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Artificial Intelligence Surgery

Review

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Application and use of artificial intelligence in colorectal cancer surgery: where are we?

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Abstract

AI is revolutionizing the landscape of colorectal cancer (CRC) surgery, permeating diverse facets ranging from intraoperative guidance to predictive modeling of postoperative outcomes. This scoping review aims to comprehensively delineate the breadth of artificial intelligence (AI) applications in CRC surgery. A search of PubMed, Embase, and Ebsco databases up to December 2023 was conducted, with registration in the international prospective register of systematic reviews (PROSPERO) (CRD42024502107). Sixty-two studies meeting stringent inclusion criteria were scrutinized, encompassing AI utilization in CRC surgery or the development of AI-driven tools for colorectal surgical practice. Five principal domains of AI application emerged: (i) Intraoperative guidance, leveraging real-time navigation, indocyanine green (ICG) angiography, and hyperspectral imaging (HSI) to enhance surgical precision; (ii) Image segmentation, facilitating phase recognition, tools recognition, and anatomical identification to optimize surgical visualization; (iii) Training and performance assessment, enabling objective evaluation and enhancement of surgical skills through AI-driven simulations and feedback mechanisms; (iv) Prediction of surgical complications, encompassing prognostication of anastomotic leakage (AL) or stricture, stoma requirements, and prediction of low anterior resection syndrome (LARS) and short-term postoperative complications; (v) Utilization of electronic health records (EHRs), harnessing AI algorithms to streamline data analysis and inform decision-making processes. This review underscores the paradigm-shifting impact of AI in CRC surgery, transcending conventional boundaries and catalyzing advancements across diverse surgical domains. Although many applications are still experimental, as AI continues to evolve, it promises to transform surgical practice, optimize outcomes, and revolutionize patient care. Embracing AI technologies is imperative for colorectal surgeons to remain at the vanguard of surgical innovation and deliver superior outcomes for CRC patients.

Keywords: Artificial intelligence, machine learning, colorectal cancer, colorectal surgery

INTRODUCTION

In recent years, the global landscape of artificial intelligence (AI) has witnessed rapid growth[1]. Driven by breakthroughs in sequencing technologies and computational methods, AI has emerged as a powerful tool for improving precision and accuracy in various fields. In the medical field, AI applications have proliferated, revolutionizing diagnostic imaging analysis, pathology interpretation, disease prognosis prediction, complication prevention, and competency assessment[2]. In addition, AI has been used to improve the quality of medical care.

Machine learning (ML), an important subfield of AI, encompasses a variety of data-driven techniques. These algorithms use historical data to gain knowledge and make predictions. Over time, they self-improve, increasing the accuracy of their predictions as they encounter more information[3]. ML can be broadly categorized into three groups. In supervised learning, algorithms trained on labeled data sets map input to output, enabling predictions to be made on unseen data. Common examples include logistic regression (LR), support vector machines (SVMs), and neural networks. In unsupervised learning, algorithms operate on unlabeled data and discover patterns and relationships without explicit guidance. Techniques such as k-means clustering, hierarchical clustering, and principal component analysis (PCA) fall into this category. Finally, in reinforcement learning, agents learn to make decisions by interacting with an environment and receiving rewards or punishments based on their actions. The goal is to optimize the cumulative rewards over time. Notable reinforcement learning algorithms include Q-learning, deep Q-networks (DQN), and policy gradient methods[4].

Deep learning (DL), a subset of ML, focuses on training artificial neural networks (ANNs) without explicit programming. Inspired by the structure of the human brain, DL mimics the neural connections that facilitate experiential learning[5]. In ANNs, interconnected layers of nodes (neurons) form the backbone of DL. Information flows through each layer, enabling hierarchical representations of data. In terms of Depth and Abstraction, DL's depth enables automatic feature extraction at different levels of abstraction. It mirrors how humans learn from complex data. Finally, in Backpropagation, DL models adjust weights and biases during training based on predicted versus actual results. Accuracy gradually improves, enabling precise predictions.

ML and DL methodologies have been used for some time, but there is a significant lack of confidence and familiarity in healthcare. Among the numerous possible applications, ML and DL techniques can be applied to large clinical datasets for the development of robust models. The learning methods offer tremendous potential to enhance medical research and clinical care. There are many areas that may benefit from the application of ML techniques in the medical field, such as diagnosis, management, and outcome prediction[6,7].

Colorectal cancer (CRC) is the third most commonly diagnosed cancer worldwide and the second leading cause of cancer death[8]. AI-guided care can play a pivotal role in clinical practice to improve strategies for screening, diagnosis, and treatment of patients with CRC[9]. These include increasing the effectiveness of screening, and improving the accuracy of diagnostic tools like colonoscopies by reducing rates of missed adenomas[10]. It also improves the performance of radiologic diagnosis[11]. Recently, there has been an exponential increase in publications regarding the use of AI in the surgical treatment of CRC. The aim of the current study was to review the currently available literature on the applications of AI in the surgical treatment of CRC patients, including all ML and DL methods that offer the colorectal surgeon a tool to improve clinical practice.

