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Review

Artificial intelligence in surgical oncology: A comprehensive review from preoperative planning to postoperative care

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ABSTRACT

While artificial intelligence (AI) has demonstrated significant potential across medical fields, its surgical applications, particularly in oncology remain largely exploratory. This review synthesizes recent advances in AI technologies and their clinical integration within surgery. Preoperatively, AI strengthens planning by increasing risk prediction accuracy, refining imaging analysis, and enabling virtual surgical training, thereby optimizing surgical preparation and safety. Intraoperatively, it facilitates real-time navigation, powers robotic assistance, enables 5G telesurgery, and provides decision support, contributing to enhanced precision and procedural efficiency. Postoperatively, AI-driven monitoring and remote care optimize recovery pathways and complication management, improving outcomes and resource utilization. Despite these advancements, key challenges persist, including data bias, the "black-box" problem, privacy concerns, model generalizability, and real-time processing constraints. Interdisciplinary collaboration, robust ethical frameworks, and sustained technical refinement are essential to fully realizing AI's potential. Future progress, driven by technological evolution and deeper multidisciplinary cooperation, is poised to advance the practice of surgical oncology toward greater precision, intelligence, and accessibility, thereby fostering innovation in global healthcare systems.

1. Introduction

In recent years, the development of artificial intelligence (AI) technology has led to significant advancements in various medical fields, particularly in medical imaging and pathology, which have seen major improvements in early disease diagnosis and prevention.[1] AI refers to computer systems designed to perform tasks that typically require human intelligence, such as learning, problem-solving, and decision-making. Numerous studies have indicated that AI can surpass most human medical experts in specific medical cases.[2–4] The adoption of AI in oncological surgery has progressed more slowly than in other medical specialties. Although AI in oncological surgery remains in the early stages of development, future advancements are anticipated to enhance its integration into surgical practice. This integration is estimated to improve surgical outcomes, reduce complications, and consequently enhance both short-term results and long-term prognosis for cancer patients.

Statistics on the annual surgical volume across 194 World Health Organization (WHO) member countries indicate that over 312.9 million surgeries are performed annually, a number that continues to rise with economic growth.[5] The survey also found a correlation between increased life expectancy and higher surgical rates. In recent years, with advancements in medical technology, the development of minimally invasive, precise, and intelligent surgery has emerged as a key goal in global healthcare. Achieving this goal will not only increase treatment efficacy, reduce postoperative complications, and promote wound healing but also improve long-term patient prognosis. AI can be integrated into all stages of the surgical process—preoperative, intraoperative, and postoperative—to improve the entire procedure. This includes enabling more accurate preoperative diagnoses, developing personalized treatment plans in collaboration with clinicians, promoting team coordination, and improving surgical outcomes. The ultimate goal is to strengthen human health by improving surgical team coordination, increasing surgical efficacy, and ensuring precise postoperative monitoring.

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Current applications of AI in surgical oncology include transformative surgeon training,[6] precise preoperative diagnosis and clinical risk prediction,[7] robotic surgery and computer vision (CV) during surgery,[8,9] real-time postoperative monitoring through sensors,[10,11] and patient care throughout the hospital stay,[12] with many other applications under development. AI is profoundly transforming surgical oncology by providing unprecedented diagnostic precision and efficiency, ushering in a new era of precision diagnosis and treatment. This review summarizes the current status of AI applications in surgical oncology, as well as the challenges and dilemmas faced in their implementation, and offers an outlook on their future development in the field.

2. Key artificial intelligence technologies in surgery

AI denotes the design of algorithms and the construction of models to enable machines to perform tasks that typically require human intelligence.[13] Applications of AI in surgery are currently expanding, and in light of ongoing advancements, they are expected to encompass the entire medical management process—from prevention and diagnosis to treatment and rehabilitation. This process mainly involves four key AI technologies and applications, which are described in Sections 2.1–2.4.

2.1. Machine learning and deep learning

Machine learning (ML) involves learning patterns from historical data using algorithms and statistical models to perform complex tasks and data analysis. The core of ML is enabling computers to optimize their performance over large datasets, which is primarily accomplished via three categories of learning: supervised, unsupervised, and reinforcement.[14] Deep learning (DL), a subset of ML, simulates the human brain's information processing through multilayer neural networks, particularly deep neural networks. DL automates feature extraction from large datasets with common architectures, including convolutional neural networks (CNNs), recurrent neural networks, and generative adversarial networks.[15] DL is particularly well-suited to processing large-scale, high-dimensional data, such as images, speech, and text. These capabilities underscore the transformative potential of DL, driving its adoption in surgical oncology. Applications of DL in surgery have recently gained considerable attention. Numerous studies have demonstrated the successful integration of DL into surgery,[16–18] highlighting its potential to revolutionize surgical practices. As AI technology continues to progress, DL is expected to play an increasingly crucial role in the future of medicine.

