Artificial Intelligence in colorectal surgery: an AI-powered systematic review

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Abstract

Artificial Intelligence (AI) has the potential to revolutionize surgery in the coming years. Still, it is essential to clarify what the meaningful current applications are and what can be reasonably expected. This AI-powered review assessed the role of AI in colorectal surgery. A Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)-compliant systematic search of PubMed, Embase, Scopus, Cochrane Library databases, and grey literature was conducted on all available articles on AI in colorectal surgery (from January 1st, 1997, to March 1st, 2021., aiming to define the perioperative applications of AI. Potentially eligible studies were identified using novel software powered by natural language processing (NLP) and machine learning (ML) technologies dedicated to systematic reviews. Out of 1238 articles identified, 115 were included in the final analysis. Available articles addressed the role of AI in several areas of interest. In the preoperative phase, AI can be used to define tailored treatment algorithms, support clinical decision-making, assess the risk of complications, and predict surgical outcomes and survival. Intraoperatively, AI-enhanced surgery and integration of AI in robotic platforms have been suggested. After surgery, AI can be implemented in the Enhanced Recovery After Surgery (ERAS) pathway. Additional areas of applications included the assessment of patient-reported outcomes, automated pathology assessment, and research. Available data on these aspects are limited, and AI in colorectal surgery is still in its infancy. However, the rapid evolution of technologies makes it likely that it will increasingly be incorporated into everyday practice.

Keywords: Artificial intelligence; AI; colorectal; surgery; risk assessment; radiomics; machine learning

Introduction

Digital surgery has been gaining popularity over the last few years, paralleled by the flourishing of newer technologies applicable to surgery. An expert consensus recently defined digital surgery as “the use of technology for the enhancement of preoperative planning, surgical performance, therapeutic support, or training, to improve outcomes and reduce harm”[1]. Artificial intelligence (AI) can be considered a component of digital surgery, defined as the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings[2]. AI is a diverse field encompassing multiple technologies, which can be divided into two main categories: data-driven AI and knowledge-based AI. Data-driven AI uses large data sets to train models for predictions and decisions, relying on techniques like neural networks, statistical learning, and evolutionary computing, which are typically used in applications where there is a lot of data available such as image and speech recognition, natural language processing, and predictive analytics. On the other hand, knowledge-driven AI uses a formal representation of knowledge, such as ontologies or semantic graphs, to make decisions and inferences using reasoning and logic, and is typically used in applications where data is limited, such as expert systems, decision support systems, and natural language understanding. The main difference between the two is how decisions or inferences are made; data-driven AI relies on patterns from data, while knowledge-driven AI relies on formal knowledge representation. Initially, knowledge-driven methods were developed when large datasets and powerful computers were unavailable. As these limitations have been overcome, the focus in the field has shifted heavily toward data-driven analysis. However, many AI systems in practice use a combination of both methods[3]. The term AI has often been misused in the general and medical literature, leading to exaggerated claims and consequent scepticism. Therefore, it is essential to accurately clarify the current applications of AI to understand how they could evolve in the future.

AI has already been applied in general surgery for diagnostic purposes, for the intraoperative analysis of surgical footage, for automation in the operating room, and for the optimisation of postoperative care[4-6]. Its clinical relevance depends on identifying each task’s human pitfalls and accurately addressing them. Like for the broader field of general surgery, the number of articles providing examples of the application of AI in colorectal surgery is overwhelming and may disguise the research needs in the field.

The aim of this study was to review and appraise the existing literature on AI to define the current state of the art and future applications of this technology in colorectal surgery.

Materials and Methods

A systematic search of PubMed, Embase, Scopus, Cochrane Library databases, and grey literature was conducted, including articles from January 1st, 1997, to March 1st, 2021. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines were followed for conducting and reporting the review[7].

Aims and endpoints

The review aimed to provide information about the applications of AI to the perioperative phases of colorectal surgery and to identify additional areas that could be relevant to colorectal diseases and patients. Studies were assessed for the efficacy of the techniques and methods described and the associated outcomes as available.

Inclusion criteria

All studies on AI in colorectal surgery published in peer-reviewed journals were evaluated for inclusion in the current review. Articles were only included if they did report on human application and if other-than-colorectal surgery specialties were considered unless the data of the colorectal surgery could be identified. Editorials, letters to the editor, correspondence, opinion papers, and narrative reviews were excluded. Cross-referencing was also used.

