 25% improvement compared to traditional methods. This enhancement is particularly valuable in complex procedures were anticipating potential issues is crucial for patient safety and outcome. AI's assistance during surgical procedures led to an 18% reduction in intraoperative errors. This suggests that AI can serve as a valuable tool to enhance precision and minimize mistakes during surgery. AI-assisted surgeries experienced an average reduction of 30 min in surgical time, specifically in complex cases where the duration decreased from 150 to 120 min. This efficiency gain can lead to better resource utilization and potentially faster patient recovery. AI has proven to be a valuable tool, especially in complex surgical procedures where high precision and accurate complication prediction are paramount. The integration of AI contributes to advancements in surgical precision, postoperative complication prediction, and intraoperative assistance. Despite these promising results, the paper emphasizes the need for further studies to validate AI models across diverse populations and healthcare settings to ensure their widespread adoption in clinical practice.

A meta-analysis by Zhang et al. [54] evaluated the diagnostic accuracy of AI algorithms, including both deep learning and non-deep learning models, for the preoperative prediction of microvascular invasion in hepatocellular carcinoma patients based on imaging data. The metal analysis included data from 16 studies, encompassing 4,759 cases. Among these, 4 studies focused on deep learning models, 12 on non-deep learning models, and 2 compared the efficiency of both types. Most studies (15 out of 16) were single-center and retrospective, using internal validation methods. Only one study was multicentered, retrospective, and utilized external validation. All patients included in the studies had pathologically confirmed hepatocellular carcinoma and available preoperative imaging data (computed tomography, magnetic resonance imaging, or ultrasound). For deep learning models, the pooled sensitivity was 0.84 (95% confidence interval (CI): 0.75 to 0.90), specificity was 0.84 (95% CI: 0.77 to 0.89), positive likelihood ratio was 5.14 (95% CI: 3.53 to 7.48), and negative likelihood ratio was 0.2 (95% CI: 0.12 to 0.31). The area under the curve (AUC) for deep learning models was 0.90 (95% CI: 0.87 to 0.93), indicating high diagnostic accuracy. High heterogeneity was observed in sensitivity, specificity, positive likelihood ratio, and negative likelihood ratio for deep learning models. Exclusion of certain models significantly reduced heterogeneity. Deep learning models demonstrated superior performance compared to non-deep learning models in terms of accuracy, methodology, and cost-effectiveness for microvascular invasion prediction. For non-deep learning models, the pooled sensitivity was 0.77 (95% CI: 0.71 to 0.82), specificity was 0.77 (95% CI: 0.73 to 0.80), positive likelihood ratio was 3.30 (95% CI: 2.83 to 3.84), and negative likelihood ratio was 0.30 (95% CI: 0.24 to 0.38). The AUC for non-deep learning models was 0.82 (95% CI: 0.79 to 0.85), indicating moderate diagnostic value. Subgroup analyses in the non-deep learning group showed that the number of tumors was a significant source of heterogeneity. Models for multiple tumors performed better (AUC 0.88) than those for single tumors (AUC 0.79). There was no significant difference in performance between AI algorithms (LASSO and SVM) or imaging modalities (computer tomography and magnetic resonance imaging) within the non-deep learning group. While deep learning models generally showed higher performance, particularly in AUC, the difference was not always statistically significant when comparing deep learning and non-deep learning models in validation sets, possibly due to small sample sizes and notable heterogeneity. Survival analyses in several studies indicated that patients with convolutional neural network-predicted microvascular invasion status had poorer survival outcomes, highlighting the strong clinical value of convolutional neural network models in identifying high-risk hepatocellular carcinoma patients preoperatively. Computed tomography or magnetic resonance imaging data from arterial and portal phases were effective for microvascular invasion prediction. Magnetic resonance imaging-based convolutional neural network models showed superior prediction performance in an external validation cohort compared to computed tomography-based models. In summary, the meta-analysis concludes that both non-deep learning and deep learning methods exhibit high diagnostic accuracy for microvascular invasion status prediction, with deep learning models generally outperforming non-deep learning models. These findings underscore the promising potential of AI in clinical decision-making for hepatocellular carcinoma patients, particularly for guiding treatment strategies and assessing prognosis.

