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NARRATIVE REVIEWS

Artificial Intelligence–Assisted Endoscopy in Diagnosis of Gastrointestinal Tumors: A Review of Systematic Reviews and Meta-Analyses

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Artificial Intelligence (AI)-assisted endoscopy has emerged as a promising tool for early and accurate detection of gastrointestinal (GI) tumors, which are associated with high morbidity, mortality, and financial burden. This review summarizes systematic reviews and meta-analyses on AI-assisted endoscopy in GI tumor diagnosis. A comprehensive search was conducted using PubMed/MEDLINE, Google Scholar, Directory of open Access Journals, African Journals Online, and the Cochrane Library, supplemented by manual searches. Eligible systematic reviews and meta-analyses were selected based on predefined inclusion criteria, and relevant data were extracted to evaluate AI-assisted endoscopy's diagnostic performance. Out of 569 identified studies, 23 systematic reviews with meta-analyses met the inclusion criteria, with 6 focusing on detection rates and 17 on diagnostic accuracy. AI-assisted endoscopy demonstrated a significantly higher detection rate for GI tumors compared to conventional endoscopy, alongside high diagnostic accuracy across different GI tumor types. However, variability in performance was observed among different AI algorithms and studies. While AI-assisted endoscopy enhances diagnostic precision, rigorous validation of AI models is necessary to ensure clinical reliability. Ethical considerations and further research are crucial for optimizing AI's role in health care.

Keywords: Artificial intelligence; cancer; endoscopy; GI tumors

Introduction

Gastrointestinal (GI) tumors, abnormal growths of tissue within the digestive system, including esophageal, gastric, colorectal, and pancreatic benign and malignant tumors, represent a major global health problem due to high morbidity and mortality rates.[1] Early detection and accurate diagnosis of GI tumors are essential in improving outcomes, as they can significantly impact treatment strategies and patient prognosis.[2] Endoscopy has long been a conventional tool for the visualization of the GI tract, serving as a critical method for diagnosing various GI conditions.[3] Traditionally, the accuracy of this procedure heavily depends on the expertise of the endoscopist, who must visually identify and interpret abnormalities. However, the subjective nature of human diagnosis can introduce variability, particularly in the detection of early or subtle lesions. This interoperator variability can result in inconsistent diagnostic outcomes, potentially impacting the early identification and treatment of GI pathologies. Hence, there is growing interest in advancing endoscopic technology to improve diagnostic precision.[4]

In recent years, artificial Intelligence (AI) has emerged as a powerful complement to medical diagnosis, including endoscopy. AI-assisted endoscopy uses advanced AI algorithms such as machine learning (ML), deep learning and convolutional neural networks (CNNs) to improve the detection and characterization of GI conditions. By analyzing high-resolution endoscopic images in real time, AI models can help identify lesions that may be missed by human operators, hence improving diagnostic accuracy and consistency.[5] Numerous systematic reviews with meta-analyses have evaluated different metrics of AI-assisted

Abbreviations used in this paper: **ADR, Adenoma Detection Rate; AI, Artificial Intelligence; AIAC, AI-Assisted Colonoscopy; AUC, Area Under the Curve; AUROC, Area Under the Receiver Operating Characteristic Curve; CAD, Computer-Aided Detection; CNNs, Convolutional Neural Networks; EGC, Early Gastric Cancer; GI, Gastrointestinal; ML, Machine Learning; PDR, Polyp Detection Rate.**

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Table 1. Boolean Operators Based Search Parameters in PubMed as of September 4, 2024

Search	Search string	Number of results
#1	((((((((((((((((Gastrointestinal cancer) OR (GI malignancies)) OR (digestive system cancer)) OR (esophageal cancer)) OR (gastric cancer)) OR (stomach cancer)) OR (small intestine cancer)) OR (colon cancer)) OR (colorectal cancer)) OR (rectal cancer)) OR (anal cancer)) OR (liver cancer)) OR (hepatocellular carcinoma)) OR (gallbladder cancer)) OR (pancreatic cancer)) OR (pancreatic adenocarcinoma)) OR (bile duct cancer)) OR (cholangiocarcinoma) filters: from 2010 - 2024	659,374
#2	((((Endoscopy) OR (endoscopic diagnosis)) OR (colonoscopy)) OR (gastroscopy)) OR (endoscopic imaging) filters: from 2010 - 2024	305,790
#3	((((((Artificial intelligence) OR (AI)) OR (machine learning)) OR (ML)) OR (deep learning)) OR (neural network)) OR (computer vision) filters: from 2010 - 2024	892,969
#4	((#1) AND (#2)) AND (#3) filters: Systematic review, meta-analysis	164

endoscopy, emphasizing its advantages over traditional methods. It has been reported to increase detection rate and reduce diagnostic errors in detecting precancerous conditions such as dysplasia and chronic atrophic gastritis.[6] These benefits have resulted to a growing interest in the integration of AI into clinical practice for the management of GI diseases, including benign and cancerous tumors diagnosis.