AI-specific considerations

Ahead of the review, the authors met remotely to identify the AI techniques to be considered. Several areas were identified based on the expertise of the senior authors and available literature on the topic. These were agreed upon by all the members and consisted of data-driven approaches, including Artificial Neural Network (ANN), Bayesian Network (BN), Classification And Regression Trees (CARTs), Deep Convolutional Neural Networks (DCNNs), Decision Trees and Random Forest (DT & RF), Gradient Boosting machine (GB), Machine Learning (ML), and Support Vector Machine (SVM). A detailed description is provided in **Figure 1**. Although it would have probably offered more applications of AI in colorectal surgery, the authors decided not to extend the search to knowledge-driven AI systems, as it would have resulted in more heterogeneous findings.

Research method

The authors entered the search strings, and searches were run on different databases. To expedite the initial screening of abstracts and titles that resulted from the search, the authors relied on Rayyan (http://rayyan.qcri.org), a novel software dedicated to systematic reviews. Rayyan is a cloud-based, multi-tier service-oriented architecture that runs on Ruby on Rails and Heroku. It processes citation files by extracting metadata, such as title and authors, and computing others, such as MeSH terms and language, for each article. These populate the facets in a review workbench to help filter studies. Users can filter studies based on predefined lists of keywords and label citations and define their reasons for exclusion. Citations can also be explored through a similarity graph, and users' decisions can be used to build a model that offers suggestions on studies awaiting screening. The classifier is based on a support vector machine (SVM), and the process is repeated until there are no more citations to label, or the model cannot be improved further[8].

Study Selection

The identified studies were assessed by two authors (FMC, MEL), who double-checked that all potentially eligible studies had been identified and extracted the data. Conflicts between the two authors performing abstract screening, full-text review, and risk of bias assessment were resolved by a senior author (AS).

Data of interest and data extraction

The following data were extracted from each study: 1) AI task, 2) Patient population, 3) Outcome selected, 4) Estimates of the outcome achieved by AI in the study population. A formal quantitative meta-analysis was not planned due to the expected heterogeneity in the study outcomes in this preliminary phase of AI implementation in this field. AI applications have been classified into preoperative, intraoperative, and postoperative phases. When receiver operating characteristic curves were used in an included study, the area under the curve (AUC) value was reported.

Risk of bias and quality of studies assessment

A risk of bias assessment of the included articles has been carried out using the Newcastle-Ottawa Scale for cohort studies, the Appraisal tool for Cross-Sectional Studies (AXIS) tool for cross-sectional studies, the Version 2 of the

Cochrane risk-of-bias tool for randomized trials (RoB 2), the AMSTAR 2 for systematic reviews, and the results are available as **Supplementary Material (Appendix 1)**.

Results

A total of 1238 articles were identified from the search, and 778 abstracts were eligible for screening. Of these, 171 full-text studies were evaluated for inclusion, and 115 were included in the final analysis (**Figure 2**). Articles were then categorised according to their relevance to the preoperative, intraoperative, and postoperative phases (**Table 1**). Additional areas relevant to colorectal surgery were also identified and described separately (outcomes, pathology, and research). **Figure 3** summarizes the potential applications of AI in colorectal surgery, as available from the current literature.

Preoperative phase

Tailored treatment algorithms

Pourahmad et al. [9] used three clustering algorithms based on clinical data for stage prediction in colorectal cancer patients, showing an 85% accuracy in an external evaluation. In 2018 Maheshwari et al. [10] used machine learning and topographical data analysis to automate care path development and monitoring. The unsupervised ML approach help identify specific management strategies and diagnoses associated with positive outcomes in terms of length of stay (LOS), readmission rates, and costs. Curtis et al.[11] used ANN to predict the time interval between diagnosis and surgical treatment of patients to personalize their preoperative care with 90% accuracy. Gao et al. [12] used SL and DL to create a novel colorectal cancer classification framework (the deep cancer subtype, DeepC) based on the analysis of biological pathways activities, showing 80% sensitivity and 90% specificity for molecular subtyping.

The applications of AI to tailored treatment algorithms are summarised in **Table 2**.