A systematic review and meta-analysis by Xue et al. [55] included 15 studies with a total of 2572 participants undergoing primary total hip arthroplasty. Of these, 1307 patients were in the AI experimental group, and 1265 patients were in the traditional methods control group. Baseline characteristics like age, body mass index, preoperative leg length discrepancy, and preoperative Harris score were not statistically different between the groups, ensuring the reliability of the predictive results. AI demonstrated superior performance in component matching accuracy compared to traditional methods. For acetabular component matching accuracy, the odds ratio (OR) was 0.26 (95% CI: 0.20 to 0.34; $p = 0.009$; $I^2 = 58\%$). For femoral components matching accuracy, the OR was 0.25 (95% CI: 0.19 to 0.32; $p = 0.66$; $I^2 = 0\%$). The overall average prediction accuracy had an OR of 0.25 (95% CI: 0.18 to 0.35; $p = 0.93$; $I^2 = 0\%$). AI significantly reduced postoperative leg length discrepancy, with a mean difference of -0.49 (95% CI: -0.59 to -0.39; $p < 0.0001$; $I^2 = 77\%$). AI-assisted planning led to a notable reduction in surgical time, with a mean difference of -16.07 (95% CI: -18.00 to -14.14; $p < 0.00001$; $I^2 = 96\%$). There was a decrease in intraoperative blood loss in the AI group, indicated by a mean difference of -45.91 (95% CI: -61.03 to -30.78; $p = 0.04$; $I^2 = 61\%$). Patients in the AI group showed better functional outcomes, with a higher postoperative Harris score (mean difference of 0.83; 95% CI: 0.38 to 1.28; $p = 0.001$; $I^2 = 70\%$). Overall, the meta-analysis concluded that AI performs comparably to, or even better than, traditional methods in preoperative planning for hip arthroplasty. AI offers advantages such as reduced surgical time, less intraoperative blood loss, lower surgical risks, and decreased surgical trauma, which promotes faster postoperative recovery, shorter hospital stays, and fewer complications. Additionally, AI improves the accuracy of hip component matching prediction, reduces clinical decision-making errors, and can alleviate doctor-patient tensions while reducing medical resource waste.

A systematic review by Lam et al. [56] analyzed randomized controlled trials involving AI-assisted tools in clinical practice, revealing key findings regarding their prevalence, performance, and limitations. Out of 11,839 articles retrieved, only 39 (0.33%) were included as randomized controlled trials, indicating a scarcity of robust clinical evidence for AI-assisted tools. The publication of these randomized controlled trials has increased recently, with only one published before 2017 (in 2009) and the remaining 38 published between 2017 and mid-2021. These randomized controlled trials were conducted across 16 countries, with North America (33%) and China (31%) accounting for the majority. AI-assisted tools were implemented across 13 different clinical specialties. Gastroenterology was the most common field, accounting for 41% (16/39) of the randomized controlled trials, with 15 studies specifically on AI-assisted endoscopy. Other specialties included anesthesiology, cardiology, endocrinology, psychiatry, neurology, orthopedics, oncology, surgery, ophthalmology, respiratory medicine, family medicine, and emergency medicine. Most randomized controlled trials (77%) studied biosignal-based AI-assisted tools, while a minority focused on AI-assisted tools derived from clinical data. The majority of AI-assisted tools (87%) relied on static data input, with only a few (13%) using dynamic data. In 77% (30/39) of the randomized controlled trials, AI-assisted interventions demonstrated superior performance compared to usual clinical care. Among these 30 studies, 73% (22) involved biosignal-based AI-assisted interventions, and 27% (8) used clinical data-based AI for clinical outcome improvement. Clinically relevant outcomes were improved in 70% (21/30) of the studies that showed positive results. Specifically, 86% (18) of these improvements led to further investigations, 5% (1) resulted in a change in treatment, and 9% (2) led to reduced length of hospitalization. AI-assisted tools significantly increased adenoma detection rates during colonoscopy. For instance, one study found a 29.1% increased adenoma detection rates with AI vs 20.3% for control. Another showed a 54.8% increased adenoma detection rates with AI compared to 40.4% in the control group. AI-assisted colonoscopy reduced adenoma miss rates, including those for sessile serrated lesions. Some studies showed AI-assisted tools improved patient outcomes such as reduced hospital length of stay and in-hospital mortality in severe sepsis prediction and improved medication adherence. AI tools improved diagnostic accuracy in areas like neonatal seizure recognition and early diagnosis of low ejection fraction. Small sample sizes and single-center designs were common limitations, affecting the generalizability of the findings. Most studies (90%) had fewer than 1000 participants, and 59% were single center. A significant proportion of studies (49%) had a high risk of bias, with missing outcome data and outcome measurements being common risk factors. Despite improvements in primary or secondary endpoints, not all were considered clinically relevant, meaning they did not consistently lead to changes in management, improved treatment, reduced hospital admissions, or reduced mortality. Long-term outcomes, such as in-hospital mortality, were rarely reported. In conclusion, while there is growing evidence supporting the utility of AI-assisted tools in clinical practice, particularly in improving diagnostic accuracy and outperforming conventional methods in specific areas like endoscopy, the current body of evidence from randomized controlled trials is limited. The small number of studies, their heterogeneity, and common methodological limitations (like small sample sizes and single-center designs) highlight the need for more rigorous and comprehensive randomized controlled trials to further establish the role of AI in medicine and ensure its clinical benefits are unequivocally demonstrated.