METHODS

This study was conducted in accordance with the preferred reporting items for systematic reviews and meta-analysis (PRISMA) statement[12]. The scoping review was conducted using the preferred reporting items for systematic reviews and meta-analyses extension for scoping reviews (PRISMA-ScR) guidelines for reporting[13]. The study protocol was registered on the international prospective register of systematic reviews (PROSPERO, registration number CRD42024502107) on 25 January 2024.

Inclusion/exclusion criteria

Inclusion criteria were established using the Patient, Concept, Context (PCC) criteria following the Joanna Briggs Institute methodology for scoping reviews[14]. All papers that used AI as a tool to analyze data specific to CRC surgery were included. Articles that used AI as a direct application to design the approach or perform surgery were included. The following study designs were considered: randomized controlled trials, controlled clinical trials, observational studies (retrospective and prospective), cohort studies, population-based studies, cross-sectional studies, and case-control studies.

Exclusion criteria were nonsurgical articles, reviews, books and book chapters, conference proceedings, and editorials. Articles related to the diagnostic pathway such as screening, endoscopy, and other nonsurgical areas were excluded. Articles in languages other than English were excluded.

Search strategy, study selection and data collection

A review of the published literature until 15 December 2023 was performed in the following databases: PubMed, Embase, and Ebsco. The keywords (including synonyms or equivalent terms) used included "artificial intelligence", "machine learning", "neural network", "deep learning", "computer vision", "natural language" and "colorectal cancer", "rectal cancer", "colon cancer", "CRC" in combination with Boolean operators (AND, OR).

Articles were screened according to the previously described inclusion criteria, and two reviewers independently screened the literature according to the predefined strategy described above. Covidence (Covidence systematic review software, Veritas Health Innovation, Melbourne, Australia) was used to remove duplicates. Two reviewers (F.C. and S.F.) independently screened the titles and abstracts and cross-checked the results of the studies. Disagreements were resolved by a third reviewer (G.S.). Each reviewer extracted the following data variables: title and reference details (first author, journal, year). During the review process, both reviewers independently recorded data in separate databases. To mitigate selection bias, a comparison was conducted at the end. Additionally, manuscripts related to AI applications in colorectal surgery were categorized into five distinct groups based on their primary focus. [i.e., Intraoperative guidance, Image segmentation, Training and performance assessment, Surgical complications prediction, Electronic Health Record (EHR)].

An overview of the study's methodology is provided in Figure 1.

RESULTS

The search identified 5,787 studies, of which 1,264 were automatically removed from Covidence (Covidence