2.2. Computer vision

CV is a field that enables computers to recognize, process, and analyze visual data using AI techniques such as DL. It holds marked potential in areas involving image or video data.[19] While humans typically perform rough qualitative assessment of visual data (e.g., images and videos), computer algorithms are better suited to fine-grained, objective qualitative and quantitative analyses, offering a more precise alternative to subjective human judgment.[8] Leveraging this capability and the widespread use of DL, CV has entered the surgical field and is evolving in intraoperative data analysis applications. The primary role of CV models is to enhance surgical safety through real-time intraoperative analysis. These models have been shown to assess surgical complexity, evaluate the surgeon's technical skills, provide real-time feedback, aid intraoperative decision-making, coordinate the surgical team, and predict postoperative adverse events.[19,20] For example, Wang et al.[21] developed the DeepSurgery system to evaluate and supervise cataract surgeries. Using 186 standard cataract surgery videos, they trained and validated DeepSurgery on two datasets (50 and 21 videos, respectively). Their study was the first to apply a 3D CNN to cataract surgery. DeepSurgery can extract temporal and spatial features, identify the order of surgical steps, and alert surgeons to errors, enabling real-time supervision and feedback. Future research is likely to leverage larger visual datasets and improved AI algorithms to create more effective models for surgery and medicine. As these models are adopted more widely in clinical practice, strengthening surgeons' ability to perform safer, minimally invasive, and smarter surgeries.

2.3. Robot-assisted surgery

Robot-assisted surgery involves AI-driven robotic systems that use precision robotic arms, real-time image guidance, and other AI technologies to assist surgeons with complex tasks such as minimally invasive manipulation, resection, and suturing during surgery.[22] As surgical techniques advance, minimally invasive and intelligent approaches are becoming increasingly prevalent, contributing to the growing demand for robot-assisted laparoscopic procedures. Compared to laparoscopy, robotic surgery offers technical advantages such as 3D vision, motion scaling, tremor filtering, image stabilization and magnification, ergonomic posture for the surgeon, and the potential for teleassisted surgery.[23] These unique features enable the expansion of robot-assisted surgery across multiple fields. With advances in AI, advanced sensing and imaging technologies, next-generation robotics, and other related fields, robot-assisted surgery is expected to achieve higher levels of intelligence and further transform surgical practices.

The Da Vinci Surgical Robot, developed by Intuitive Surgical Inc., is currently one of the most widely used robotic systems and was the first surgical robotic system approved by the U.S. Food and Drug Administration (FDA) for general laparoscopic surgery.[24] It has applications across various fields, including abdominal surgery, urology, gynecology, and thoracic and cardiothoracic surgery. Despite its technical advantages, the Da Vinci system also has disadvantages, such as high instrument costs, a lack of tactile feedback, and a limited ability to quickly switch instruments during surgery. In addition to the widely used Da Vinci robot, several other FDA-approved or in-trial robotic systems are improving surgical accuracy and safety while advancing the field toward minimally invasive and intelligent procedures. The number of platforms used for robot-assisted surgery is steadily increasing, driven by rapidly evolving technologies that aim to meet the demands of modern smart surgery. The shift from traditional to robot-assisted surgery may represent the future of surgery. However, further research is needed to assess the benefits and drawbacks of robotic systems and determine the optimal use of robot-assisted techniques.

2.4. Natural language processing

Natural language processing (NLP) is a key branch of AI that explores how machines can understand, generate, and process human language by integrating knowledge from fields such as linguistics, computer science, and statistics.[25] Its primary goal is to enable machines to interact with human language as naturally as humans do, encompassing tasks from text comprehension to generation. The capabilities of NLP techniques have significantly improved in recent years with the development of large language models such as GPT-4, BERT, Llama, and Mistral.[26]

In surgery, NLP technology is widely used for recording and analyzing electronic medical records, preoperative diagnosis and planning, intraoperative intelligent assistance, and postoperative follow-up monitoring. Wu et al.[27] developed an NLP-based automated surveillance system to accurately identify patients, assign appropriate surveillance intervals, and proactively follow up after colorectal polypectomy. The study included 47,544 patients in the training and test sets and found that the system increased early diagnosis of precancerous polyps while reducing unnecessary over-testing and easing the workloads of physicians and nurses. The integration of NLP with AI technologies, such as DL, will drive the surgical field toward intelligent transformation and enable smart healthcare delivery through big data and electronic health record (EHR) systems.

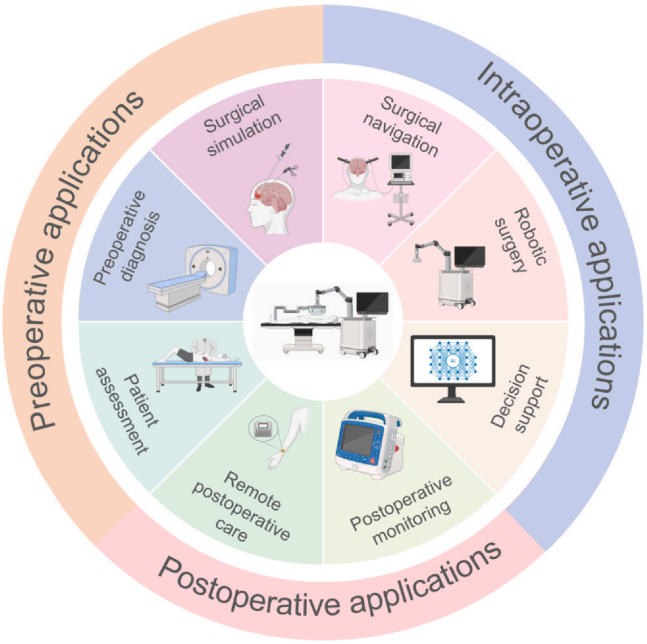


Figure 1. Artificial intelligence in surgical oncology.

3. Artificial intelligence in surgical oncology

With the rapid advancement of medical technology and computer science, AI applications in surgery are undergoing a transformative change. AI is enhancing the precision, efficiency, and safety of surgical procedures, from preoperative assessment and personalized planning to intraoperative navigation and robotic assistance, and postoperative monitoring and recovery guidance (Figure 1). Through advanced technologies such as DL, CV, and NLP, AI supports more accurate decision-making, reduces human error, and improves patient outcomes and postoperative prognosis.[28] This technology is reshaping surgical practice, driving the medical field toward greater efficiency, precision, and safety.