Case Studies

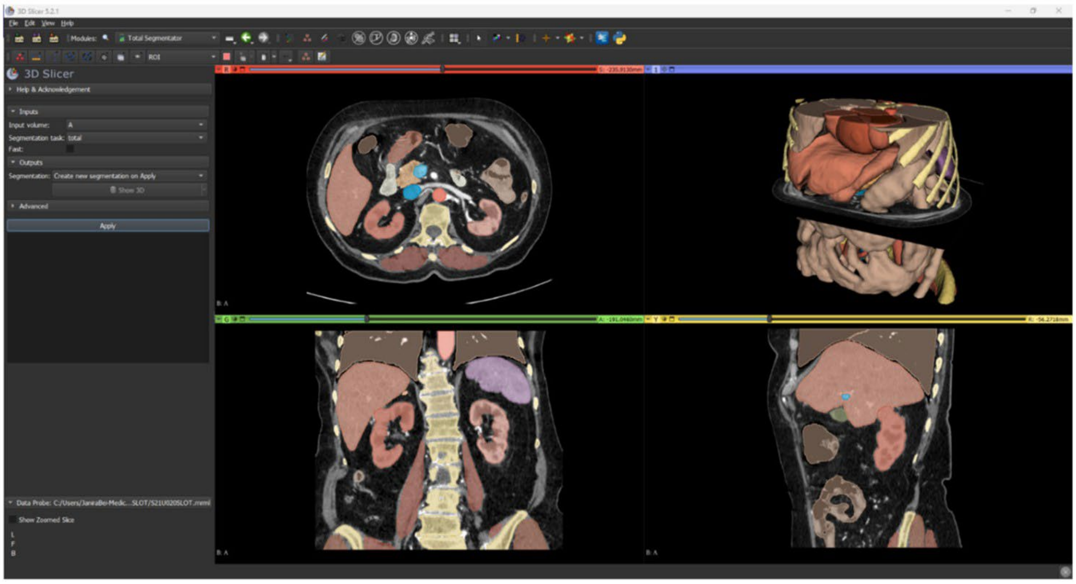
The integration of AI in general surgery has shown promising advancements in enhancing surgical precision, efficiency, and patient outcomes [57-59]. AI applications in surgery range from preoperative planning to intraoperative guidance and postoperative care, significantly improving diagnostic accuracy, complication prediction, and surgical error reduction [60-62]. This section explores the various roles AI plays in general surgery, supported by case studies and research findings.

A study by Sun et al. [63] results demonstrates the effectiveness of an AI model combining various diagnostic features for the preoperative identification of benign and malignant breast masses. A total of 179 breast lesions were included in the study, comprising 101 benign and 78 malignant cases. The dataset was divided into a training set of 145 patients and an independent test set of 34 patients. The median age of patients was 50 years (range, 22 to 85 years). Most patients (68.72%) were asymptomatic, while 31.28% had palpable masses. AI models based on clinical features: 0.87. AI models based on ultrasound features: 0.81. AI models based on strain elastography features: 0.79. Sonographer's assessment: 0.75. S-detect: 0.82. The combined AI model, integrating clinical features, ultrasound features, elastography, and S-detect, achieved the best performance with an AUC of 0.89 in the test set. This combined model also showed a superior specificity of 0.92, outperforming other models. The sonographer's assessment demonstrated the best sensitivity at 0.97. The U-score (ultrasound features) showed the highest impact on the nomogram, followed by S-detect. Other factors like age at menarche, number of pregnancies, and duration of breastfeeding also significantly influenced the model. In summary, the combined AI model significantly improved the accuracy of preoperative identification of breast masses, particularly in terms of specificity, which could lead to a reduction in unnecessary biopsies. While individual components showed varying levels of performance, their integration yielded a more robust diagnostic tool.