However, existing research presents several challenges and limitations. One of the main problems is the variability in AI performance due to the lack of standardized datasets. Many studies use their collected data, which may differ in image quality, screening procedures, and imaging modalities. This inconsistency hinders the generalizability of AI models to different clinical settings.[7] In addition, many models are trained on small sample sizes, which raise concerns about overfitting and limit their applicability to real-world settings.[8] Also, most studies do not make their AI algorithms publicly available, which limits external validation and reproducibility.[9]

Given these gaps, there is a need for a comprehensive review of systematic reviews and meta-analyses on AI-assisted endoscopy, particularly in diagnosing GI tumors. Such a review would provide a critical evaluation of existing studies, enabling the identification of various performance metrics for AI-assisted endoscopy in the detection and diagnosis of GI tumors. By synthesizing findings from multiple systematic reviews with meta-analyses, this review aims to describe the overall diagnostic efficacy of AI systems in enhancing endoscopic procedures, thereby informing future advancements and clinical practices in the field of gastroenterology.

Methodology

Database Search

We conducted a comprehensive literature search across multiple databases, including PubMed/MEDLINE, Google Scholar, the Directory of Open Access Journals, the African Journals Online, and the Cochrane Library, to identify systematic reviews and meta-analyses focusing on AI-assisted endoscopy for the diagnosis of GI tumors. In addition, manual searches through Google were performed to locate relevant grey literature. The search strategy employed key terms such as "Artificial Intelligence," "Machine Learning," "Deep Learning," "Neural Network," "Computer Vision," "Endoscopy," and terms related to GI tumors. All searches were limited to publications from 2010 onward to ensure inclusion of the most up-to-date studies. In addition, searches were filtered to systematic reviews and meta-analyses to reduce potential of including other irrelevant study designs. Table 1 provides a detailed overview of the Boolean operator search strategy used in PubMed. The gathered references, including those from grey literature, were imported into Rayyan software for deduplication. Following this, the references were screened based on established inclusion and exclusion criteria (Table 2).

Data Extraction

Three independent data extractors systematically retrieved the required information using a pre-defined data extraction spreadsheet in Excel. The extracted data encompassed the author identifier, total number of included studies, total number of patients, GI area studied, tumor type, type of AI (ML, deep learning, convolutional network, computer-aided), outcome of interest, and a summary of the results. The third data extractor cross-verified the extracted information and any discrepancies were resolved through discussion and consensus.

Table2. Inclusion and Exclusion Criteria

Criterion	Included	Excluded
Study design	Systematic review and meta-analysis	Systematic reviews without meta-analyses, original studies, other types of studies
Year of publication	2010 to 2024	Before 2010
Outcome of interest	GI tumors diagnosis (benign and malignant)	Diagnosis of other GI diseases which are not classified as tumors
Accessibility	Abstract and full text accessible	Abstract and full text inaccessible
Language	English	Non – English

Data Synthesis

The extracted data were descriptively synthesized and summarized to present various metrics related to AI-assisted endoscopy in the diagnosis of GI tumors. The data were reported in their original form, with no new variables or modifications introduced. In addition, no further meta-analyses were conducted beyond the initial descriptive synthesis.

Results

Study Selection

The initial search yielded 569 systematic reviews and meta-analyses. After removing 43 duplicates, 526 records were screened against the predefined inclusion and exclusion criteria. A total of 448 records were excluded based on their titles and abstracts, leaving 78 for full-text examination. Of these, 55 were excluded for the following reasons: systematic reviews without meta-analyses (n = 16), other study designs (n = 19), focus on the diagnosis of GI diseases unrelated to tumors (n = 12), and inaccessible full texts (n = 8). Finally, 23 systematic reviews and meta-analyses were included in the final review (Figure 1).

Characteristic of Included Systematic Reviews and Meta-analyses

A total of 23 systematic reviews with meta-analyses were included in this review. All included systematic reviews and meta-analyses were published from 2020 onwards, reflecting their contemporary relevance. Specifically, one review was published in 2020,[10] four in 2021,[11–14] seven in 2022,[15–21] eight in 2023,[22–29] and three in 2024.[30–32] A study that included few original studies included 5,[10] while the study with the highest number of included original studies had 34.[15] This was contrasted by another study that, despite including 48 studies, utilized only 13 in the meta-analysis, with the remainder being employed for qualitative synthesis.[24]

The studies encompassed four primary areas within GI: esophagus, stomach, bowels, and pancreas. GI cancers and polyps were the predominant categories of GI tumors discussed. AI algorithms studied included general AI, ML, deep learning, CNNs, and computer-assisted technologies. The primary outcomes of interest were the detection rate (6 studies) and accuracy (17 studies) of AI-assisted endoscopy in diagnosing gastric tumors (Table 3).