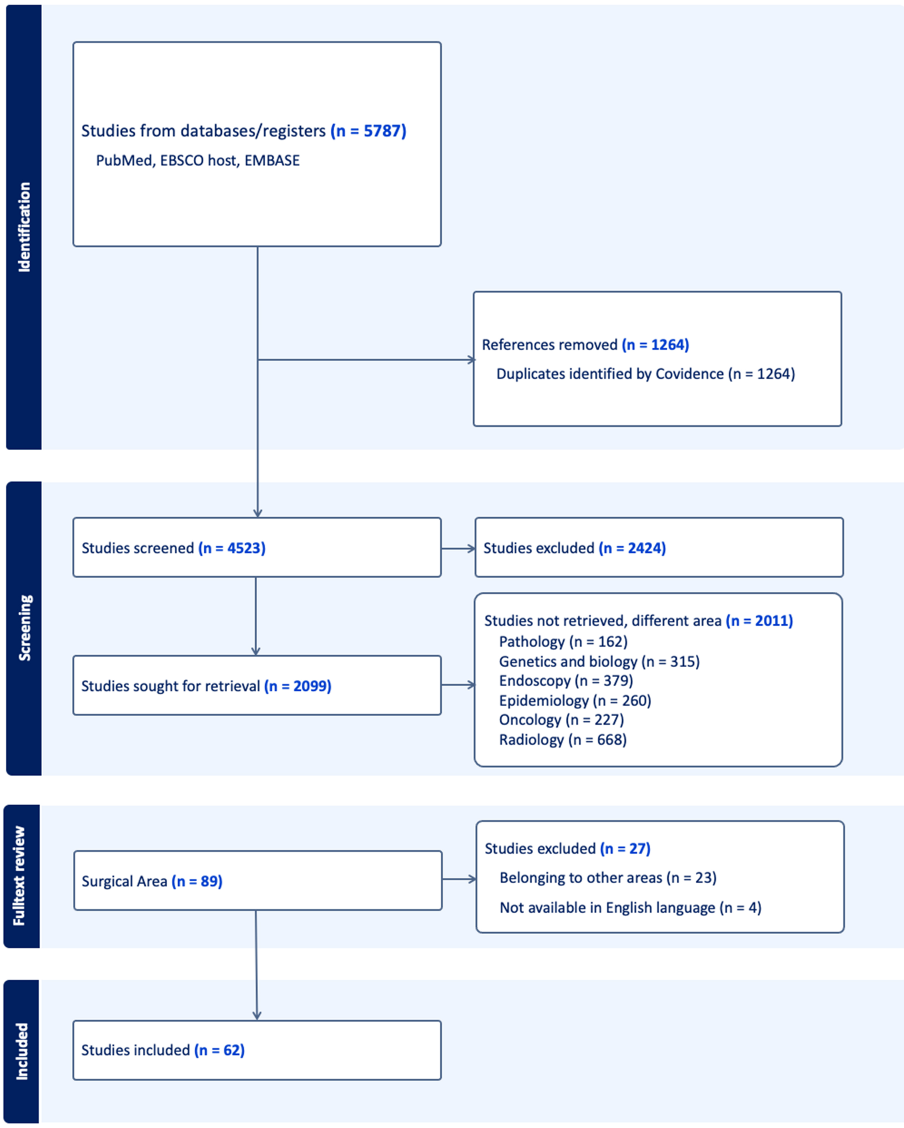

Figure 1. Overview of study selection.

systematic review software, Veritas Health Innovation, Melbourne, Australia) as they were automatically identified as duplicates. Eighty-nine articles were selected for full-text evaluation, and 27 were excluded based on the above exclusion criteria. Finally, 62 studies were included.

The application of AI to the surgical treatment of CRC or the analysis of surgery and its outcomes revealed five primary themes.

Intraoperative guidance

AI-based image recognition has rapidly advanced, nearing human-level capabilities, particularly in minimally invasive surgery (MIS), encompassing both laparoscopic and robotic approaches, to aid surgeons in intraoperative decision making and navigation. In several areas, the use of image-guided surgery has demonstrated significant benefits. For example, in liver surgery during hepatectomy for liver tumors, guidance systems can be used to allow the surgeon to see the tumor and its relationship to major intraparenchymal vascular structures in real time. Similarly, in spine surgery, real-time image-guided procedures have been shown to provide significant benefits in terms of safety and outcomes.

Seven studies were identified, focusing on real-time navigation, indocyanine green (ICG) angiography, and hyperspectral imaging (HSI) [Table 1] during colorectal surgeries.

Real-time navigation

Several models employing DL algorithms demonstrated high detection rates (ranging from 66% to 100%) for identifying nerve structures during sigmoid and anterior rectal resections[15-17] Kitaguchi *et al.* and Kojima *et al.* additionally observed that the models outpaced surgeons in nerve identification in over 50% of cases[15,16].

ICG-angiography

The application of AI in fluorescence laparoscopic systems for intraoperative angiography using ICG enables the prediction of hypoperfusion-related complications, such as anastomotic leakage (AL)[18]. Park *et al.* developed an AI-based real-time analysis of microcirculation system employing ANNs to interpret fluorescence curves, achieving an F1 score of 0.75 in discriminating well-vascularized from poorly vascularized intestinal tissue[18].

HSI

HSI offers contrast-free optical imaging, enabling quantitative assessment of physiological tissue parameters and visualization of anatomical structures. In colorectal surgery, HSI provides valuable insights into tissue composition, oxygenation levels, and metabolic activity, aiding in precise interventions and complication mitigation.

The included papers utilize operative and specimen images taken outside of the surgical piece, and thus, the application of these models is usable intraoperatively.

Okamoto *et al.* proposed a convolutional neural network (CNN)-based model to differentiate colic and mesocolic tissues from retroperitoneal tissues in pigs, achieving high sensitivity (86.0% ± 16.0%) and F1 score (0.90 ± 0.11) for colon-mesocolon discrimination[19]. Moreover, several studies utilized ML algorithms for HSI image analysis, achieving > 90% sensitivity and > 80% specificity in discriminating pathological from healthy tissue in colon specimens[20,21], showcasing the potential for real-time hyperspectral technology integration during colorectal surgery. The use of the HSI can also be aimed at evaluating the resected surgical specimen after extraction, in order to check whether the resection margin can be adequate, as has been effectively demonstrated in several publications. Jansen-Winkeln *et al.* developed a multi-layer perceptron (MLP) model to differentiate CRC from healthy mucosa and adenomas with an accuracy of 94%[22]. Several models have been developed with the same objective, all with excellent results in discriminating between healthy and malignant colon tissue[23-25].

Image segmentation

Semantic segmentation, a groundbreaking image recognition methodology grounded in pixel-level classification, stands as a transformative force in the realm of surgical applications. Its implications span the entire spectrum of clinical processes, including diagnosis, intervention planning, and computer-assisted surgery. However, despite its immense potential, the application of semantic segmentation for organ delineation using intraoperative video presents unique challenges, primarily stemming from the demands of manual annotation and the intricacies of deploying sophisticated automatic segmentation algorithms.