3.1. Preoperative applications

During the preoperative phase, AI is predominantly utilized for patient assessment, surgical planning and simulation, and image analysis. This technology enables clinicians to comprehensively evaluate patients' health status, predict surgical risks, and deliver data-driven decision-making support. The clinical benefits of preoperative AI integration have been extensively demonstrated in multiple studies (Table 1).[29–33] Furthermore, AI can minimize human error, reduce surgical risks, and enable the development of personalized surgical plans through the analysis of preoperative diagnostics and patient data, thereby significantly improving patient outcomes.

3.1.1. Patient assessment and surgical risk prediction

Accurate preoperative patient assessment and surgical risk prediction are essential for personalized treatment decisions. They also support preoperative optimization and resource allocation and enhance perioperative clinical decision-making.[34] AI analyzes the patient's EHR, imaging data, biochemical indicators, and other data to assess overall health and surgical risks. It identifies high-risk patients, predicts potential postoperative complications, and provides valuable decision support to help surgeons develop more effective preoperative treatment plans. For instance, Shad et al.[35] developed an echocardiogram-based ML system to predict postoperative right ventricular failure in patients with left ventricular assist devices. The system achieved an area under the curve of 0.729, significantly outperforming human experts in independent evaluations. In a retrospective study, Jiang et al.[36] developed a multitask DL model to predict peritoneal recurrence and disease-free survival in gastric cancer patients using preoperative computed tomography (CT) images. The model accurately predicts peritoneal recurrence and survival in patients with gastric cancer and helps identify stage II and III patients most likely to benefit from adjuvant chemotherapy. However, these results require prospective verification in future randomized trials to assess the clinical utility of combining the model with clinical pathological criteria for individualized treatment guidance.

The use of AI in predicting surgical risk is still an emerging field. Currently, due to insufficient randomized trials and external validation,

Table 1
Preoperative applications of AI.

Study	Objective	Cases	Results
Yu et al.[29]	To design a machine learning-based MRI radiomics model for predicting preoperative ALN metastasis in breast cancer, aiming to support surgical decision-making	Training cohort (n = 803), external validation cohort (n = 179), prospective-retrospective validation cohort (n = 106)	AUCs of 0.90, 0.91, and 0.93 in the training cohort, the external validation cohort, and the prospective-retrospective validation cohort, respectively.
Bihorac et al.[30]	To develop a machine learning-based preoperative risk assessment model (MySurgeryRisk) for calculating the risk of postoperative complications and death after surgery	Validation cohort (n = 10,291), development cohort (n = 41,166)	MySurgeryRisk calculates probabilistic risk scores for 8 postoperative complications with AUC values ranging from 0.82 to 0.94 and predicts the risk for death at 1, 3, 6, 12, and 24 months, with AUC values ranging from 0.77 to 0.83.
Shi et al.[31]	To develop and validate a web-based AI model for predicting massive blood loss in metastatic spinal surgery for surgical planning and intraoperative decision support	Model development and internal validation (n = 200), external validation cohort (n = 76)	AUC (LR vs. KNN vs. DT vs. XGBM vs. RF vs. SVM = 0.710 vs. 0.821 vs. 0.677 vs. 0.857 vs. 0.826 vs. 0.726) and accuracy (0.627 vs. 0.735 vs. 0.602 vs. 0.771 vs. 0.723 vs. 0.663).
Bian et al.[32]	To develop and validate an AI algorithm using CT for tumor and lymph node segmentation to predict metastasis in pancreatic ductal adenocarcinoma	Training (n = 545) and validation (n = 189)	AUC of 0.92, 0.65, 0.77, and 0.68 in the AI model, the radiologists, the clinical model, and radiomics model.
Xiong et al.[33]	To develop CT-based deep learning models for differentiating benign from malignant renal masses and indolent from aggressive renal masses	Training set (n = 2,400), internal test set (n = 598), external test set (n = 561), prospective test set (n = 610), TCIA test set (n = 388)	The AUC values of the degree of malignancy of kidney tumors reached 0.899, 0.856, 0.871, and 0.881 in the internal test set, external test set, prospective test set, and TCIA test set, respectively. The AUC values for distinguishing between aggressive and noninvasive tumors in the internal test set, external test set, prospective test set, and TCIA test set were 0.792, 0.763, 0.784, and 0.755.

Abbreviations: 1. MRI: magnetic resonance imaging 2. CT: computed tomography 3. AUC: area under the curve 4. ALN: axillary lymph node 5. RF: random forest 6. SVM: support vector machine 7. LR: logistic regression 8. KNN: k-nearest neighbor 9. DT: decision tree 10. XGBM: XGBoosting machine 11. TCIA: The Cancer Imaging Archive.

a high risk of bias remains. Future research should focus on integrating AI models with clinical practice to increase their accuracy and reliability in specific patient populations.[28] As technology advances, AI is expected to play a growing role in surgical decision-making and drive the development of medicine toward greater accuracy and efficiency.

3.1.2. Preoperative diagnosis and imaging analysis

Accurate preoperative diagnosis is key in surgery because it significantly influences clinicians' decision-making and surgical planning. AI-based imaging and diagnosis is one of the most advanced areas in surgical AI, with AI-based imaging and diagnostic models increasingly being integrated into clinical practice.[37] Traditional medical image analysis relies on manual visual inspection and interpretation by physicians. By contrast, AI employs DL algorithms to automatically analyze medical images for lesion and abnormality detection, thereby enhancing diagnostic accuracy.