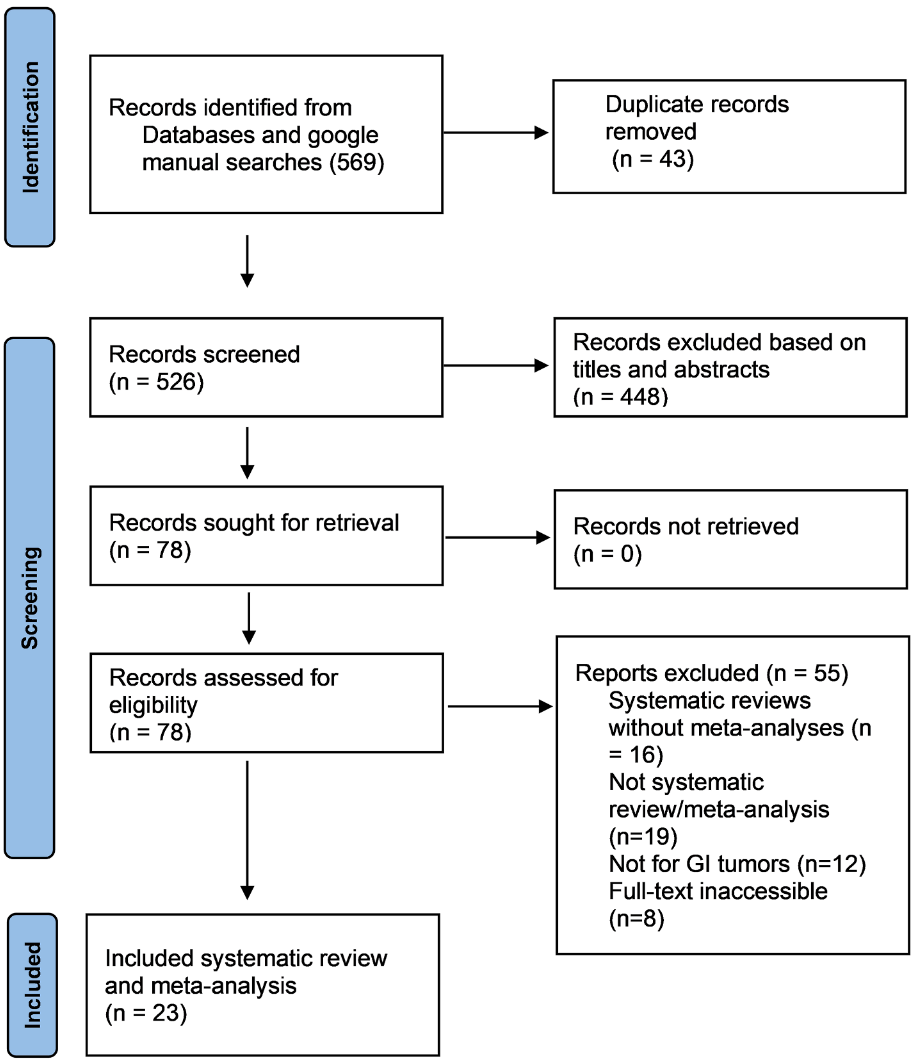

Figure 1. Framework of literature search.

Table 3. Detailed Characteristics of Included Systematic Reviews With Meta-analyses

Study	Total number of included studies	Total number of included patients	Area of GI	Type of tumor	Type of AI algorithm	Outcome of interest	Summary of results
Ashat et et al.[11]	6	5058	Colon	Colon adenoma and polyp	AI	Detection rate	Adenoma detection rate (ADR) and polyp detection rate (PDR) were significantly higher with AI -assisted colonoscopy (AIAC) compared to conventional colonoscopy (CC), showing increased detection rates (33.7% vs 22.9% for ADR; 45.6% vs 30.6% for PDR). However, AIAC was associated with a slightly longer procedure time, with a mean difference of 0.46 min
Barua et al.[10]	5	4311	Colon	Colon adenoma and polyp	AI	Detection rate	Colonoscopy using AI significantly improved adenoma detection rates (ADRs) and polyp detection rates (PDRs) compared to non-AI colonoscopy. ADR with AI was 29.6% versus 19.3% without AI (RR 1.52), while PDR was 45.4% with AI compared to 30.6% without AI (RR 1.48), both with high certainty.
Li et al.[32]	12	11,173	Stomach	Gastric intestinal metaplasia	AI	Accuracy	AI assisted endoscopy had pooled sensitivity of 94% and specificity of 93%, with an area under the ROC curve of 0.97. Meta-regression and subgroup analysis showed that factors like study design, endoscopy type, training images, and algorithm significantly influenced AI's diagnostic performance, which outperformed endoscopists (95% vs 79% sensitivity).
Luo et al.[15]	34		Upper gastrointestinal tract	Upper gastrointestinal cancer	AI	Accuracy	Among 17 image-based studies on early esophageal cancer (EEC), pooled AUC, sensitivity, and specificity were 0.98, 0.95, and 0.95, respectively. For 7 patient-based studies, these were 0.98, 0.94, and 0.90. In 15 image-based studies on early gastric cancer (EGC), pooled AUC, sensitivity, and specificity were 0.94, 0.87, and 0.88, respectively.