Table 1. Intraoperative guidance

Group	Authors	Year	Model	Objectives
Real-time navigation	Kitaguchi *et al.*[15]	2023	ANN	Ureter and nerves identification
Real-time navigation	Kojima *et al.*[16]	2023	CNN	Nerves identification
Real-time navigation	Ryu *et al.*[17]	2023	DL	Nerves identification
ICG angiography	Park *et al.*[18]	2020	ANN	Microcirculation assessment
HSI	Okamoto *et al.*[19]	2022	CNN	Fat tissue discrimination
HSI	Beaulieu *et al.*[20]	2018	SVM	Pathologic tissue identification
HSI	Manni *et al.*[21]	2020	CNN	Pathologic tissue identification
HSI	Jansen-Winkeln *et al.*[22]	2021	ANN	Pathologic tissue identification
HSI	Collins *et al.*[23]	2022	CNN	Pathologic tissue identification
HSI	Baltussen *et al.*[24]	2019	SVM	Pathologic tissue identification
HSI	Tkachenko *et al.*[25]	2023	CNN	Pathologic tissue identification

ANN: Artificial neural network; CNN: convolutional neural network; DL: deep learning; ICG: indocyanine green; HSI: hyperspectral imaging; SVM: support vector machine.

In the surgical field, semantic segmentation becomes a guiding light for surgeons. By facilitating the real-time identification and delineation of organs and structures, it assists in preoperative planning and intraoperative decision making. This not only enhances surgical precision but also contributes to the overall safety and efficacy of procedures.

Several studies have been identified that have used image segmentation with different objectives: segmentation of entire surgeries with the aim of classifying different stages, or segmentation of specific steps with the aim of creating an algorithm for recognizing anatomical structures (e.g., blood vessels) and dissection planes [Table 2].

Phases recognition

Automated recognition of surgical steps through image segmentation serves multiple purposes, aiding in accurately identifying and localizing different anatomical structures within the surgical field, enhancing understanding of the surgical site, and improving decision making throughout various stages of the intervention. Several algorithms have been developed for automatic stage detection in colorectal surgery. Jalal *et al.* and Kitaguchi *et al.* developed CNN-based DL models for automatic recognition of laparoscopic sigmoid resection phases, achieving overall accuracy rates of 91.9% and 89.4% for extracorporeal action and irrigation recognition, respectively[26,27]. Moreover, Kitaguchi *et al.* devised CNN-based models for video segmentation of transanal total mesorectal excision (TaTME), achieving overall accuracies of 93.2% for main surgical steps and 76.7% for sub-steps[28,29]. Kolbinger *et al.* trained ML models to recognize phases of robotic rectal resection, with their best-performing model achieving a dice similarity coefficient of 0.82 and an accuracy of 0.84[30].

Tools recognition

Automatic recognition of surgical instruments offers several benefits, including standardization of surgical technique, facilitating instrument management in operating rooms, and enabling automatic storage. Kitaguchi *et al.* developed CNN-based models for automatically recognizing surgical instruments commonly used in laparoscopic colorectal surgery, achieving mean average precision rates exceeding 90%[31,32]. In 2021, Maier-Hein *et al.* published the Heidelberg Colorectal (HeiCo) dataset based on images from 30 videos of colorectal surgery for laparoscopic instrument recognition[33].

Table 2. Image segmentation

Group	Authors	Year	Model	Objectives
Phases recognition	Jalal *et al.*[26]	2018	CNN; HMM	Sigmoid resection segmentation
Phases recognition	Kitaguchi *et al.*[27]	2020	CNN	Sigmoid resection segmentation
Phases recognition	Kitaguchi *et al.*[28]	2022	CNN	TaTME segmentation
Phases recognition	Kitaguchi *et al.*[29]	2021	CNN	TaTME segmentation
Phases recognition	Kolbinger *et al.*[30]	2023	CNN	Robotic rectal resection segmentation
Phases and tools recognition	Kitaguchi *et al.*[31]	2020	CNN	Colorectal resection segmentation
Tools recognition	Kitaguchi *et al.*[32]	2022	CNN	Instrument identification
Tools recognition	Maier-Hein *et al.*[33]	2021	CNN	Instrument identification
Anatomy identification	Ryu *et al.*[34]	2023	DL	Vessels recognition
Anatomy identification	Igaki *et al.*[35]	2022	DL	Mesorectal plain identification
Anatomy identification	Kitaguchi *et al.*[36]	2022	CNN	Vessels recognition

CNN: Convolutional neural network; HMM: hidden Markov model; TaTME: transanal total mesorectal excision; DL: deep learning.

Anatomy identification

Ryu *et al.* constructed a DL model to automatically recognize major blood vessels during right hemicolectomy with central vascular ligation, achieving DSC scores of 0.78 for the superior mesenteric vein, 0.55 for the ileocolic artery, and 0.54 for the ileocolic vein[34]. Igaki *et al.* developed a DL model to identify the correct plane for mesorectal dissection during laparoscopic total mesorectal excision (TME), achieving a DSC of 0.84[35]. Additionally, Kitaguchi *et al.* developed a DL model to identify the inferior mesenteric artery during sigmoid resection, achieving a mean DSC of 0.798 and demonstrating potential for real-time surgical use[36].

Training and performance assessment

The segmentation of surgical videos can also be used for educational purposes and evaluation purposes. After the surgery, segmented images can be used for postoperative assessment, allowing surgeons to review the outcomes and identify any issues that may require further attention or intervention. The automatic indexing of documented procedures can be useful for educational purposes, analysis of complications, consultations, patient briefs, and treatment planning.