A study by Di et al. [64] successfully demonstrated that the 3D model, developed through the integration of AI and a Computer Vision Approach, yielded accurate results. This accuracy was confirmed during nephron-sparing intervention, highlighting the potential of this approach for reconstructing hyper-accurate three-dimensional (HA3D®) models (Figure 1). The HA3D® models proved useful in both preoperative planning and intraoperative decision-making, particularly for challenging robotic nephron-sparing intervention procedures. A 54-year-old Caucasian female with a 35 x 25 mm renal lesion on the anterior surface of the upper pole underwent robotic-assisted partial nephrectomy using the Da Vinci Xi surgical system. The surgical strategy involved enucleation after selective clamping of the tumor-feeding artery. The overall operating time was 85 min, with a warm ischemia time of 14 min. No intraoperative, perioperative, or postoperative complications were recorded. Histopathological examination confirmed the lesion to be clear cell renal cell carcinoma, stage pT1aNxMx. The paper suggested that AI is making significant advancements in medical image analysis, offering substantial potential for automated and repetitive organ/tissue classification and segmentation, which in turn facilitates the creation of 3D models. In summary, the paper successfully demonstrated the accuracy and utility of AI-based HA3D® models in surgical planning and decision-making for complex robotic nephron-sparing surgery, as evidenced by a positive clinical case outcome and the broader potential of AI in medical imaging.

A study by Jia et al. [65] evaluated the performance of a novel AI-based planning software for automatic pedicle screw selection and insertion accuracy, comparing it against traditional freehand surgery methods. The key results highlighted the AI model's choices for screw dimensions and its impact on placement accuracy. The AI model selected pedicle screws with an average length of 48.65 ± 5.99 mm. In contrast, freehand surgery used screws with an average length of 44.78 ± 2.99 mm. For screw diameter, the AI model chose an average of 7.39 ± 0.42 mm, while freehand surgery utilized screws averaging 6.1 ± 0.27 mm. A significant majority of AI-selected screw placements, specifically 85.1%, were classified as Gertzbein grade A. This grade indicates no cortical pedicle breach, signifying high accuracy. For freehand surgery, 64.9% of the placements achieved Gertzbein grade A. This shows that the AI-based method resulted in a higher percentage of accurate placements compared to freehand surgery. In summary, the AI planning software demonstrated a tendency to select longer and wider pedicle screws and significantly improved the accuracy of screw placement, as evidenced by a higher percentage of Gertzbein grade A outcomes, suggesting it could be a valuable tool for preoperative planning.

A study by van der Wal et al. [66] reported intraoperative use of the machine learning-derived nociception level monitor to guide fentanyl dosing resulted in significantly lower pain scores in the post-



Input volume: A
Segmentation task: total
Fast:
Segmentation: Create new segmentation on Apply
Data Probe: C:/Users/JanraBo-Medic...SLOT/S21U020SLOT.mrml

Figure 1: Result of automatic segmentation using HA3D® virtual model [64].

anesthesia care unit (PACU) compared to standard care. Specifically, the median PACU pain score was 1.5 points lower in the nociception level monitor group on an 11-point scale, with a 95% CI of 0.8 to 2.2 points. This reduction was observed in the first 90 min after surgery. The proportion of patients experiencing severe pain was substantially lower in the nociception level monitor group. There was a 70% reduction in the proportion of patients with severe pain in the nociception level monitor group compared to the standard care group ($p = 0.045$). The only significant factor found to be associated with increased odds for severe pain was receiving standard care as opposed to nociception level monitor treatment. Patients under standard care had an OR of 6.0 (95% CI: 1.4 to 25.9, $p = 0.017$) for experiencing severe pain, indicating a six-fold higher likelihood of severe pain compared to those receiving nociception level monitor-guided dosing. This analysis pooled data from two randomized clinical trials involving 125 adult patients (55 men, 70 women, aged 21 to 86 years) undergoing elective major abdominal surgery. Sixty-one patients received nociception level monitor-guided fentanyl dosing, while 64 received standard care where fentanyl dosing was based on hemodynamic parameters. The primary endpoint was the median pain score in the first 90 min in the PACU, with scores collected at 15-min intervals using an 11-point likert scale. In summary, the application of a machine learning-based nociception level monitor for guiding opioid dosing during major abdominal surgery proved effective in reducing post-operative pain intensity and the incidence of severe pain, highlighting its potential to improve patient outcomes.