Table 3. Continued

Study	Total number of included studies	Total number of included patients	Area of GI	Type of tumor	Type of AI algorithm	Outcome of interest	Summary of results
Visaggi et al.[16]	19		Esophagus	Different esophageal diseases	AI	Accuracy	For diagnosing Barrett's neoplasia, AI achieved an area under the receiver operating characteristic curve (AUROC) of 0.90, sensitivity of 0.89, and specificity of 0.86, performing similarly to endoscopists ($P = .35$). For esophageal squamous cell carcinoma, AI had an AUROC of 0.97, sensitivity of 0.95, and specificity of 0.92, slightly outperforming endoscopists, but the difference was not statistically significant.
Adiwinata et al.[22]	13		Colon	Colon poly and adenoma	AI	Detection rate	Colonoscopy assisted AI showed a significantly higher polyp detection rate (PDR) compared to colonoscopy without AI (pooled OR 1.46, 95% CI 1.13-1.89, $P = .003$) and a higher adenoma detection rate (ADR) (pooled OR 1.58, 95% CI 1.37-1.82, $P < .00001$).
Islam et al.[17]	28	703,006 (images)	Esophagus	Esophageal cancer	DL	Accuracy	Deep learning (DL) models demonstrated high diagnostic accuracy for esophageal cancer, with a pooled accuracy of 92.90%, sensitivity of 93.80%, and specificity of 91.73%. The positive and negative predictive values were 93.62% and 91.97%, respectively. The area under the ROC curve (AUROC) was 0.96, indicating strong diagnostic performance.
Zhang et al.[12]	16		Esophagus	Esophageal cancer and neoplasms	AI	Accuracy	AI-assisted models for detecting esophageal neoplasms showed a pooled sensitivity of 94% and specificity of 85%. The positive likelihood ratio was 6.40, while the negative likelihood ratio was 0.06. The diagnostic odds ratio was 98.88, and the area under the curve (AUC) was 0.97. AI models outperformed endoscopists, with higher sensitivity (94% vs 82%).

Table 3. Continued

Study	Total number of included studies	Total number of included patients	Area of GI	Type of tumor	Type of AI algorithm	Outcome of interest	Summary of results
Wei et al.[23]	12	11,660	Colon	Colon adenoma	Computer-aided	Detection rate	The adenoma detection rate (ADR) was significantly higher with computer-aided detection (CADe) (36.3% vs 35.8%, RR 1.13, 95% CI 1.01–1.28), particularly in prospective studies (37.3% vs 35.2%, RR 1.15, 95% CI 1.01–1.32). However, retrospective studies showed no significant difference (RR 1.12, 95% CI 0.92–1.36). adenomas per colonoscopy (APC) rate ratio was also not significantly different with CADe (RR 1.12, 95% CI 0.95–1.33), and GI Genius showed no ADR difference (RR 0.96, 95% CI 0.85–1.07).
Dumitrescu et al.[19]	10	1871	Pancreas	Pancreatic cancer	AI	Accuracy	The combined diagnostic sensitivity and specificity of AI-assisted endoscopic ultrasound for pancreatic cancer were 0.92 (95% CI, 0.89–0.95) and 0.90 (95% CI, 0.83–0.94), respectively. The area under the summary receiver operating characteristic curve was 0.95, with a diagnostic odds ratio of 128.9 (95% CI, 71.2–233.8), reflecting excellent diagnostic accuracy for detecting pancreatic cancer.
Guidozzi et al.[24]	48 (13 for meta-analysis)	2068	Esophagus	Esophageal squamous cell carcinoma and adenocarcinoma	AI	Accuracy rate	For esophageal squamous cell carcinoma, the combined sensitivity and specificity of AI assisted endoscopy were 91.2% (84.3%–95.2%) and 80% (64.3%–89.9%), respectively. For esophageal adenocarcinoma, the pooled sensitivity and specificity were 93.1% (86.8%–96.4%) and 86.9% (81.7%–90.7%).
Prasoppokakorn et al.[14]	8	870	Pancreas	Pancreatic ductal adenocarcinoma	AI	Accuracy rate	AI-assisted endoscopic ultrasound (EUS) for diagnosing pancreatic ductal adenocarcinoma (PDAC) showed a pooled sensitivity of 91%, specificity of 90%, and a diagnostic odds ratio of 81.6, with an area under the curve of 92.3%. AI-assisted B-mode EUS had sensitivity, specificity, positive predictive value, and negative predictive value of 91%, 90%, 94%, and 84%, respectively. Other methods also demonstrated high diagnostic accuracy.

Table 3. Continued

Study	Total number of included studies	Total number of included patients	Area of GI	Type of tumor	Type of AI algorithm	Outcome of interest	Summary of results
Yin et al.[18]	7	1110	Pancreas	Pancreatic ductal adenocarcinoma	AI	Accuracy rate	AI demonstrated high accuracy in predicting pancreatic cancer, with an AUC of 0.95, sensitivity of 93%, and specificity of 90%. The positive likelihood ratio was 9.1, and the negative likelihood ratio was 0.08, indicating reliable AI performance
Jiang et al.[13]	16	22,621 (images)	Stomach	Gastric cancer	AI	Accuracy	The application of AI in detecting early gastric cancer (EGC) via endoscopy achieved an AUC of 0.96, with 86% sensitivity and 93% specificity. For AI-assisted depth diagnosis of EGC, the AUC was 0.82, with 72% sensitivity and 79% specificity.
Kim et al.[20]	12	28,148 (images)	Intestines	Gastrointestinal protruded Lesions	Computer-aided	Accuracy	The combined area under the curve for computer-aided detection (CAD) models diagnosing protruded lesions was 95%, with a sensitivity of 89%, specificity of 91%, and a diagnostic odds ratio of 74 (95% CI, 43–126).
Lou et al.[25]	33	27,404	Colon	Colorectal neoplasia	AI	Detection rate	AI assisted colonoscopy significantly reduced poly missed detection rate (RR 0.475) and adenoma miss rates (RR 0.495), while increasing poly detection rate (RR 1.238), adenoma detection rate (RR 1.242), poly detected per colonoscopy rates (IRR 1.388), and adenomas detected per colonoscopy rates (IRR 1.390). The procedure led to 0.271 more poly detected per colonoscopy PPCs and 0.202 more adenomas detected per colonoscopy, demonstrating improved detection and outcomes across key metrics.
Shiha et al.[26]	12	11,340	Colon	Colon adenoma and polyp	AI (computer aided)	Detection rate	The pooled adenoma detection rate was significantly higher with computer-aided detection (CAD) group compared to standard colonoscopy SC group (41.4% vs 33%; RR 1.26). CAD improved adenoma detection across all sizes (5mm, 6–9mm, and 10mm), locations (proximal and distal colon), and morphologies (polypoid and nonpolypoid), demonstrating its effectiveness in enhancing detection.