The AI-Guided Gastric Cancer Risk Assessment (GRAPE) model utilizes 3D non-contrast CT scans to detect and segment gastric cancer, demonstrating the potential to significantly reduce mortality rates. Studies have demonstrated that the GRAPE model outperforms radiologists in early gastric cancer screening, showing a 21.8% higher sensitivity and a 14.0% higher specificity, particularly for early-stage lesions.[38] In subsequent implementations at two regional hospitals, the GRAPE model achieved detection rates of 24.5% and 17.7%. Among the detected cases, 23.2% and 26.8% were identified as T1/T2 stage cancers, respectively. This capability enables the early detection of gastric cancer, thereby improving the overall survival of patients and aiding surgeons in optimizing surgical planning and developing personalized treatment strategies.

Zhang et al.[39] developed a radiomics-driven model, RadioLOGIC, which integrates medical marker cognition. The model extracts omics features from unstructured EHRs and uses transfer learning to assess health status and predict pathological outcomes in breast diseases, thereby enhancing imaging diagnosis. The researchers found that transfer learning outperformed non-transfer learning in predicting pathological results, with an area under the receiver operating characteristic curve (AUROC) of 0.945 vs. 0.912. However, prospective studies are needed to further validate the model's ability to assist in clinical decision-making before its real-world application.

In a multicenter study, a DL model was developed using preoperative multiphase CT imaging.[33] This model noninvasively predicts the severity, invasiveness, and long-term patient survival outcomes of renal tumor malignancy, achieving high AUC values in distinguishing benign from malignant tumors and inert from aggressive subtypes across multiple cohorts. Notably, the AI-aggressiveness score yielded a higher survival prediction C-index than both the Tumor-Node-Metastasis staging and International Society of Urological Pathology grading systems. This approach provides a noninvasive diagnostic tool for precision oncology, enabling surgical decision optimization and facilitating personalized treatment strategy development.

Although AI technology has advanced in imaging, its applications in preoperative diagnosis extend to fields such as endoscopy, histology, genomics, and pathology, providing more accurate support for preoperative diagnosis and tumor staging. Accurate diagnosis and staging help optimize surgical plans, develop personalized treatment strategies, and improve patient outcomes, ultimately enhancing the success of surgical operations.

3.1.3. Surgical simulation and virtual training

Surgical skills are crucial for every surgeon, which makes surgical training a vital component of the field. Surgical training predominantly relies on apprenticeship-based methods. Residents assist in surgical procedures and receive training through hands-on practice. However, during actual procedures, they often perform auxiliary tasks, such as instrument handling, and rarely have the chance to perform surgery themselves. This results in lengthy training cycles and a lack of objective evaluation criteria.[40] AI-assisted virtual surgery is now being used for surgical training. Using virtual reality and augmented reality technologies, surgeons can simulate surgical operations to improve their skills without risk to patients. Additionally, AI can simulate various surgical plans and pathways, allowing surgeons to practice in virtual settings repeatedly, which enhances their judgment and accuracy during actual surgery. This virtual training significantly shortens the training cycle and improves surgeons' ability to manage complex procedures. It also plays a crucial role in ensuring surgical safety, reducing postoperative complications, and promoting patient recovery.

In a randomized clinical trial, researchers developed an AI tutoring system, the Virtual Operative Assistant, which uses ML to assess learners' performance and provide goal-oriented, indicator-based feedback in virtual reality simulations. Compared to remote expert guidance, AI tutor feedback during simulated brain tumor resection was more effective, enhancing students' performance in both practice and real simulation scenarios, and improving surgical quality and skills.[6]

With the ongoing development of AI technology, future surgical training will become more intelligent and personalized, which will in turn improve the professional skills of surgeons worldwide and ensure patient safety during surgery.

3.2. Intraoperative applications

The intraoperative period is a critical phase of surgery that tests surgeons' skills. Furthermore, events during surgery can markedly affect postoperative recovery, complications, and the overall disease outcome. With the ongoing advancement of AI technology, AI is being actively integrated into surgical automation to monitor and integrate patients' overall conditions and local characteristics of tumors, enhance intraoperative decision-making, and improve the practicality of AI in the operating room.

3.2.1. AI-assisted surgical navigation and real-time image guidance

Accurate real-time guidance and visualization are essential throughout the surgical process. Current AI technologies can analyze intraoperative data in real time and provide guidance to surgeons through intelligent navigation systems. Technological advancements, such as CV, allow AI to analyze intraoperative CT, magnetic resonance imaging (MRI), or ultrasound images in real time. This enables accurate localization of critical anatomical structures—such as tumors, blood vessels, and nerves—helping surgeons precisely remove lesions and avoid damage to vital tissues. Additionally, AI-assisted navigation systems can automatically adjust the angle and position of surgical tools, ensuring operational accuracy and reducing the risk of postoperative complications.

Ning et al.[41] proposed a real-time, multi-information fusion image-guided diagnosis and treatment system for high-intensity focused ultrasound. By integrating this intelligent system into commercial high-intensity focused ultrasound equipment, real-time monitoring and automated diagnosis and treatment were achieved, offering a non-invasive, intelligent approach to treating uterine fibroids. Human interpretation of dynamic indocyanine green perfusion angiography may be prone to errors. To address this, Hardy et al.[42] introduced a novel method combining indocyanine green perfusion angiography with ML, reducing manual interpretation errors and enhancing the early detection and diagnosis of conditions such as abnormal blood flow and tumors.