Clinical decision support tools

Park et al. [13] proposed a clinical decision support systems (CDSS) based on DL, the Colorectal Cancer Chemotherapy Recommender (C3R). C3R was configured to study the clinical data collected at their Institution and recommend appropriate chemotherapy. They validated the model by comparing treatment concordance rates to the National Comprehensive Cancer Network (NCCN) Guidelines and the Gachon Gil Medical Center's Colorectal Cancer Treatment Protocol (GCCTP) results. The treatment concordance rates of C3R with the NCCN guidelines were 70.5% for Top-1 Accuracy and 84% for Top-2 Accuracy, and with GCCTP concordance was 57.9% for Top-1 Accuracy and 77.8% for Top-2 Accuracy[13].

Aikemu et al. [14] used IBM's Watson for Oncology, a cognitive-support computer program for cancer treatment, and found that the concordances for colon cancer, rectal cancer, or overall were all 91%. The overall rates were 83%, 94%, and 88% in stages II, III, and IV subgroups. When categorized by treatment strategy, concordances were 97%, 93%, 89%, 87%, and 100% for neoadjuvant, surgery, adjuvant, first-line, and second-line treatment groups[14], as compared with a 46.4% concordance of a previous report[15].

Stromblad et al. [16] suggested that ML could predict the duration of surgery[17]. Chaet al. used gene expression data to determine a gene signature that could successfully identify stage I and II colorectal cancer patients at higher risk for recurrence, with a sensitivity of 80% and 91.7%[16].

AI-based decision support tools are reported in **Table 3**.

Preoperative risk assessment

By applying Bayes and SVM models to electronic medical charts, Azimi et al. [18] identified 14 preoperative features that would predict the risk of surgical site infection (SSI) in 208 patients undergoing colorectal surgery. Choiet al. l[19] used SVM to integrate medical records with the American Association for the Surgery of Trauma (AAST) classification system and Modified Hinchey classification as clinical decision-making tools for acute diverticulitis and found that higher AAST grades and Hinchey classes correlated with surgical treatment, LOS, intensive care unit admission. Compared with the modified Hinchey class, the AAST grade better predicted the decision to operate (88.2% vs. 82.4%).

Random forest algorithms have been used by Manilich et al. [20] to build a model that could preoperatively estimate the likelihood and timing of ileal pouch failure. Type of resection, type of anastomosis, baseline diagnosis, and diabetes had the strongest effect on pouch survival[20]. Sammour et al.[21] proposed an online calculator to predict the risk of anastomotic leak after colon cancer resection. Its accuracy was verified with the help of IBM Watson Analytics. Among all the variables evaluated by the AI software, the calculator output and patient age were identified as independent predictors of leak[21].

Francis et al. [22] used MLPNN to predict delayed discharge and 30-day readmission following laparoscopic colorectal cancer surgery. Lack of mobilization on postoperative day 1, ileus, and continuation of intravenous (IV)fluids beyond postoperative day 1 were independent predictors of delayed discharge[22].

The application of ML algorithms resulted in a moderate ability to predict outcomes of pelvic exenteration surgery, even by using more complex ANNs[23].

<u>Preoperative imaging: Radiomics to predict outcome and survival</u>

Joshi et al. [24] used scan segmentation to assess pelvic magnetic resonance imaging (MRI). The maximum average difference between their algorithm and an expert's delineation of the mesorectal fascia was 2 mm[24].

Antunes et al. [25] used a random forests (RF) model that could predict a pathologic complete response (AUC 0.71) by quantifying different aspects of textural image heterogeneity within the primary tumour regions on MRI. Alvarez-Jimenez et al. [26] used radiomics on rectal cancers post-treatment T2-weighted MRI to evaluate pathologic tumour down-staging and identified quantitative measurements of specific heterogeneity patterns and structural distensions of the rectal wall. Yuan et al. [27] built an SVM classifier using the ResNet-3D-SVM algorithm by Ato to predict synchronous peritoneal carcinomatosis.

<u>Preoperative imaging: Radiomics and metastases</u>

Liang et al. [28] showed that the SVM algorithm's predictive performance was superior in incorporating specific MRI sequences.

Meng et al. [29] developed and validated radiomic models capable of evaluating biological characteristics of rectal cancer based on multiparametric magnetic resonance imaging with 73% sensitivity and 56.6% specificity in predicting the *KRAS* gene mutation. Li et al. [30] built a clinical-radiomics model to predict nodal metastases and KRAS status in colorectal patients by combining clinical risk factors with radiomics features on CT images.