Table 3. Continued

Study	Total number of included studies	Total number of included patients	Area of GI	Type of tumor	Type of AI algorithm	Outcome of interest	Summary of results
Gangwani et al.[31]	26	22,560	Colon	Colon adenoma	AI	Detection rate	AI showed a higher adenoma detection rate (ADR) compared to a single observer (odds ratio: 0.668, 95% CI 0.595–0.749, $P <$ .001). A dual observer also had a higher ADR than a single operator (odds ratio: 0.771, 95% CI 0.688–0.865, $P <$ .001). Network meta-analysis revealed no significant difference between AI and a second observer (relative risk 1.1, $P =$ .3).
Shi et al.[30]	21	16,074	Stomach	Gastric cancer	ML	Accuracy	ML-based models for gastric cancer diagnosis achieved sensitivity (SEN) of 91% and specificity (SPE) of 85% with an SROC of 0.94 in the training set, and SEN of 90% and SPE of 90% with an SROC of 0.96 in the validation set. Nonspecialist clinicians had SEN of 0.64 and SPE of 0.84, while specialists had SEN of 0.80 and SPE of 0.88. ML models significantly improved nonspecialist SEN for EGC diagnosis to 0.76.
Ma et al.[21]	7		Esophagus	Esophageal cancer	CNN	Accuracy	Convolutional neural networks (CNN) based AI showed strong diagnostic performance for early esophageal cancer (EC) on endoscopic images, with sensitivity of 90% and specificity of 91%. The positive likelihood ratio was 9.8, and the negative likelihood ratio was 0.11. The AUC was 0.95, indicating high accuracy in confirming or excluding early EC.
Keshtkar et al.[29]	24		Colon	Colorectal polyps and cancer	CNN	Accuracy	The sensitivity and specificity of convolutional neural networks (CNN) for predicting colorectal polyps ranged from 84.7% to 91.6% and 86.0%–93.8%. For colorectal cancer, sensitivity was 93.2%–94.1%, and specificity was 94.6%–97.7%. Diagnostic odds ratios for polyps ranged between 36% and 162%, with accuracy between 80.5% and 88.6%, while for cancer, diagnostic odds ratios ranged from 239.63% to 677.47% with accuracy from 88.2% to 96.4%. AUC varied from 0.92 to 0.99.

Table 3. Continued

Study	Total number of included studies	Total number of included patients	Area of GI	Type of tumor	Type of AI algorithm	Outcome of interest	Summary of results
Gomes et al.[27]	8	2355	GI tract	Gastrointestinal stromal tumors	AI	Accuracy	AI-assisted endoscopic ultrasonography (EUS) for diagnosing gastrointestinal stromal tumor (GIST) showed a sensitivity of 92%, specificity of 80%, and area under the curve (AUC) of 0.949. In differentiating GIST from gastrointestinal leiomyoma (GIL), AI had a specificity of 90% and AUC of 0.966. Expert endoscopists demonstrated lower sensitivity (72%) and specificity (70%) with an AUC of 0.777.
Zhang et al.[28]	28		Esophagus	Esophageal cancer or high-grade dysplasia	CNN	Accuracy	For esophageal cancer or high-grade dysplasia (HGD) diagnosis using still image-based analysis, the pooled sensitivity was 95% and specificity was 92%, with an area under the curve (AUC) of 0.98. Video-based analysis yielded lower sensitivity (85%) and specificity (73%), with an AUC of 0.87. Predicting invasion depth had a sensitivity of 90%, specificity of 83%, and an AUC of 0.95.

IRR, incidence rate ratio; SROC, summary receiver operating characteristic.