Image segmentation aids in the creation of realistic 3D models and simulations for training purposes. Surgeons and surgical trainees can practice and enhance their skills in a simulated environment, improving their understanding of the different stages of surgical procedures [Table 3].

Ryu *et al.* successfully applied the DL-Eureka model developed by Kumazu *et al.* for real-time surgical training, demonstrating the safe performance of TME with nerve identification and preservation[37,38]. Kitaguchi *et al.* developed an automatic skill assessment system for purse-string suture in TaTME using a DL-based approach[39]. Moreover, Igaki *et al.*, Kitaguchi *et al.*, and Kolbinger *et al.* devised DL models based on intraoperative videos of laparoscopic colorectal surgery for automatic surgical skill assessment[40-42]. Igaki's model[40] exhibited favorable performance compared to the endoscopic surgical skill qualification system (ESSQS), achieving sensitivity and specificity exceeding 80% and 90%, respectively. Sasaki *et al.* developed a model for laparoscopic tissue handling evaluation using intraoperative videos of laparoscopic colorectal surgery[43]. They trained a ML model to classify pixel RGB values into blood and non-blood, achieving an overall accuracy of 85.7%.

Table 3. Training and performance

Group	Authors	Year	Model	Objectives
Training and performance	Ryu *et al.*[37]	2023	DL	Real-time training for TME
Training and performance	Kitaguchi *et al.*[39]	2023	CNN	Purse-string suture in TaTME
Training and performance	Igaki *et al.*[40]	2023	CNN	Assess surgical skill
Training and performance	Kitaguchi *et al.*[41]	2021	CNN	Assess surgical skill
Training and performance	Kolbinger *et al.*[42]	2023	CNN	Assess surgical skill
Training and performance	Sasaki *et al.*[43]	2023	LR	Tissue handling evaluation

DL: Deep learning; TME: total mesorectal excision; CNN: convolutional neural network; TaTME: transanal total mesorectal excision; LR: logistic regression.

Surgical complications prediction

A total of 34 articles employing AI to predict surgical complications following colorectal surgery were identified.

Anastomotic complications

AL stands as one of the most common and serious complications following CRC surgery, with reported incidences ranging from 3% to 21%[44]. AL significantly impacts patient outcomes, often necessitating prolonged hospital stays, re-operation, and increased mortality rates. Despite efforts to identify risk factors for AL[45], predicting its occurrence remains challenging. Various models, including random forest classifiers[46], regression models[47,48], and ANN-based models[49], have been developed to predict AL risk factors and occurrence. Risk factors identified include tumor distance from the anal verge, T4 stage tumors, male sex, preoperative stenosis, preoperative anemia, massive blood loss, diabetes, hypertension, neoadjuvant radiotherapy, and surgeon volume. Models developed by Adams *et al.*, Shao *et al.*, Baker *et al.*, and Sammour *et al.* demonstrated efficacy in predicting AL occurrence[50-53].

Non-malignant anastomotic stenosis following rectal cancer surgery presents a significant concern, with incidences ranging from 2% to 19%[54,55]. Su *et al.* developed ML models, with random forest exhibiting superior discriminatory and predictive efficacy for predicting anastomotic stenosis[56]. Prophylactic ileostomy, operative time, and AL were found to significantly influence the model [Table 4].

Ostomy prediction after rectal surgery

Temporary or permanent ostomy creation following TME for rectal cancer remains a vital consideration to prevent AL. Shao *et al.* employed SVM models to predict the need for a temporary ileostomy, while Liu *et al.* and Kuo *et al.* identified risk factors using various ML models to predict the necessity for definitive stoma formation after rectal cancer surgery[57-59] [Table 5].

Low anterior resection syndrome

Up to 40% of patients may experience low anterior resection syndrome (LARS) following rectal surgery, adversely impacting quality of life[60]. LR models[61,62] and random forest models[63] have been utilized to predict LARS risk factors, including length of distal rectum, AL, neoadjuvant therapy, presence of diverting stoma, and type of surgery [Table 6].

Early complications after colorectal surgery

Studies investigating AI models for predicting early complications after colorectal surgery encompass a range of algorithms, including LR, neural networks, and random forest classifiers[64-70]. These models, developed by various researchers, utilize clinical risk factors to comprehensively predict postoperative

Table 4. Anastomotic complication prediction

Complication prediction	Authors	Year	Model	Risk factors
AL	Wen *et al.*[46]	2021	RF	Distance from AV, male sex, preoperative stenosis, anemia, blood loss, diabetes, Neoadj CRT, surgeon volume
AL	Shen *et al.*[47]	2023	LR	Hypertension, cT4 stage, intraoperative blood loss > 100 mL, operating time > 160 min, and tumor location
AL	Arezzo *et al.*[48]	2019	LR	Male sex, short-course neoadjuvant RT, T4 tumor, blood transfusion, and tumor distance
AL	Mazaki *et al.*[49]	2021	ANN	pT4, double-row circular stapler
AL	Adams *et al.*[50]	2014	ANN	Main predictors were CRP on POD 4-5, PLT count on POD 1-5, preoperative hemoglobin
AL	Shao *et al.*[51]	2022	RF	Transverse diameter of abdominal cavity (TD), anterior to posterior diameter of abdominal cavity (APD) and visceral fat area (VFA)
AL	Baker *et al.*[52]	2022	ML	*Clostridium difficile* infection
AL	Sammour *et al.*[53]	2017	DT	AL risk calculators evaluation
Non-malignant anastomotic stenosis	Su *et al.*[56]	2023	RF	Prophylactic ileostomy, operative time, AL