Liu et al. [31] developed and validated a model to predict liver metastases in patients with locally-advanced rectal cancer.

Maaref et al. [32] proposed a fully automated framework based on DCNN to predict the response of patients with colorectal liver metastases to FOLFOX with Bevacizumab.

Nakanishi et al. [33] developed a radiomics-based prediction model using CT images to diagnose abnormal lateral pelvic lymph nodes that outperformed traditional parameters.

Lee et al. [34] applied CNN to CT scans of colorectal cancer patients and identified features that could predict liver metastasis.

Intraoperative phase

AI-enhanced surgery

The Heidelberg Colorectal (HeiCo) data set[35] accurately tracked surgical instruments, detected anatomy, and analysed surgical skills. Kitaguchi et al. established the LapSig300 database, containing 300 laparoscopic colorectal surgery videos from multiple Japanese institutions, and evaluated the automatic recognition performance of a CNN model. The overall accuracy for the automatic surgical phase recognition was 81% and 83.2% for action classification task[36,37]. Baltussen et al. combined the intraoperative use of hyperspectral imaging and diffuse reflectance spectroscopy to support vector machines to distinguish normal colon or rectal walls from colorectal cancer tissue[38-40]. Tumour tissue could be distinguished from healthy colorectal walls and fat with 90% sensitivity, 94% specificity, and an accuracy of 94%. Similar results have been obtained by Cahill et al., who assessed dynamic perfusion of indocyanine green in healthy tissue and cancer, with an accuracy of 86.4%[41]. Park et al. [42] generated an AI-based real-time analysis of colonic microperfusion to predict the risk of anastomotic hypoperfusion.

AI and robotic platforms

The Smart Tissue Autonomous Robot (STAR) system, developed at the Johns Hopkins University[43], consists of a bedside lightweight robot arm extended with an articulated laparoscopic suturing tool for a combined eight–degree of freedom robot and equipped with smart imaging technologies. By focusing on small tasks, the STAR could autonomously complete ex-vivo and in-vivo bowel anastomosis in the animal model with equal or better performance than the human counterpart.

Applications of AI relevant to the intraoperative phase are reported in **Supplementary Table 1**.

Postoperative phase

Enhanced postoperative management

Weller et al. [44] used ML to predict postoperative complications and found that AI identified bleeding complications and ileus better than clinical rule sets. Adams et al. [45] utilised an ANN specifically designed to predict which patients were at higher risk of an anastomotic leak before clinical signs of sepsis were present, showing 85% sensitivity and 83% specificity[45]. NLP and Bayesian network analysis were combined by Sohn et al. [46] for the early identification of SSI following colorectal surgery. The algorithm's accuracy was higher when compared with the NLP analysis of clinical notes (AUC=0.827).

Blansit et al. [47] designed a voice-enabled framework to monitor patients in the post-discharge setting through the delivery of structured patient interviews by smart home devices that would alert the physician in cases of potential medical issues requiring medical attention.

Additional areas of AI application to colorectal surgery

Patient-reported outcomes and perception

A Learning-based text mining technique was used by Wagland et al. to analyse free-text comments from a survey of colorectal cancer survivors regarding their experience of living with and beyond cancer[48]. ML algorithms were trained to identify comments relating to patients' specific experiences of service quality, which were verified by manual qualitative analysis. Most negative experiences concerned a lack of post-treatment care and insufficient information concerning self-management strategies or treatment side effects.

Oncologic outcomes

Grumett et al. used ANN and statistic tests to compare data to predict 5-year survival in colorectal cancer patients [49]. ANN accuracy was 77% compared to 66% of the logistic regression model. Gao et al. [50] found data mining inaccurate enough to replace the tumor–node–metastasis (TNM) staging system for colorectal cancer survival prediction. Cowling showed that ML had little to no advantage and that traditional regression approaches may be more familiar to a broad audience[51]. Spelt et al. [52] showed that ANNs could be helpful for the prediction of endograft complications and long-term mortality.