Detection Rate of AI-assisted Endoscopy in Diagnosing Gastrointestinal Tumors

A thorough review of six systematic reviews with meta-analyses demonstrates a marked improvement in the detection rates of GI tumors with AI-assisted endoscopy compared to conventional endoscopy. Studies consistently show that AI-assisted colonoscopy (AIAC) enhances both adenoma detection rate (ADR) and polyp detection rate (PDR). For instance, Ashat et al. reported that AIAC yielded an ADR of 33.7%, significantly higher than the 22.9% observed with conventional colonoscopy (odds ratio [OR]: 1.76, 95% confidence interval [CI]: 1.55–2.00; $I^2 = 28\%$). The PDR was similarly elevated with AIAC at 45.6%, compared to 30.6% with conventional colonoscopy (OR 1.90, 95% CI 1.68–2.15; $I^2 = 0\%$). Meanwhile, the mean procedure time was longer with AIAC (mean difference: 0.46 minutes, 95% CI 0.00–0.92; $I^2 = 94\%$), reflecting increased detection rates, even though associated with longer time.[11]

Further supporting these findings, Barua et al. found that AIAC achieved an ADR of 29.6% versus 19.3% without AI, while PDR was 45.4% with AI compared to 30.6% without AI.[10] Adiwinata et al. also reported significant improvements with AI, showing a higher PDR (pooled OR 1.46, 95% CI 1.13–1.89, $P = .003$) and ADR (pooled OR 1.58, 95% CI 1.37–1.82, $P < .00001$).[22] Additional evidence from Shiha et al. revealed that the pooled ADR was significantly higher with computer-aided detection compared to standard colonoscopy (41.4% vs 33%; risk ratio [RR] 1.26).[26] Gangwani et al. also found that AI demonstrated a higher ADR compared to a single observer (OR 0.668, 95% CI 0.595–0.749, $P < .001$), while a dual observer also had a higher ADR compared to a single observer (OR 0.771, 95% CI 0.688–0.865, $P < .001$), but with network meta-analysis showing no significant difference between AI and a second observer (relative risk 1.1, $P = .3$).[31]

Lastly, Lou et al. observed that AI-aided colonoscopy significantly reduced both polyp miss rates (RR: 0.475) and adenoma miss rates (RR: 0.495), while increasing the PDR (RR: 1.238) and ADR (RR: 1.242). The procedure also led to an increase of 0.271 polyps and 0.202 adenomas detected per colonoscopy (incidence rate ratio: 1.388 and 1.390, respectively)[25] (Table 4). Collectively, these findings highlight the superior capabilities of AI-assisted endoscopy in enhancing the detection of GI tumors, underscoring its potential as a valuable tool in improving diagnostic accuracy.

Accuracy of AI-assisted Endoscopy in Diagnosing Gastrointestinal Tumors

Seventeen systematic reviews with meta-analyses highlighted the high accuracy of AI-assisted endoscopy in diagnosing GI tumors, particularly in terms of sensitivity and specificity. AI models have shown promising results in detecting various GI malignancies. Islam et al. reported that DL models exhibited a pooled accuracy of 92.90%, sensitivity of 93.80%, and specificity of 91.73% in diagnosing esophageal cancer (EC).[17] Similarly, AI-assisted models for esophageal neoplasms achieved a pooled sensitivity of 94% and specificity of 85%, according to Zhang et al.[12]

CNN-based AI models also demonstrated high diagnostic performance for early EC on endoscopic images, as noted by Ma et al., with sensitivity and specificity rates of 90% and 91%, respectively.[21] In a related study by Visaggi et al., AI models showed comparable performance to endoscopists with area under the receiver operating characteristic curve (AUROC) of 0.90, sensitivity of 0.89, and specificity of 0.86 in diagnosing Barrett's neoplasia, and AUROC of 0.97, sensitivity of 0.95, and specificity of 0.92 in detecting esophageal squamous cell carcinoma.[16]

For gastric cancer, AI-assisted endoscopy has shown remarkable accuracy in early detection. Jiang et al. reported that AI achieved an area under the curve (AUC) of 0.96, with a sensitivity of 86% and specificity of 93% for detecting early gastric cancer (EGC).[13] AI-assisted depth diagnosis of EGC also demonstrated promising results, with an AUC of 0.82, 72% sensitivity, and 79% specificity.[13] Li et al. further supported these findings, showing pooled sensitivity of 94% and specificity of 93% in diagnosing gastric intestinal metaplasia.[32] Shi et al. reported that ML-based models for gastric cancer diagnosis achieved 91% sensitivity and 85% specificity in the training set, and 90% sensitivity and specificity in the validation set, with an overall summary receiver operating characteristic of 0.96.[30]

AI's performance in detecting pancreatic cancer has also been significant. Prasoppokakorn et al. demonstrated that AI-assisted endoscopic ultrasound (EUS) for diagnosing pancreatic ductal adenocarcinoma achieved a pooled sensitivity of 91% and specificity of 90%.[14] Similarly, Yin et al. found that AI models predicted pancreatic cancer with an AUC of 0.95, sensitivity of 93%, and specificity of 90%.[18]

In the context of colorectal polyps and cancer, Keshtkar et al. found that CNN models for colorectal polyps showed sensitivity ranging from 84.7% to 91.6% and specificity from 86.0% to 93.8%. For colorectal cancer, sensitivity ranged from 93.2% to 94.1%, and specificity from 94.6% to 97.7%. Diagnostic ORs for polyps ranged between 36% and 162%, with accuracy between 80.5% and 88.6%, while for cancer, diagnostic ORs ranged from 239.63% to 677.47%, with accuracy between 88.2% and 96.4%. The AUC for these models ranged from 0.92 to 0.99, indicating high diagnostic accuracy.[29] These findings collectively underscore the significant accuracy of AI-assisted endoscopy in diagnosing GI tumors across different organ systems, offering robust sensitivity and specificity rates. Table 4 presents a summary of detection rates and diagnostic accuracy ranges across studies.