AL: Anastomotic leakage; RF: random forest; AV: anal verge; CRT: chemoradiotherapy; LR: logistic regression; RT: radiotherapy; ANN: artificial neural network; CRP: C-reactive protein; POD: postoperative day; PLT: platelet; TD: transverse diameter of abdominal cavity; APD: anterior to posterior diameter of abdominal cavity; VFA: visceral fat area; ML: machine learning; DT: decision tree.

Table 5. Ostomy prediction after rectal surgery

Stoma prediction	Authors	Year	Model	Risk factors
Temporary ileostomy	Shao *et al.*[57]	2023	SVM	Operative time, location of the tumor, preoperative albumin levels, the incidence of diabetes and the electrolyte disorders
Definitive ostomy	Liu *et al.*[58]	2023	XGBoost	Tumor distance from dentate line, advanced age, previous chemoradiotherapy, rectal stricture, diabetes, hypertension
Definitive ostomy	Kuo *et al.*[59]	2023	DT, LightGBM	Distance of the lesion from the anal verge, clinical N stage, age, sex, ASA score, and preoperative albumin and CEA levels

SVM: Support vector machine; XGBoost: eXtreme Gradient Boosting; LightGBM: light gradient-boosting machine; ASA: American Society of Anesthesiologists; CEA: carcinoembryonic antigen.

Table 6. LARS prediction

Complication prediction	Authors	Year	Model	Risk factors
LARS risk	Qin *et al.*[61]	2023	RF, LR, SVM, DT	Length of distal rectum, AL, proximal colon of neorectum (sigmoid/descending), and pathologic nodal stage
LARS risk	Huang *et al.*[62]	2023	LR, SVM, DT, RF, ANN	Distance from the anal verge, presence of diverting stoma, exsufflation, and type of surgery
LARS risk	Wang *et al.*[63]	2023	RF	Anastomotic height, neoadjuvant therapy, presence of stoma, BMI

LARS: Low anterior resection syndrome; RF: random forest; LR: logistic regression, SVM: support vector machines, DT: decision tree; AL: anastomotic leakage; ANN: artificial neural network, BMI: body mass index.

complication rates. Identified risk factors include surgical site infection[71,72], length of stay, readmissions, mortality[73], textbook outcome[74], and conversion from MIS to open surgery[75]. These findings underscore the potential of AI models in predicting surgical complications following colorectal surgery, aiding clinicians in risk assessment and patient management [Table 7].

Table 7. Early complications prediction

Complication prediction	Authors	Year	Model	Risk factors
Early complications	Wang *et al.*[64]	2023	RF	Inflammation-related prognostic index, prognostic nutrition index, tumor location, T stage
Early complications	Lin *et al.*[65]	2022	LR	ASA ≥ 3, ECOG-PS ≥ 2, open surgery, emergency surgery and tumor perforation
Early complications	Wei *et al.*[66]	2023	XGBoost	Distance from the anus, age at diagnosis, surgery time, comorbidities
Early complications	Merath *et al.*[67]	2020	DT	Best performance in prediction of stroke, wound dehiscence, cardiac arrest, progressive renal failure
Early complications	Francis *et al.*[68]	2015	ANN	Non-mobilization on postoperative day 1, development of ileus, and continuation of IV fluids beyond postoperative day 1
Early complications	Manilich *et al.*[69]	2013	RF	Readmission rates, rates of transfusions, SSI: BMI, operative time, identity of the surgeon
Myocardial infarction risk	Liu *et al.*[70]	2023	XGBoost	Advanced age, preoperative and intraoperative tachycardia, BMI ≥ 25 kg/m^2, history of smoking, NLR ≥ 3, CRP ≥ 10 mg/L, intraoperative blood transfusion, intraoperative SPO2 < 90%, operative time ≥ 270 min, and intraoperative bleeding ≥ 100 mL
SSI	Chen *et al.*[71]	2023	ANN	SSI present at the time of surgery, operative time, oral antibiotic bowel preparation, and surgical approach
SSI	Ohno *et al.*[72]	2022	ANN	Length of hospital stay, blood loss, lymphocyte to monocyte ratio, and insulin use
LOS, readmission, mortality	Masum *et al.*[73]	2022	SVM, Bi-LSTM	LOS: age, ASA, operative time. Readmission: age, laparoscopic procedure, stoma performed. Mortality: age, ASA, BMI
Textbook outcome	Ashraf Ganjouei *et al.*[74]	2024	XGBoost	Surgical approach, patient age, preoperative hematocrit, preoperative oral antibiotic bowel preparation
Conversion risk	Guidolin *et al.*[75]	2023	LR, RF	Age, BMI, sex, diabetes, ASA class, wound class, ascites, T stage, weight loss, pneumonia

RF: Random forest; LR: logistic regression; ASA: American Society of Anesthesiologists; ECOG-PS: Eastern Cooperative Oncology Group - Performance Status; XGBoost: eXtreme Gradient Boosting; DT: decision tree; ANN: artificial neural network; SSI: surgical site infection; BMI: body mass index; NLR: neutrophil-to-lymphocyte ratio; CRP: C-reactive protein; SPO2: oxygen saturation; LOS: length of stay; SVM: support vector machine; Bi-LSTM: bidirectional long short-term memory.