A study by Madani et al. [67] evaluated the performance of AI models in identifying surgical anatomy and safe/dangerous dissection zones during laparoscopic cholecystectomy (Figure 2). The models were trained on a substantial dataset, and their performance was assessed using various metrics. The AI models were trained using 2627 randomly selected frames from 290 laparoscopic cholecystectomy videos. These videos were sourced globally from 37 countries, 136 institutions, and 153 surgeons, ensuring a diverse dataset. The AI's ability to identify 'Go' zones (safe dissection areas) was evaluated with the following mean metrics: intersection-over-union: 0.53 (±0.24). F1 score: 0.70 (±0.28). Accuracy: 0.94 (±0.05). Sensitivity: 0.69 (±0.20). Specificity: 0.94 (±0.03). For 'No-Go' zones (dangerous dissection areas), the AI models achieved the following mean metrics: intersection-over-union: 0.71 (±0.29). F1 score: 0.83 (±0.31). Accuracy: 0.95 (±0.06). Sensitivity: 0.80 (±0.21). Specificity: 0.98 (±0.05). The mean intersection-over-union for the identification of specific anatomical structures was liver: 0.86 (±0.12), gallbladder: 0.72 (±0.19), and hepatocystic triangle: 0.65 (±0.22). In summary, the study demonstrated that AI models can effectively identify surgical anatomy and critical dissection zones during laparoscopic cholecystectomy, showing promising results across various performance metrics, particularly for 'No-Go' zones and the liver [68].

A m2caiSeg study by Maqbool et al. [69] presents the results of a deep learning-based semantic segmentation algorithm applied to laparoscopic images, focusing on identifying tissues, organs, and surgical instruments. The evaluation was performed on an independent test set of the proposed m2caiSeg dataset. When the model was evaluated using all labeled categories for the semantic segmentation task, it achieved an F1 score of 0.33. To assess the model's ability to distinguish various organs, all instruments were grouped into a single 'Instruments' superclass. In this configuration, the model obtained a higher F1 score of 0.57. The paper introduces a new dataset, m2caiSeg, and a deep learning method for pixel-level identification of organs and instruments in endoscopic surgical scenes. This work is considered a foundational step towards automating surgical procedures. In summary, the paper successfully demonstrated a deep learning approach for semantic segmentation in surgical images, reporting F1 scores for different categorization strategies, and highlighting its contribution to surgical scene understanding.