Discussion

This study reviewed systematic reviews with meta-analyses on AI-assisted endoscopy for the diagnosis of GI tumors. The included studies reported that AI-assisted

Table 4. Summary of Detection and Accuracy Ranges

Study	GI region	AI model	Detection rate	Sensitivity (%)	Specificity (%)	AUROC
Kim et al.[20]	Intestines	CAD	DOR: 74%	89%	91%	0.95
Ashat et al.[11]	Colon	AI	ADR: 33.7 vs 29.6 (CC) PDR: 45.6 VS 30.6 (CC)	–	–	–
Barua et al.[10]	Colon	CNN-based AI	ADR: 29.6 vs 19.3 (CC)	–	–	–
Adiwinata et al.[22]	Colon	CNN-based AI	PDR: AI significantly increased detection (OR: 1.46, 95% CI: 1.13-1.89, $P = .03$) ADR: AI significantly increased detection (OR: 1.58, 95% CI: 1.37-1.82, $P = .00001$)	–	–	–
Lou et al.[25]	Colon	AI	Miss rate reduced: Polyp: RR-0.475; adenoma: RR-0.495 Detection rate increased: PDR: RR-1.238; ADR: RR-1.242	–	–	–
Keshtkar et al.[29]	Colon	CNN-based AI	Polyps- accuracy: 80.5%–88.6%, DOR: 36%–162%; cancer- Accuracy: 88.2%–96.4%, DOR: 239.63%–677.47%	Polyps: 84.7%–91.6% Cancer: 93.2%–94.1%	Polyps: 86.0%–93.8% Cancer: 94.6%–97.7%	0.92-0.99
Wei et al.[23]	Colon	Computer-aided	ADR: 36.3% (AI) vs 35.8% (CC)	–	–	–
Shiha et al.[26]	Colon	AI	ADR: 41.4% (AI) vs 33% (CC)	–	–	–
Gangwani et al.[31]	Colon	AI	Higher ADR vs Single observer (OR: 0.668, 95% CI 0.595-0.749, $P < .001$)	–	–	–
Visaggi et al.[16]	Esophagus	AI	–	Barrett's neoplasia: 89% Esophageal SCC: 95%	Barrett's neoplasia: 86% Esophageal SCC: 92%	Barrett's neoplasia: 0.90 Esophageal SCC: 0.97
Ma et al.[21]	Esophagus	CNN	–	90%	91%	0.95
Islam et al.[17]	Esophagus	DL	Diagnostic accuracy for esophageal cancer: 92.9%	93.8%	91.73%	0.96
Zhang et al.[12]	Esophagus	AI	DOR: 98,88%	94%	85%	0.97
Zhang et al.[28]	Esophagus	CNN	–	Image-based: 95% Video-based-85%	Image-based: 92% Video-based-73%	Image-based: 0.98% Video-based- 0.87%
Guidozzi et al.[21]	Esophagus	AI	–	SCC: 91.2% Adenocarcinoma: 93.1%	SCC: 80% Adenocarcinoma: 86.9%	–
Luo et al.[15]	Upper GI	AI	–	EEC (image-based): 95% EEC (patient-based): 94% EGC (Image-based):87%	EEC (image-based): 95% EEC (patient-based): 90% EGC (Image-based):88%	EEC (image-based): 0.98 EEC (patient-based): 0.98 EGC (image-based): 0.94
Gomes et al.[27]	GI tract	AI	–	GIST: 92%	GIST: 80% GIL: 90%	GIST: 0.949 GIL: 0.966
Dumitrescu et al.[19]	Pancreas	AI	–	92%	90%	0.95
Prasoppokakorn et al.[14]	Pancreas	AI	–	91%	90%	0.923
Yin et al.[18]	Pancreas	AI	–	93%	90%	0.95

Table 4. Continued

Study	GI region	AI model	Detection rate	Sensitivity (%)	Specificity (%)	AUROC
Jiang et al.[13]	Stomach	AI	–	EEG: 86% DD: 72%	EEG: 93% DD: 79%	EEG: 0.96% DD: 0.82%
Shi et al.[30]	Stomach	ML- based AI	–	Training: 91% Validation: 90%	Training: 85% Validation: 90%	Training: 0.94 Validation: 0.96
Li et al.[32]	Stomach	AI	–	94%	93%	0.97

Note: Studies that did not specify the AI algorithm are labeled as "AI" in the AI model column.
*ADR, Adenoma Detection Rate; CAD, Computer Aided Detection; CC, Conventional Colonoscopy; DD, Depth Diagnosis; DOR, Diagnostic Odd Ratio; EEC, Early Esophageal Cancer; EGC, Early Gastric Cancer; GIL, Gastrointestinal Leiomyoma; GIST, Gastrointestinal stromal tumor; PDR, Polyp Detection Rate; RR, Risk Ratio; SCC, Squamous Cell Carcinoma.

endoscopy significantly increased the detection rates of both benign and malignant tumors in various GI regions, including the esophagus, stomach, bowels, and pancreas, when compared to conventional endoscopy. Furthermore, AI models demonstrated superior diagnostic performance, with higher accuracy in terms of sensitivity and specificity for detecting GI tumors. These findings suggest that AI-assisted endoscopy may enhance the early identification and accurate diagnosis of GI tumors, offering a potential improvement over traditional endoscopic methods in clinical practice.