EHR

AI has revolutionized the interpretation and utilization of vast amounts of data, particularly within EHRs. EHRs serve as a digital repository of a patient's medical history, encompassing clinical analyses, imaging results, surgical records, laboratory tests, and pathology reports. They aim to enhance patient care quality and safety by providing a comprehensive, accessible, and accurate record for healthcare professionals. EHRs facilitate improved communication, coordination among healthcare providers, informed clinical decision making, and streamlined healthcare processes. Moreover, they offer extensive opportunities for research and clinical practice improvement through automated processes. The automation of EHR data analysis is crucial in clinical settings to distill complex data into actionable insights, thus enabling new avenues for research and development. Several AI models have been developed to analyze EHRs in order to identify and predict the occurrence of complications in patients undergoing colorectal surgery [Table 8]: Ruan *et al.* utilized a Gated Recurrent Unit with Decay based DL architectures and atemporal LR models to predict wound and organ space infections, superficial infections, and bleeding post-surgery[76]. Weller *et al.* achieved an AUROC of 0.86 for bleeding complications on POD2 using various ML models, including random forest[77]. Chen *et al.* designed a GBM model to predict postoperative bleeding risk, identifying risk factors such as anemia, hemophilia, surgery length, heart failure, and kidney disease[78]. Soguero-Ruiz *et al.* developed a Bag-of-Words and SVM-based feature selection model capable of detecting AL occurrence[79]. Jo *et al.* identified an eXtreme Gradient Boosting; (XGBoost) model to predict prolonged length of stay after surgery using EHR data, with main risk factors including surgeon, cooperation, albumin levels, specific surgeries, urinary symptoms, marital status, N stage, and urine white blood cell count[80]. Furthermore, Strömblad *et al.* developed a ML model to predict surgery duration, leading to improved accuracy in

Table 8. EHR

Group	Authors	Year	Model	Objectives
EHR	Ruan *et al.*[76]	2022	RNN	Early diagnosis of complications
EHR	Weller *et al.*[77]	2018	RF	Early diagnosis of complications
EHR	Chen *et al.*[78]	2018	GBM	Early diagnosis of bleeding
EHR	Soguero-Ruiz *et al.*[79]	2016	SVM	AL detection in EHR
EHR	Jo *et al.*[80]	2021	XGBoost	LOS
EHR	Strömblad *et al.*[81]	2021	ML	optimizing operating room time

EHR: Electronic health record; RNN: recurrent neural network; RF: random forest; GBM: gradient boosting machine; SVM: support vector machine; AL: anastomotic leakage; XGBoost: eXtreme Gradient Boosting; LOS: length of stay; ML: machine learning.

predicting case duration and reduced patient waiting time for colorectal surgery[81]. These advancements highlight the transformative potential of AI-driven EHR analysis in enhancing patient care outcomes and optimizing healthcare delivery in CRC surgery.

DISCUSSION

The application of AI in colorectal surgery represents a burgeoning field with significant potential to augment various aspects of surgical practice. This comprehensive review highlights five major areas where AI is making substantial contributions, including intraoperative guidance, image segmentation, training and performance assessment, prediction of surgical complications, and HER analysis. AI-driven image recognition technologies are advancing rapidly, offering surgeons real-time navigation aids during colorectal procedures[81].

These innovations, such as ICG angiography and HSI, provide invaluable insights into tissue perfusion and anatomical structures, aiding in surgical decision making and enhancing patient safety[22,23].

Moreover, DL algorithms have demonstrated remarkable proficiency in identifying nerve structures and anatomical landmarks, surpassing human capabilities in certain instances[19,20].

Despite these advancements, challenges remain in integrating these technologies seamlessly into the surgical workflow and ensuring their reliability in diverse clinical scenarios. Semantic segmentation techniques, facilitated by CNNs, offer precise organ delineation and surgical phase recognition, thereby improving preoperative planning and intraoperative navigation[27,28]. However, the complexity of deploying automatic segmentation algorithms in real-world surgical settings poses significant challenges, including the need for extensive training data and robust validation protocols[30]. Additionally, ensuring the accuracy and reliability of these algorithms across different patient populations and surgical variations requires further investigation.

AI-driven models for surgical skill assessment and performance evaluation offer promising avenues for enhancing surgical training and proficiency[41]. By analyzing surgical videos and extracting relevant metrics, these models provide objective feedback to surgeons and trainees, facilitating targeted skill development and continuous improvement[40,43]. Nevertheless, the generalizability of these models to diverse surgical contexts and the incorporation of subjective elements, such as intraoperative decision making, present notable challenges[37]. Moreover, the reliance on retrospective data and the lack of standardized evaluation criteria limits the applicability of these models in real-time surgical settings.