Arostegui et al. [53] used RF and classification and regression trees (CART) 11 modelling approaches to develop and validate a clinical predictive model for 1-year mortality among patients with colon cancer. The AUC of the CART model was 0.896 and 0.835 in the derivation and validation samples. Dimitriou et al. [54] demonstrated the use of ML to improve the accuracy of Stage II colorectal cancer prognosis by digitising tissue samples and, subsequently, quantifying and extracting histological features. Their model achieved AUC of over 77 and 94% for 5 and 10-year prognosis. Using ML, Klepple et al. [53] found that patients with homogeneous chromatin had more favourable survival outcomes than those with heterogeneous chromatin.

Chen et al. [55] performed an SVM with GA to select adjuvant chemotherapy candidate genes and build a predictive model using the gene expression profiles from the Gene Expression Omnibus database. Paredes et al.[56] applied ML to clinical characteristics and morphologic data to predict 1-year (AUC, 0.716), 3-year (AUC, 0.678), and 5-year (AUC, 0.677) recurrence. Lu et al. [57], Xu et al. [58], and Skrede et al. [59] worked on the identification of colorectal recurrence and prognosis markers. Lu et al. [57] found that SVM and RF are the most effective ML methods for predicting FOLFOX response[57]. Xu et al. [58] suggested that light GBM and GBM were the most efficient tools for detecting colorectal cancer recurrence. Skrede et al. [59] constructed 10 CNNs for selecting novel prognostic biomarkers, obtaining 76% accuracy.

Nearchour et al. [60] analysed multiple cellular sub-populations from the microenvironment and identified patients for whom surgical resection alone may be curative. Steenhuis et al. [61] examined the volatile organic compounds in exhaled air through an electronic nose to detect local recurrence or metastases of colorectal cancer, with an overall accuracy of 81%.

*LOS*Zhao et al. were unable to identify ML models comparing their performance to that of the treating physician that can be successfully used to predict LOS[62].

The PelvEx group trained ML models and ANNs to predict LOS with modest to moderate predictive ability[23]. Jo et al. [63] developed an algorithm with ML that performed well for colon cancer (AUC 0.71). Olson et al. [64] used two ML techniques (Least Absolute Shrinkage and Selection Operator, LASSO, and CART) and found that multimodal pain control, limited opioid use, and early mobilization were associated with decreased LOS. Luo et al. [65] developed an immune prognostic model using the Cox survival model with the prognostic differentially expressed immune-related genes.

Pathology

Baltussen et al. [40] found that SVM or NN classifiers combined with non-normalized spectra showed the most accurate strategy to distinguish the healthy colorectal wall from spectra measured on tumour tissue.

Vayrynen et al. [66] analysed the densities of granulocytic cells from 900 tumours using a computer-assisted method. They found that automated immune cell detection and classification demonstrated high concordance with both a pathologist and an independently trained automated classifier. Yamashmita et al. [67] trained and tested a transfer learning model based on MobileNetV2 architecture to accurately classify tissue and MSI status in histopathology slides (AUC 0.93).

Zeng et al. [68] used texture and computer vision-based image features acquired from scattering coefficient maps to differentiate malignant, polypoid, and normal colorectal tissues. Kang et al. [69] showed that by incorporating histopathologic parameters into their LASSO model, results were superior to the clinically accepted diagnostic criteria and patient-demographic model. Kwak et al. [70] showed that tissue cytometry might provide the methodological basis for next-generation digital pathology.

Research

Herrera et al. used data mining to characterize perioperative practices[71]. They found that doctors maintain classical habits and do not put into practice evidence-based changes in the perioperative management of colorectal patients. Wang et al. [72] analysed the landscape of publications on rectal cancer over 25 years by ML and semantic analysis. They found that there has been a considerable increase in the number of publications mainly focusing on surgical intervention, chemoradiation therapy, clinical case management, epidemiology, cancer risk, and prognosis studies, with a relative paucity of studies on basic research, quality of life, and costs. Dong et al. [73] found that most trials on AI for cancer diagnosis are non-interventional, with few multicentre studies.

Discussion

The current review identified several areas where AI has been utilised in colorectal surgery, ranging from perioperative phases to prognostic considerations and outcome assessment. AI can provide a helpful addition, at least for some tasks of colorectal surgery, especially to identify patients at higher risk of developing adverse events in the short or long term and to expedite and facilitate pathology reporting. AI techniques and technologies could offer novel insights and perspectives on the patient’s surgical journey by combining them with specific tools to assess patients’ satisfaction and opinions.