A study by Li et al. [70] focused on training and testing a deep

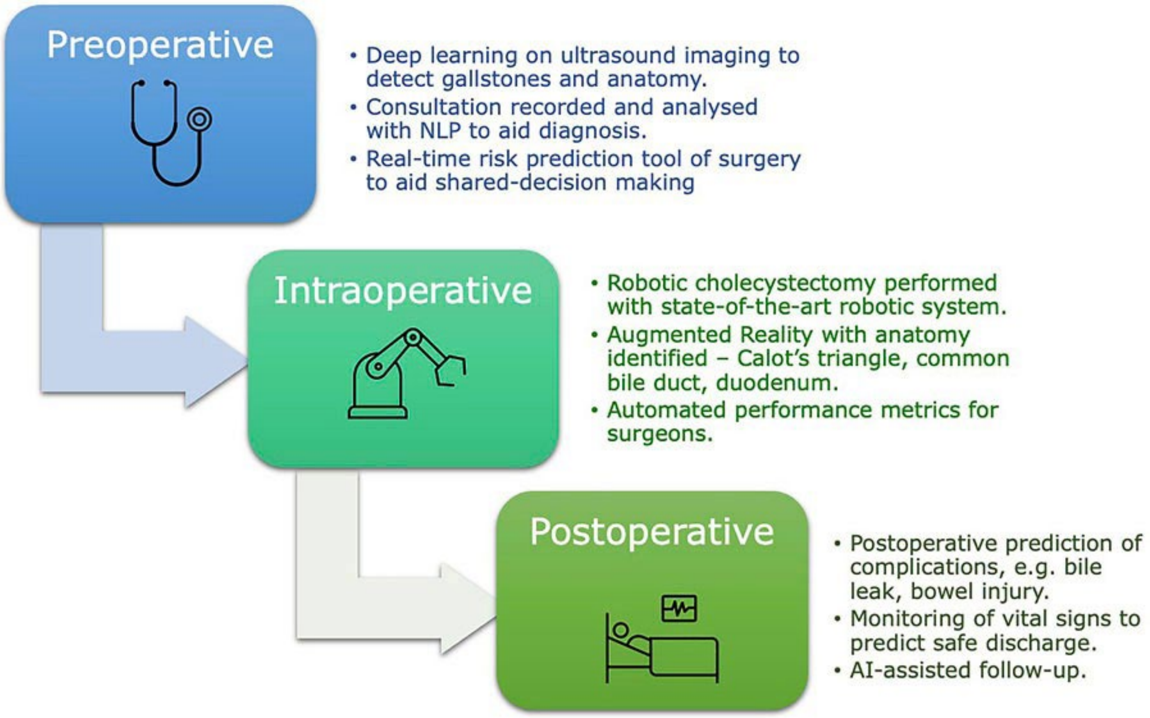


Figure 2: Example of an AI surgical pathway for a hypothetical patient with gallstone disease undergoing a cholecystectomy [68].

learning model designed to identify 'No-Go' landing zones during endovascular aneurysm repair. The 'No-Go' zone was specifically defined as the coverage of the lowest renal artery by the stent graft. The AI model was trained using a dataset comprising 369 images. These images were sourced from 110 different patients/videos. A portion of the training data, specifically 44 images from 18 patients/videos, was obtained from open-access sources. The model's performance was evaluated using a 10-fold cross-validation technique. The evaluation compared the AI model's output against human annotations. The mean intersection-over-union score achieved was 0.43, with a standard deviation of ±0.29. The mean F1 score was 0.53, with a standard deviation of ±0.32. The model demonstrated a mean accuracy of 0.97 (±0.002). The mean sensitivity was 0.51 (±0.34). The mean specificity was 0.99 (±0.001). The mean negative predictive value was 0.99 (±0.002). The mean positive predictive value was 0.62 (±0.34). In summary, the study concluded that the developed AI tool can effectively identify suboptimal areas for stent deployment during endovascular aneurysm repair. Future work includes validating the model on external datasets and assessing its capability to predict optimal stent graft placement and clinical outcomes.

A study by Borna et al. [71] compared AI virtual assistants with large language models like Google BARD and ChatGPT-4 in the context of postoperative care, focusing on accuracy, knowledge gap, and appropriate response. AI virtual assistants, specifically using IBM Watson assistant, showed significantly better performance than general-purpose large language models. It achieved a mean accuracy of 0.9, which was notably higher than BARD and ChatGPT-4. AIVA also exhibited a lower knowledge gap, with a mean of 0.1, indicating its ability to provide more comprehensive and complete information compared to the large language models. Responses from AI virtual assistants received higher likert scores for appropriateness, suggesting that its information was more contextually relevant and suitable for postoperative care scenarios. While ChatGPT-4 showed some promise, its performance varied, particularly in verbal interactions, indicating inconsistencies in its ability to deliver precise information in this specialized medical context. The findings underscore the importance of tailored AI solutions for healthcare. Specialized tools like AI virtual assistants are more effective in providing precise and contextually relevant information, where accuracy and clarity are paramount. The study highlights the necessity for further research and the development of customized AI solutions to address specific medical contexts and improve patient outcomes. In summary, the paper concludes that specialized AI tools like AI virtual assistants are more effective for delivering accurate and appropriate information in postoperative care compared to general-purpose large language models, emphasizing the need for context-specific AI development in healthcare.