Predictive models leveraging AI algorithms enable early identification of surgical complications, thereby informing preoperative planning and optimizing patient outcomes[57]. However, the effectiveness of these models hinges on the availability of comprehensive and high-quality data, as well as the accurate identification of relevant risk factors[44]. Moreover, the interpretability of these models and the integration of probabilistic predictions into clinical decision making frameworks require careful consideration and validation in prospective clinical studies.

AI-driven analysis of EHR data holds great potential for enhancing clinical decision making, improving patient outcomes, and advancing research endeavors[76-81]. By automating data analysis and extracting actionable insights from large-scale EHR repositories, AI algorithms enable clinicians to identify patterns, predict outcomes, and personalize treatment strategies[77,79]. Nonetheless, challenges related to data privacy, interoperability, and algorithmic bias necessitate robust governance frameworks and interdisciplinary collaboration to mitigate risks and maximize the benefits of AI in healthcare.

The application of AI models in colorectal surgery has a number of advantages but also current limitations. On the one hand, AI enhances intraoperative guidance, significantly improving decision making and navigation during minimally invasive procedures. Techniques such as real-time navigation and ICG angiography have demonstrated high detection rates of critical anatomical structures, which can lead to safer procedures and better outcomes. HSI further enhances the surgical experience by providing detailed information about tissue characteristics. In addition, AI supports semantic segmentation, enabling accurate identification of anatomical structures and surgical steps, which can improve surgical training and performance evaluation[82].

In the landscape of AI applications in colorectal surgery, several limitations warrant acknowledgment.

Firstly, the inclusion criteria may have introduced selection bias, potentially overlooking relevant studies or emerging technologies. Additionally, the reliance on published literature may have overlooked unpublished studies or ongoing research initiatives, leading to incomplete coverage of the field. Furthermore, the heterogeneity of study designs, patient populations, and outcome measures across the included studies may limit the generalizability of the findings. Finally, the dynamic nature of AI technologies and the rapid evolution of surgical practices necessitate continuous updates and revisions to reflect the latest advancements and insights in the field.

Despite the encouraging outcomes reported in preliminary investigations, significant knowledge gaps remain that need to be addressed. Challenges persist in the deployment of AI models, necessitating rigorous validation and oversight to ensure accuracy, as inaccuracies in image recognition can result in severe complications. Moreover, the incorporation of AI into clinical workflows may require additional training for surgical teams, which could complicate established practices. Ethical concerns surrounding data privacy and the implications of using AI in patient care further complicate matters. Lastly, while AI has the potential to enhance efficiency, its implementation demands considerable investment in technology and infrastructure, which may not be attainable for all healthcare environments. Balancing these advantages and challenges is essential for the successful integration of AI into colorectal surgery. Many preliminary studies have been conducted in the realm of AI and CRC; however, the studies included in this review exhibit significant variability in sample size and presentation methods. This variability impedes meaningful comparisons across studies, particularly in models designed to predict postoperative complications. Consequently, this review is limited to a descriptive summary of the studied methods without a comprehensive evaluation of their actual clinical applicability in practice.

Although, as mentioned above, these models are largely experimental and their clinical applicability is currently undefined, they certainly open the door to the future of surgery, not only in the colorectal field, but with a broader thought, in all branches of surgery. The integration of AI models into minimally invasive and, in particular, robotic surgery will make it possible to perform surgeries with increasing safety, precision and better results. The application of complication prediction models will improve patient selection and treatment management, reduce the occurrence of adverse events, and optimize resources, including economic ones. The training of trainee surgeons is already supported by 3D simulators and AI-modeled video material; in the future, augmented reality will enable further advancements in this training. In the more distant future, automatic real-time recognition of anatomical structures, instruments, and surgical steps will lay the groundwork for a future of autonomous actions in surgery.

However, we remain focused on how AI will be implemented and applied in all clinical settings, with the hope that it will enable an overall improvement in surgical practice in the field of CRC.

CONCLUSION

While AI holds immense promise in transforming colorectal surgery, addressing the aforementioned limitations and navigating the complex interplay between technological innovation, clinical practice, and patient care are essential for realizing its full potential. Collaborative efforts between clinicians, researchers, policymakers, and industry stakeholders are paramount to harnessing the benefits of AI while safeguarding patient safety and advancing the quality of surgical care.

DECLARATIONS

Authors' contributions

Conception and design of the study: Celotto F, Ferrari S
Acquisition, analysis, and interpretation of data: Celotto F, Ferrari S, Capelli G, Scarpa M
Manuscript draft preparation: Celotto F, Capelli G, Scarpa M, Pucciarelli S, Spolverato G
Manuscript review and editing: Celotto F, Ferrari S, Capelli G, Scarpa M, Pucciarelli S, Spolverato G

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Conflicts of interest

Spolverato G is the Associate Editor of the journal *Artificial Intelligence Surgery*, while the other authors have declared that they have no conflicts of interest.

Ethical approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

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