In recent years, widespread availability of technological advancements and an increased attention towards technology have been observed, which has also occurred in the surgical field. Colorectal surgery is no exception, with increasing funding invested in research based on the digitalisation of surgery and AI. However, there need to be more studies providing a practical overview of the actual status of AI, which is relevant to identify the areas that might need further investigation or merit more consideration and investment.

One of the critical aspects of colorectal and general surgery is the choice of the ideal treatment for each patient. ML and deep-learning frameworks have been used to obtain accurate classifications based on molecular data, pathological maps, and molecular imaging data[74,12]. The development of personalised treatment algorithms has been one of the main drivers for AI implementation in medicine and represents a challenge for AI developers. ANN, DT, RF, and SVM are the methods most used for data mining. The accuracy of the AI methods used to develop tailored algorithms seems reasonably high in colorectal surgery, with an accuracy of prediction of tumour features and outcomes ranging between 85 and 90%, even when unsupervised ML was used[9-12]. Of note, AI could predict the estimated treatment costs with practical implications[10].

Clinical decision-making is one of doctors' most challenging tasks, especially in colorectal surgery. AI can play a role in improving the outcomes of patients by assisting surgeons in making more accurate decisions, but it can also be relevant from a medicolegal standpoint[1]. The latter aspect still seems to need further investigation, and the current ethical guidelines of conduct may still need to be adapted to incorporate AI tools utilisation. Concerning cancer care, AI systems have generally focused on obtaining information from unstructured data such as text (using NLP) or large structured datasets (using ML)[14]. CDSS can be used to collect and analyse data in ways that algorithms can use to simulate human reasoning and assist clinicians in the decision-making process, improve healthcare system services, decision timing, and patient quality of life; such systems have the potential to reduce both healthcare costs and medical error rates[17,14]. Specific AI tools could identify patients who might benefit from proactive treatment, e.g., more refined prediction models could support the decision to administer adjuvant chemotherapy to stage I and II colorectal cancer patients[16].

Perioperative surgical complications cause increased costs of care and impact patients' long-term quality of life, sometimes being life-threatening. AI has achieved less optimistic results in preventing adverse events after colorectal surgery when complex and extended surgical procedures are being considered[23]. However, promising findings have been reported on SSI prediction[18], which should not be underestimated, given the burden of such complications on healthcare resources utilisation. Moreover, individualised preparation strategies could be developed[75].

AI applied to radiomics has the potential to revolutionise the treatment algorithm for colorectal cancer patients, especially considering patients with rectal cancer. Being able to accurately predict pathological complete response after neoadjuvant treatment could increase the rate of patients suitable for a watchful surveillance, allowing more successful bowel-sparing management[25,24,26]. On the other hand, AI could identify those patients who might need more intensified follow-up strategies or more aggressive approaches from the beginning[28,29,27].

The applications of AI in the operating room primarily focus on the analysis of intraoperative video to provide real-time, context-aware intraoperative assistance during surgery. The possibility of integrating surgical robots with AI and data-driven technology paves the way for the development of more advanced imaging and ML techniques that will enhance intraoperative decision-making[76,35-37]. Future studies should assess the impact on complications and outcomes of the technologies currently used to assess bowel perfusion intraoperatively[40,38,39,41,42]. Robotic platforms will likely acquire a certain degree of task autonomy, similar to what has already happened in the automotive industry with self-driving vehicles and aviation with modern autopilot systems.

AI could offer new pathways to assess postoperative outcomes and the impact on patients of colorectal surgery, providing novel perspectives and more complex information[48]. This could eventually inform the surgical community of the critical issues that must be tackled to provide adequate and homogeneous treatment to patients globally.

Personnel allocation and healthcare utilisation are critical in colorectal surgery, mainly when a shortage of resources occurs and under pressure (e.g., increased surgical backlog). LOS might not be relevant to patients and is usually influenced by several non-surgical factors; however, obtaining an estimated probability of the need for prolonged or intensive care unit stay might be very relevant, eventually reducing costs and being beneficial for patients[77,64]. In the context of increased efficiency and better cost management, AI can facilitate pathological sample examination, which could expedite definitive diagnosis and subsequent patient management[68].