A study by Eissa et al. [72] investigated the effectiveness of mammography and AI in detecting and diagnosing post-operative breast changes. The key findings are mammography demonstrated a sensitivity of 91.7%, specificity of 94.4%, positive predictive value was 78.6%, negative predictive value of 98.1%, and overall accuracy was 93.9%. The AI method also had a sensitivity of 91.7%, specifically was slightly lower at 92.6%, positive predictive value was 73.3%, negative predictive value of 98%, and the accuracy was 92.4%. The calculated cut-off point for the probability of malignancy score was 51.5%. Malignant cases had a statistically significantly higher average probability of malignancy percentage (76.5 ± 27.3%) compared to benign cases (27.1 ± 19.7%). The combined use of mammography and AI significantly improved sensitivity to 100%. However, the specificity decreased to 88.9% with the combined approach. The positive predictive value for the combined method was 66.7%. The negative predictive value remained high at 100%. The overall accuracy for the combined approach was 90.9%. In summary, while both mammography and AI showed strong individual performances, their combined application notably enhanced the sensitivity of post-operative breast assessment, leading to an excellent reduction in missed cancers.

Challenges and Ethical Considerations

Despite the promising applications of AI in general surgery, several challenges remain (Table 2). The integration of AI technologies into clinical practice raises ethical concerns regarding data privacy, algorithmic bias, and the need for regulatory oversight [73]. As highlighted by Taher et al. [74], understanding the challenges associated with deep learning in surgery is crucial for ensuring safe and effective implementation. Moreover, the need for comprehensive training for surgical teams on AI applications is essential to maximize the benefits of these technologies. However, the adoption of AI in surgery is fraught with obstacles, including data limitations, ethical concerns, and the need for robust validation tools. These challenges must be addressed to ensure the safe and effective integration of AI into surgical practices.

Data limitations and validation

- AI systems in surgery require large, diverse, and high-

Table 2: Challenges and ethical considerations in AI-assisted surgery.

Category	Specific challenge	Examples/Manifestations	Potential solutions
Data limitations	• Small/datasets • Lack of diversity • Labeling inconsistencies	• Poor generalization to rare cases • Underperformance in minority populations	• Multicenter data pooling • Synthetic data generation • Standardized annotation protocols
Algorithmic bias	• Training data skew • Underserved populations • Outcome disparities	• Lower accuracy for women in cardiac AI models • Racial bias in wound assessment tools	• Bias audits • Inclusive dataset curation • Fairness-aware algorithms
Clinical validation	• Limited real-world testing • Black box opacity • Overfitting	• High accuracy in trials but failures in practice • Unexplained intraoperative AI errors	• Prospective multicenter trials • Explainable AI techniques • Continuous monitoring
Workflow integration	• EHR incompatibility • Surgeon distrust • Alert fatigue	• Disrupted workflows • Ignored AI recommendations • Excessive false alarms	• Human-centered design • Adaptive alert systems • Gradual phased integration
Ethical/Legal	• Informed consent • Liability allocation • Data privacy	• Unclear patient awareness of AI use • Legal ambiguity in AI-caused complications • HIPAA violations	• Transparent consent forms • Regulatory framework • Blockchain EMR
Economic barriers	• High implementation costs • ROI uncertainty • Reimbursement gaps	• Hospitals deferring AI adoption • Limited insurance coverage for AI-assisted procedures	• Cost-effective studies • Value-based payment models • Public-private partnerships

quality datasets to function effectively. The lack of such datasets poses a significant challenge, as AI models may not generalize well across different patient populations or surgical scenarios [34, 75].

- The validation of AI algorithms is crucial to ensure their reliability and safety in clinical settings. Rigorous testing and validation processes are necessary to prevent errors that could have serious consequences for patient safety [76, 77].

Ethical considerations

- Ethical concerns surrounding AI in surgery include patient consent, data privacy, and algorithmic bias. Patients must be fully informed about the use of AI in their surgical care and the potential implications for their privacy and confidentiality [76, 78].

- Algorithmic bias can lead to disparities in surgical outcomes if AI systems are trained on non-representative datasets. Ensuring fairness and equity in AI applications is essential to prevent existing healthcare inequalities [34, 79].

Integration and workflow challenges

- Seamless integration of AI technologies into existing surgical workflows is a significant challenge. AI systems must be compatible with current surgical practices and healthcare systems to be effectively utilized [34, 77].