He et al.[43] proposed LSFP-Net, an innovative solution for real-time MRI reconstruction, which reduces imaging time while maintaining image quality, significantly improving real-time monitoring of intraoperative dynamic images and surgical navigation. In a large-scale randomized controlled trial, the AI-customized group demonstrated significantly longer operative parameters than the control group: total surgical time (178 ± 60 min vs. 92 ± 36 min) and radiofrequency duration (42 ± 17 min vs. 20 ± 11 min; both $P < 0.001$).[44]

However, the AI-customized approach achieved a markedly higher treatment success rate (88% vs. 70%; $P < 0.0001$). Postoperative rates of serious adverse events did not differ significantly between groups (4% vs. 3%; $P > 0.05$). These models can be further improved through continuous learning, iteration, and external validation, leading to more accurate real-time image guidance and surgical navigation. Furthermore, interdisciplinary integration is expected to advance the clinical application of these technologies, enhancing their accuracy and reliability in oncological surgery.

3.2.2. Robotic surgery

Robot-assisted surgery is a key application of AI in the field of surgery. It transforms the modern surgical model through the integration of precision electromechanical systems and digital technologies. Its core technical architecture consists of three modules: a multi-degree-of-freedom robotic arm system with submillimeter accuracy, a high-definition 3D imaging platform supporting tissue depth perception, and a motion scaling control system enabling human–machine collaboration.[45] The clinically proven Da Vinci surgical system has demonstrated significant advantages in prostatectomy. Clinical data show that the system reduces intraoperative bleeding by 30%–50%, postoperative infection rates to 2.1% (compared to 8.3% in traditional surgery), urinary incontinence incidence by 40%, and the average hospital stay by 2.3 days.[46,47]

While extensive research has demonstrated that robot-assisted surgery reduces intraoperative complications and significantly decreases short-term postoperative complications, studies have reported inconsistent findings regarding long-term clinical outcomes, with no statistically significant differences observed between robot-assisted and conventional surgical approaches in some trials (Table 2).[48–54] This apparent discrepancy between robust short-term benefits and heterogeneous long-term outcomes may arise from multiple potential biases, including limitations in sample size, heterogeneity in surgical techniques, and variations in follow-up duration/completeness. Notably, many comparative studies possess insufficient statistical power due to limited cohort sizes, thereby reducing their capacity to detect clinically meaningful differences in long-term endpoints such as overall survival and disease-free survival. Furthermore, outcome comparisons are potentially confounded by interinstitutional variations in surgeon expertise, procedural learning curves, standardization protocols, and center-specific practices. Inadequate follow-up intervals or incomplete data collection in certain studies may additionally obscure genuine long-term differences in survival or recurrence rates. Crucially, disparities in adjuvant therapies, baseline patient comorbidities, and postoperative care protocols between compared cohorts could mask or dilute procedure-specific effects on longitudinal outcomes. Therefore, these methodological considerations highlight the necessity for large-scale, prospective, multicenter trials employing standardized techniques, rigorous patient selection criteria, and extended follow-up periods to definitively evaluate the comparative long-term efficacy of robot-assisted surgery.

The application of fifth-generation mobile communication technology (5G) has overcome the geographical limitations of conventional surgery. Surgeons can control robotic arms in real time, 2000 km away, using low-latency (< 10 ms) and high-bandwidth (> 1 Gbps) transmission channels to perform complex surgeries.[55] Marescaux et al.[56] conducted the world's first successful transatlantic robot-assisted remote surgery. It completed a 6200 km remote cholecystectomy between Strasbourg, France, and New York, United States. During this surgery, the intraoperative end-to-end delay was maintained at 155 ms, with instrument operation accuracy reaching 97%. Between June and August 2020, 12 spinal disorder patients underwent telerobotic surgery using the TiRobot system via 5G at Beijing Jishuitan Hospital, China. The maximum master-operating room distance achieved 3154 km, with a mean procedure time of 142.5 ± 46.7 min. Screw placement deviation measured 0.76 ± 0.49 mm (planned vs. actual) with zero intraoperative adverse events. This breakthrough demonstrates AI-assisted telerobotics' potential to address medical resource disparities in developing regions.[57,58]

Zhang et al.'s AI copilot bronchoscopic robot allows novices to conduct bronchoscopic procedures with safety and skill levels comparable to those of expert physicians. This capability addresses medical resource disparities and enhances global health outcomes. The system represents an innovative AI-assisted approach to mitigating medical resource inequity.[59] Building upon these 5G foundations, emerging technologies, including 6G networks, edge computing, and haptic feedback systems, are poised to drive transformative advances. While current 5G provides sufficient latency for basic telesurgery, achieving remote microsurgery requires 6G networks—operating in the terahertz band (0.1–10 THz)—with a theoretical latency below 1 ms. By reducing latency to sub-millisecond levels and enabling real-time tremor compensation, 6G will facilitate previously unattainable microsurgical procedures.[60]

Edge computing addresses core latency instability in cloud-dependent systems through localized data processing within 10 m of the surgical site,[61] while haptic feedback systems transmit tissue resistance as tactile cues to enhance force perception and reduce accidental damage.[62] This milestone will continue to evolve as communication technology improves, achieving lower latency and higher bandwidth, and as surgical robots become lighter and more user-friendly. In the future, as AI algorithms are further integrated and breakthroughs in tactile feedback technology occur, robotic surgery systems are expected to become more intelligent and versatile, promoting the equitable distribution of global medical resources.