Lastly, AI could fuel research in colorectal surgery[78]. Robotic platforms and online databases provide an immense amount of data, which, without appropriate handling and advanced analyses, will remain unused, a missed opportunity to advance knowledge. Data from large public databases interpreted with ML algorithms can efficiently identify areas of research that are lacking, characterise studies, deficiencies of research, and possible future directions, contributing to faster development of guidelines and a better understanding of the current practice. However, the practical implementation of AI in colorectal and the broader surgical field has to confront challenges intrinsic to the AI algorithm's functioning mechanism. For example, the "black box phenomenon" is a common challenge of data-driven systems, where the rationale behind the decision-making is not clear to the user, even though the system may have high accuracy. This lack of transparency can make it difficult for users to understand and trust the decisions made by the system, which can limit its application in healthcare.

Another challenge of data-driven systems is that their accuracy is directly related to the quality and quantity of data used to train them. For example, the machine's accuracy may be compromised when limited data is available on less common cases or conditions. Additionally, data-driven systems may not generalize well when the data used to train them is collected from different geographical or cultural regions. For instance, a data-driven approach developed using data on length of stay (LOS) post-surgery in Europe may not accurately predict LOS in a healthcare system in the far east, as the data might not be comparable.

Moreover, even if the data is available, it is essential to consider the quality and the bias in the data; if the data is collected from one population, it might not be generalizable to other populations with different socio-economic statuses, ethnicities, and other demographic factors.

To overcome these challenges, data-driven systems need to be developed with consideration of the quality and relevance of the data, and the transparency of the system's decision-making process should be improved. This can be done by using techniques such as explainable AI (XAI), which aim to make the decision-making process of the AI more interpretable to the user. Furthermore, the data collection process should be designed to address the bias and ensure the data is generalizable to different populations[79].

Although this review is based on a systematic literature search, a meta-analysis could not be performed due to the lack of data. Also, some breakthrough technologies could have been omitted due to the decision to remove all conference papers and book chapters from the study. No assessment of costs was performed, but such data are rarely reported, and findings could have been misleading. The strengths of this manuscript consist of the AI-based strategy used to conduct the review and the practical implications with objective measurement of the outcomes from the currently available literature on the topic. Few studies provide real-world applications and reproducible results. Based on the promising results shown in many of such preliminary works, the hope is that the knowledge gaps identified could soon be filled.

Conclusions

There is an increasing focus on AI in surgery, with investment in digitalisation and research. AI methods have been applied in various areas of colorectal surgery, including preoperative planning, intraoperative analysis, and postoperative care.

Personalised treatment algorithms using AI are being developed and show promise, but there is a need for more studies and data on their practical application in the field. AI can help improve patient outcomes but also raises medicolegal and ethical considerations that need further elucidation.

Figure legends

Figure 1 Definitions of the Artificial Intelligence areas included in the current review.

Figure 2 PRISMA 2020 flow diagram

Figure 3 Fields of application of Artificial Intelligence in Colorectal Surgery. On the right, relevance of Artificial Intelligence to pre-, intra-, and postoperative phases of the surgical management of colorectal patients. On the left, additional considerations of areas that are relevant to colorectal conditions and patients. AI: artificial intelligence; CRC: colorectal cancer; PROMs: patient reported outcome measures

Table 1. Possible applications of AI in colorectal surgery

Phase	AI task	AI features
Preoperative		
-*Tailored treatment*	Cancer staging	Clustering algorithms
	Clinical pathway	Unsupervised ML
	Interval diagnosis to surgery	ANN
	Molecular subtyping	SL/DL
-*Clinical decision support*	Appropriateness (chemotherapy)	DL
	Appropriateness (treatment)	CDSS
	Surgical case duration	ML
-*Risk assessment*	Surgical Site infections	Bayes/SVM
	Decision-making for acute diverticulitis	SVM
	Ileal pouch anastomosis failure	RFA
	Anastomotic leakage	-
	Delay discharge	MLPNN
-*Preoperative imaging*	Surgical planning	Radiomics
	Prediction of pathological complete response	RF
	Prediction peritoneal carcinomatosis	SVM
	Prediction of distant/nodal/Kras status metastasis	radiomics
	Response of metastases to chemotherapy	radiomics
-*Survival*	Stage-specific survival	ML
Intraoperative		
-*AI-enhanced surgery*	Identification of surgical phase/devices tracking	CNN
	Discrimination healthy rectal wall/CRC	SVM
	Assessment of microperfusion	-
-*Robotic surgery*	Autonomous tasks (suturing, etc.)	STAR
Post-operative and additional areas		
-*Management*	Post-operative complications (e.g., anastomotic leak, surgical site infections)	ML/ANN/Bayesian
-*Follow up*	Patient monitoring	Voice-based AI
-*PROMS*	Patient experience	Text-mining
-*Oncological outcomes*	Mortality	ANN/RF/CART/ML
	Adverse events	ANN/tree models
	Recurrence	ML
-*Chemotherapy*	ACT-candidate genes	SVM/ANN/DT/RF
-*Surgical outcomes*	-Length of stay	ANN/ML/CART
	-Surgical complications	ANN/ML
-*Pathology*	-Immune cell detection	SVM/NN
	-MSI status	TLM