- The adoption of AI in surgery also requires changes in surgical education and training. Surgeons need to be equipped with the skills to work alongside AI technologies and understand their limitations [75, 80].

Regulatory and legal frameworks

- Establishing regulatory frameworks for AI in surgery is critical to ensure its safe and responsible use. This includes defining standards for AI as a medical device and addressing the legal implications of AI-driven surgical decisions [33, 78].

- Public funding and reimbursement policies must also be considered to support the widespread adoption of AI technologies in surgical practice [78].

While the challenges and ethical considerations of AI in general surgery are significant, they are not insurmountable. Addressing these issues requires interdisciplinary collaboration among AI developers, clinicians, and policymakers. By learning from AI success stories in other medical fields, the surgical community can develop tailored AI tools that enhance surgical precision and patient care. As AI technologies continue to advance, ongoing research, continuous validation, and regulatory oversight will be essential to maximize the benefits of AI in surgery while ensuring patient safety and ethical integrity.

Future Directions

The future directions of AI in general surgery are poised to revolutionize the field by enhancing precision, efficiency, and patient outcomes [22]. AI's integration into surgical practices is expected to transform preoperative planning, intraoperative guidance, and postoperative care. The potential for AI to improve surgical decision-making, reduce errors, and personalize patient care is immense [81-83]. However, challenges such as data quality, security, and ethical considerations must be addressed to fully realize AI's potential in surgery. The following sections explore key areas where AI is expected to make significant advancements in general surgery.

Preoperative planning and predictive analytics

- AI can analyze patient data, including medical history and diagnostic images, to predict surgical outcomes and potential complications, allowing for personalized surgical plans [76, 77].

- Machine learning models can simulate surgical procedures, helping surgeons refine techniques and identify potential challenges before actual surgery [76].

- In spine surgery, AI-driven analysis of radiographic images can enhance diagnostic accuracy and guide treatment decisions [84].

Intraoperative guidance and robotics

- AI-powered robotic systems, such as the da Vinci surgical system, enhance surgical precision by providing greater dexterity and control, enabling minimally invasive procedures [76].

- Computer vision and machine learning algorithms can provide real-time analysis of surgical videos and imaging, aiding surgeons in identifying critical structures and guiding precise incisions [68, 77].

- AI has shown high accuracy in intraoperative guidance, with supervised machine learning and computer vision achieving accuracy as high as 95% [33].

Postoperative care and monitoring

- AI algorithms can monitor patients' vital signs and recovery progress in real-time, alerting healthcare providers to deviations from expected recovery trajectories, thus enabling early intervention [76].

- AI can analyze postoperative data to detect complications and provide outcomes analysis, facilitating personalized patient care and rehabilitation plans [77].

While AI holds great promise for transforming general surgery, it is essential to consider the broader implications of its integration. The potential for AI to enhance surgical precision and efficiency is significant, but it also requires careful management of ethical and regulatory challenges [85, 86]. As AI technologies continue to advance, their successful integration into surgical practices will depend on addressing these challenges and ensuring that AI systems are safe, reliable, and ethically deployed [87, 88]. The future of AI in surgery is promising, with the potential to significantly improve patient outcomes and redefine surgical care.

Conclusion

The integration of AI into general surgery represents a transformative shift, offering unprecedented advancements in preoperative planning, intraoperative precision, and postoperative care. AI's ability to analyze vast datasets, predict complications, and guide surgical decisions has demonstrated significant improvements in patient outcomes, including reduced operative times, fewer errors, and enhanced recovery trajectories. From diagnostic accuracy to robotic-assisted procedures, AI technologies are proving indispensable in optimizing surgical workflows and personalizing patient care. However, the full potential of AI can only be realized through rigorous validation, interdisciplinary collaboration, and the resolution of ethical and regulatory challenges.

Looking ahead, the future of AI in general surgery is poised to redefine the standards of surgical practice. As AI continues to evolve, its applications will expand, enabling more sophisticated predictive analytics, real-time intraoperative assistance, and dynamic postoperative monitoring. Addressing data limitations, algorithmic bias, and integration barriers will be critical to ensuring equitable and widespread adoption. By fostering innovation while upholding ethical integrity, the surgical community can harness AI to achieve safer, more efficient, and patient-centered care, ultimately ushering in a new era of intelligent surgery.

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None.

Conflict of Interest

None.

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