3.2.3. Intraoperative AI-assisted real-time decision support

With the development of minimally invasive surgery and precision medicine, surgical procedures now face three key challenges: anatomical complexity, refined operations, and time-sensitive decision-making. The traditional intraoperative decision-making model, which relies on the surgeon's experience and judgment, has limitations such as cognitive bias and delayed information processing.[63] Meanwhile, AI-based real-time decision support systems are transforming surgical decision-making through multimodal data fusion, dynamic risk prediction, and intelligent decision reasoning.[64]

For example, the DL method developed by Vermeulen et al. uses simulated nanopore sequencing data generated from methylation array data to provide accurate molecular subclassification of central nervous system (CNS) tumor types during surgery. This enables accurate and reliable intraoperative diagnosis of CNS tumors, assisting in neurosurgical decision-making, preventing neurological comorbidities, and avoiding additional surgeries.[65] During surgery, AI can analyze and identify abnormalities in real time, dynamically adjusting the surgical plan based on intraoperative data. AI can also predict potential complications and generate emergency decision plans. Intraoperative hypotension is closely linked to postoperative outcomes. The ML-based intraoperative hypotension early warning system provides real-time patient data during surgery, predicts impending hypotension events, and supports clinical decision-making.[66,67]

Ebigbo et al.[68] developed an AI-based clinical decision support system for real-time detection of blood vessels, tissue structures, and surgical instruments during endoscopic submucosal dissection and peroral endoscopic myotomy. This system reduced the time of surgical treatment and the incidence of adverse events by highlighting submucosal blood vessels and other tissue structures. Accurate intraoperative diagnosis is critical for surgical decision-making. The DL model RapidLymphoma, based on self-supervised learning, quickly detects primary CNS lymphoma and differentiates it from common CNS tumors during surgery.[69] The model achieved an overall balanced accuracy of 97.81% ± 0.91%, matching or exceeding the performance of frozen section analysis in detecting primary CNS lymphoma. This high accuracy aids surgeons in making rapid clinical decisions and planning subsequent treatment strategies.

Table 2
Applications of robotic surgery.

Study	Disease	Surgical approach (Cases)	Operation time (min)	Estimated blood loss (mL)	Postoperative complications	Long-term outcomes	Evidence level
Chang et al.[48]	Colorectal cancer with synchronous liver metastases	Robotic rectum resection + liver resection (n = 86) vs. open rectum resection + liver resection (n = 85)	NA	Mean (125.5 vs. 211.6)	31.4% vs.57.6%	3-year DFS rate (39.5% vs. 35.3%), 3-year OS rate (76.7% vs. 72.9%)	RCT
Corrado et al.[49]	Endometrial cancer	Laparotomy (n = 177) vs. laparoscopy (n = 277) vs. robotics (n = 72): hysterectomy + bilateral salpingo-oophorectomy ± lymphadenectomy	Median (120 vs. 100 vs. 115)	Median (200 vs. 100 vs. 100)	Early complications (14% vs. 11% vs. 1%), late complications (4.5% vs. 3.6% vs. 2.7%)	3-year OS rate (86.7% vs. 91.7% vs. 91.5%), 3-year DFS (92.1% vs. 88.4% vs. 91.5%)	Retrospective cohort study
Dhanani et al.[50]	Inguinal hernia	Robotic ventral hernia repair (n = 54) vs. laparoscopic ventral hernia repair (n = 47) ventral hernia repair	NA	NA	13% vs. 9%	2-year hernia recurrence rate (4% vs. 13%)	RCT
Park et al.[51]	Right-sided colonic cancer	Robot-assisted right colectomy (n = 35) vs. laparoscopically-assisted right colectomy (n = 35)	Mean (195 vs. 130)	Mean (35.8 vs. 56.8),	17% vs. 20%	NA	RCT
Nix et al.[52]	Bladder cancer	Robotic (n = 21) vs. Open (n = 20) radical cystectomy	Mean (252.0 vs. 211.2)	Mean (258 vs. 575)	33% vs. 50%	NA	RCT
Catto et al.[53]	Bladder cancer	Robotic (n = 156) vs. open (n = 149) radical cystectomy	Median (295.2 vs. 270.0)	Median (200 vs. 550)	63.4% vs. 67.9%	Cancer recurrence rate (18% vs. 16%), overall mortality (14.3% vs. 14.7%)	RCT
van der Sluis et al.[54]	Esophageal cancer	Robot-assisted minimally invasive esophagectomy (n = 54) vs. open transthoracic esophagectomy (n = 53)	Mean (349 vs. 296)	Median (400 vs. 568)	59% vs. 80%	Recurrence (56% vs. 58%)	RCT

Abbreviations: 1. DFS: disease-free survival 2. OS: overall survival 3. RCT: randomized controlled trial 4. NA: not applicable.

In summary, AI is reshaping surgical models through real-time data analysis and dynamic decision-making, overcoming the limitations of empirical medicine with multimodal fusion and self-supervised learning, significantly reducing intraoperative risks and decision-making delays. Its core value lies in transforming passive responses into proactive prevention and offering clinicians real-time clinical decision support during surgery. In the future, with advancements in edge computing and cross-modal data, surgery will enter an intelligent era characterized by controllable risks and standardized operations. Algorithm interpretability and medical–engineering collaboration will be key enablers of technological implementation.