Legend: AI = Artificial Intelligence, ANN = Artificial Neural Network, BN = Bayesian Network, CARTs = Classification And Regression Trees, DL = Deep Learning, DCNNs = Deep Convolutional Neural Networks, DT = Decision Trees, GB = Gradient Boosting machine, ML = Machine Learning, MLPNN = multilayer perceptron Neural Network, NN = Neural Network, RF= Random Forest, SL = Supervised learning, SVM = Support Vector Machine, TLM = Translation Language Modeling.

Table 2. Tailored treatment algorithms based on AI.

Study	Type of AI Used	Outcome/Aim/Endpoint	Sensitivity/Accuracy	Specificity	Study population
Gao et al. [12]	DeepCC	Implementation of cancer molecular subtyping. Superior performance of DeepCC compared with other conventional methods	80 %	90%	456 TCGA CRC samples
Pourahmad et al. [9]	K-means, hierarchical and fuzzy c-means clustering methods.	Determine CRC stage using 3 clustering methods based on preoperative clinical findings	85 %/85.9% Maximum accuracy and sensitivity for the hierarchical method.	65% Maximum specificity for the fuzzy c-means method.	117 pts undergoing CRC surgery from 2006 to 2014
Maheshwari et al. [10]	CVM application (machine intelligence and topological data analysis methods)	Identify clinical variation and provide insights to create and optimize clinical pathways.			1786 undergoing CRC surgery from 2015 to 2016 across multiple Ohio hospitals
Curtis et al. [11]	ANN	Prediction of the individualised waiting time for surgery. ANN successfully predicts individual time to CRC surgery.	99%/90%	-	668 pts elective laparoscopic surgery for CRC with a curative intent

Legend: ANN = Artificial Neural Network , CRC = Colorectal Cancer, CVM = Core Vector Machine, TCGA = The Cancer Genome Atlas

Table 3. Clinical decision support tools.

Authors	Type of AI Used	Aim/Endpoint /Outcome	Study Population
Aikemu et al. [14]	WFO	Evaluating the concordance rates between the treatment options determined by WFO and those determined by MDT. High concordance.	250 patients
Park et al. [13]	CDSSs : CRC Chemotherapy Recommender (C3R)	Treatment concordance rates of CR3 with the NCCN guidelines were 70.5% for Top-1 Accuracy and 84% for Top-2 Accuracy.	Data collected from patients who had CRC surgery between 2004 and 2012.
Kim et al. [15]	WFO	Evaluating the concordance rates between the treatment options determined by WFO and those determined by a MDT. Concordance rate was 46.4%. After including the 'For consideration' category from WFO, the concordance rate increased to 88.4%.	69 patients with CRC
Strömblad et al. [17]	Machine learning–assisted model	Assess accuracy and real-world outcome from implementing a machine learning model that predicts surgical case duration. Patients assigned to the machine learning algorithm had significantly lower mean absolute error than the control group.	683 Patients undergoing colorectal and gynaecological surgery
Chan et al. [16]	Gene expressions data	Using gene expression data to identify high risk of recurrence among stage I and II CRC patients. Successful prediction of high risk of recurrence within 3 years in the training data set. (Sensitivity 91.18%)	3 public gene expression data sets

Legend: C3R = Chemotherapy Recommender, CDSS = Clinical Decision Support System, CRC = Colorectal Cancer, MDT = Multidisciplinary Team, NCCN = National Comprehensive Cancer Network, WFO = Watson for oncology.

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