3.3. Postoperative applications

The intraoperative AI system enhances surgeons' perception and prediction capabilities through real-time analysis of multimodal data streams. More fundamentally, intraoperative AI applications lay a crucial data foundation for postoperative management, which is a critical stage for patient prognosis. Transitioning from the operating room to recovery requires an intelligent computing framework that enables early warnings of subclinical complications through continuous physiological monitoring and expert follow-up care via remote systems. This AI integration, from surgical instruments to mobile terminals, marks a shift from discrete interventions to full-cycle optimization in surgical diagnosis and treatment.

3.3.1. Intelligent postoperative monitoring

Postoperative complications and tumor recurrence are frequently clinically occult and represent primary contributors to mortality.[70] Their early detection has historically been dependent on clinicians' subjective evaluation. However, AI-driven multimodal perception networks are transforming this passive approach into an active, data-enabled defense system. Postoperative physiological parameters are collected through devices such as flexible electronic skin[71] and implantable microsensors.[72] These high-dimensional dynamic data streams are decoded by spatiotemporal graph convolutional networks and Bayesian DL,[73] enabling the detection of subclinical compensation states missed by traditional postoperative complication scores.[74]

The electrocardiogram (ECG) remains a fundamental method in postoperative monitoring. Integrating AI with ECG data has enabled the development of an AI-powered alert system. This system generates automated reports and alerts for physicians, facilitating the identification of patients at high mortality risk. A multicenter randomized controlled trial demonstrated that implementing this AI-ECG alert system was associated with a significant reduction in 90-day all-cause mortality.[75] This AI-driven approach effectively identifies high-risk postoperative patients, facilitates timely interventions, and reduces mortality.

The GSU-Pulmonary Score, a prognostic model for estimating postoperative pulmonary complication risks before elective surgery, predicts the likelihood of pulmonary complications within 30 days post-surgery by integrating ten preoperative clinical variables.[76] The model's AUROC is 0.773 (internal validation) and 0.746 (external validation), with a sensitivity of 93.05%, making it the first preoperative pulmonary risk assessment tool suitable for diverse global environments. Numerous algorithms for predicting postoperative complications have been validated in multiple studies.[30,77,78] This demonstrates that AI-based postoperative complication prediction systems not only enhance prediction accuracy but also enable personalized care through real-time analysis of dynamic data streams, reducing complication rates and improving survival and quality of life. As technology advances, integrating these innovations with clinical practice will be a key challenge.

3.3.2. Remote postoperative surgical care

Traditional postoperative follow-up is constrained by geographical boundaries and limited human resources. Intelligent remote monitoring systems can overcome these limitations and enable personalized medicine.[79] Advancements in sensor technology,[80] wearable devices,[81] and mobile networking[82] have led to the emergence of commercial devices capable of continuously collecting vital signs, physical activity, and health data, including patients' medication dosages and administration times. However, utilizing AI to analyze monitored signals in real time and make corresponding treatment decisions remains a challenge.[83,84] ClinAIOps is an AI-based integrated framework with three feedback loops: patients adjust treatment based on AI output, clinicians use AI to monitor patient progress, and AI developers receive continuous feedback from both patients and clinicians to ensure ongoing treatment adjustments—thus improving patient prognosis.[84]

The integration of AI and continuous monitoring translates directly into postoperative home care, enabling more frequent and accurate measurement of patients' health status and timely adjustment of treatment decisions, facilitating comprehensive and effective patient management. However, the effective monitoring of tumor recurrence necessitates the development of biomarkers possessing superior sensitivity and specificity for its accurate detection. Collectively, the integration of AI technology with remote monitoring systems is transforming postoperative medical management. This innovation signals a shift in postoperative medical and health management toward intelligent, real-time, and precision-based approaches, offering a practical pathway for creating a smart medical system that is both efficient and collaborative.

4. Challenges associated with AI in surgical oncology

AI is advancing at an unprecedented rate in surgery. As the technology matures, AI is poised to become a cornerstone of modern cancer medicine, offering accurate, efficient, and personalized medical services to patients. However, it still faces considerable challenges related to ethics, morality, and technology.

AI models are developed by humans; thus, biases arising from historical or social inequalities often surface during the data input process. Training AI models on clinical trial data with selection bias can result in discriminatory decisions and treatment recommendations. These biased outcomes may lead to unpredictable consequences, eroding trust between patients and clinicians.[85] The WHO's 2024 Guidelines explicitly mandate algorithmic transparency audits and fairness validation for medical AI systems. To effectively address these critical challenges, implementation of the following is essential: diversified training data, established bias-detection mechanisms, and compliance with evolving regulatory frameworks—particularly Article 9 of the General Data Protection Regulation (GDPR), which restricts sensitive health data processing by requiring explicit patient consent and purpose limitation.[86,87] The GDPR stipulates stringent breach notification timelines and substantial financial penalties, necessitating designated data protection officers and privacy-by-design architectures within medical institutions, and clinicians must proactively maintain data integrity while operating within these regulatory constraints.[88–90]

Federated learning is a collaborative ML approach that addresses data privacy concerns by enabling model training on decentralized data without centralization. Using a central coordinator, this approach enables multiple institutions to collaboratively train models while keeping their raw data locally stored. This method has been successfully applied in various healthcare domains, including COVID-19 lung anomaly detection,[91] brain tumor segmentation,[92] and surgical phase recognition.[93] The integration of complementary technologies—including federated learning, blockchain, and distributed systems—enables healthcare institutions to comprehensively address data privacy challenges. The Distributed Cross-Learning for Equitable Federated Models

framework provides a fully decentralized solution for cross-institutional collaboration. It supports privacy-preserving modeling with horizontally or vertically partitioned data across healthcare facilities while ensuring patient data security.[94]

Regarding liability attribution for AI-driven surgical decisions, establishing a three-tier accountability framework may be imperative: AI developers bear accountability for algorithm-related deficiencies, healthcare institutions assume liability for implementation failures, and clinicians maintain responsibility for overriding erroneous AI recommendations. This framework aligns with the WHO's emphasis on human oversight and graduated accountability, requiring statutory revisions to medical malpractice legislation.

Beyond data bias and privacy issues, the "black-box" nature of complex models presents a fundamental barrier to clinical adoption of surgical AI. Although such models frequently achieve high predictive accuracy, their opaque decision-making processes impede clinician comprehension.[95] Surgeons are fundamentally responsible for patient outcomes. When AI systems lack transparency—especially when outputs conflict with clinical experience or lack a clear rationale—clinicians may reject AI recommendations. This trust gap substantially constrains AI's capacity to enhance surgical decision-making.

Current approaches to addressing algorithmic interpretability deficits—including attention mechanisms, post-hoc explanation tools, and model visualizations—can mitigate trust and acceptance issues in high-stakes surgical settings. Integrated into DL architectures, attention mechanisms identify the input regions that are most critical to model predictions.[96] Intraoperatively, this visualizes AI-focused regions in video frames during lesion identification or anatomical structure recognition. After a complex model makes a prediction, post-hoc explanation tools such as Local Interpretable Model-agnostic Explanations and SHapley Additive exPlanations can be applied.[97] These tools approximate model behavior locally for specific predictions, identifying primary contributing input features. This capability is particularly valuable for risk prediction and diagnostic models, elucidating high-risk patient classifications or malignant lesion assessments. Furthermore, saliency maps, activation maps, and feature importance maps visualize model attention patterns and feature prioritization. In image-guided surgery or robotic systems, visualization overlays enhance intraoperative situational awareness and AI guidance trust.[98]

Although promising, these methods may produce approximate or unstable explanations. Balancing model complexity and interpretability remains challenging. Validating the explanation of clinical utility and usability in fast-paced surgical workflows is essential. Future research must focus on developing standardized evaluation metrics for interpretability in medical settings and designing human–AI collaborative interfaces. Such interfaces must integrate interpretable AI insights into surgical cognition while preventing cognitive overload. Therefore, clinically meaningful interpretability is essential for bridging the trust gap and realizing AI's full potential in surgery.

On a technical level, clinical applications of surgical AI still face numerous challenges. First, the acquisition of high-quality, multimodal surgical data is restricted due to privacy concerns, and anatomical differences and rare cases limit the model's ability to generalize.[99,100] Second, real-time, low-latency image response during surgery requires efficient fusion and spatiotemporal synchronization of multimodal data, supported by lightweight models[101] and edge computing.[102] Finally, the AI system must maintain stability in complex intraoperative scenarios, such as bleeding and perforation, and address practical issues such as integration of multiple hardware devices and high development costs. Interdisciplinary collaboration and technological innovation are required to overcome these challenges and ensure the safe integration of AI technology into clinical practice.

5. Conclusions

The rapid advancement of AI is fundamentally reshaping surgical oncology by enhancing the accuracy and efficiency of the entire surgical care continuum, including preoperative planning, intraoperative execution, and postoperative management. Driven by core technologies such as ML, CV, robot-assisted surgery, and NLP, AI has become integral to modern surgical practice and a key enabler of improved surgical safety and patient outcomes.

This review aimed to synthesize current evidence on the applications and implications of AI in surgical oncology. Through a comprehensive analysis of the literature, we examined how AI facilitates tumor diagnosis and staging, supports personalized surgical planning, and enables postoperative risk prediction via multimodal data integration. During surgery, AI-enhanced real-time navigation, robotic platforms, and decision-support systems have been shown to reduce intraoperative errors and complications. The adoption of robotic systems such as the Da Vinci platform, alongside emerging innovations like 5G-enabled telesurgery, signifies substantial progress toward minimally invasive and intelligent surgical care. In the postoperative phase, AI-driven monitoring systems—often coupled with wearable sensors—allow early complication detection and personalized rehabilitation, transcending traditional temporal and spatial constraints and promoting smarter, more precise healthcare delivery.

However, the predominance of retrospective studies and early-stage clinical validation in the current literature may limit the generalizability of the findings. In addition, variability in data quality, annotation standards, and algorithm performance across studies introduces potential bias. The rapid evolution of AI technologies also means that some of the findings presented here may soon be superseded by newer evidence.

These limitations highlight the need for more robust, prospective, and multicenter clinical trials to validate the efficacy and safety of AI technologies in real-world surgical settings. Future research should prioritize overcoming technical challenges, such as poor model generalizability and processing latency, and address ethical and legal concerns related to data privacy, algorithmic bias, and accountability. Interdisciplinary collaboration and health policy reform are essential to ensure equitable access and responsible integration of AI into surgical practice.

In the future, we should vigorously develop convergent technologies, such as AI-nanotechnology platforms for real-time tissue characterization and intraoperative molecular diagnostics during tumor resection, as well as closed-loop brain–computer interfaces for adaptive intraoperative monitoring and feedback. Such innovations have the potential to redefine surgical precision, improve patient outcomes, and ultimately contribute to a new era of intelligent and inclusive surgical oncology.

CRediT authorship contribution statement

Maoyun Liu: Resources, Investigation. **Ai Shen:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Xu Peijun:** Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization. **Miao Liu:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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