The benefits of AI-assisted endoscopy extend beyond high detection accuracy. When factoring in costs, AI-assisted endoscopy has been shown to be cost-effective and beneficial in reducing mortality. A modeling study by Areia on the cost-effectiveness of AI in colonoscopy screening demonstrated that AI detection tools lowered the discounted cost per screened individual from $3400 to $3,343, resulting in a $57 saving per person. Regarding cancer outcomes, screening colonoscopy without AI reduced colorectal cancer incidence by 44.2%, while AIAC achieved a 48.9% reduction, representing a 4.8% incremental gain. In terms of mortality, non-AI colonoscopy reduced colorectal cancer mortality by 48.7%, compared to 52.3% with AI tools, reflecting a 3.6% improvement.[33] This is further supported by a real-world study from Italy, which found that AIAC resulted in an average savings of €14.34 per patient, with probabilistic sensitivity analysis confirming its cost-effectiveness at nearly 80%.[34] AIAC significantly improves lesion detection. Studies by Ashat et al., Barua et al., and Adiwinata et al. found that AI increased ADRs and PDRs, with ADR rising up to 33.7% vs 22.9% and PDR up to 45.6% vs 30.6%.[10,11,22] Lou et al. reported that AI reduced polyp and adenoma miss rates (RR: 0.475 and 0.495, respectively) while increasing detection rates (PDR: RR 1.238, ADR: RR 1.242),[25] showcasing the added advantage of AI – aided endoscopy.

The consistently higher adenoma and PDRs observed with AIAC across multiple studies underscore its potential of broad applicability in diverse endoscopy settings. Given that ADR is a key quality indicator for colonoscopy,[35] the improvement demonstrated by AI-assisted endoscopy can be particularly valuable in centers with limited access to highly experienced endoscopists by providing an added layer of support, helping clinicians detect more adenomas and polyps with greater accuracy. Given its ability to reduce operator-dependent variability, this technology can help standardize detection performance in both high-resource and especially resource-constrained settings.[36] In environments where clinician expertise is inadequate, training opportunities are limited, or procedural volume is high, this AI support can play a critical role in improving tumor detection and reducing the likelihood of missed diagnoses.[37]

AI also enhances diagnostic accuracy across various GI cancers. Islam et al. found that deep learning models achieved 92.90% accuracy, 93.8% sensitivity, and 91.73%

specificity for EC (AUROC: 0.96).[17] Similarly, Jiang et al. reported 86% sensitivity and 93% specificity for EGC detection (AUROC: 0.96), while AI-assisted depth diagnosis had slightly lower sensitivity (72%) and specificity (79%) (AUROC: 0.82).[13] For esophageal diseases, Visaggi et al. and Luo et al. showed that AI models achieved up to 95% sensitivity and 92% specificity for Barrett's neoplasia and esophageal squamous cell carcinoma, performing comparably to endoscopists.[15,16] In pancreatic and GI stromal tumors, Dumitrescu et al. and Gomes et al. reported that AI-assisted endoscopic ultrasound achieved 92% sensitivity and 90% specificity for pancreatic cancer and GIST, respectively.[19,27] Meanwhile, AI model choice affects performance. Shi et al. reported that ML models achieved 91% sensitivity and 85% specificity for gastric cancer, while Keshtkar et al. found that CNNs provided higher accuracy for colorectal cancer (sensitivity up to 94.1%, specificity up to 97.7%).[29,30] AI improves lesion detection and diagnostic precision in early cancer detection, with CNNs excelling in endoscopic imaging due to their spatial learning and adaptability. However, challenges include computational demands, overfitting, and data bias.[8] Despite this, CNN-based AI outperforms ML models, making it ideal for real-time endoscopic applications.

Despite its promises, AI integration in endoscopy present challenges. One critical issue is the potential for overreliance on AI, which clinicians must actively mitigate. If clinicians become overly dependent on AI to detect GI abnormalities, their diagnostic proficiency may deteriorate over time. This erosion of clinical skills could pose significant risks, particularly in scenarios where AI systems are unavailable, malfunction, or produce inaccurate results. Such situations may compromise patient safety and lead to adverse outcomes. Therefore, it is essential to maintain a careful balance between human expertise and AI assistance, ensuring that AI serves as a complementary tool rather than a replacement for clinical judgment in endoscopic practice.

For developers of AI-assisted endoscopy systems, ensuring the quality and diversity of data is of utmost importance. AI models should be trained on extensive datasets that encompass a variety of patient demographics and GI conditions, which is essential for minimizing bias and enhancing generalizability. External validation is also critical, as it involves testing AI systems across diverse clinical environments to confirm consistent performance across different settings. Close collaboration with clinicians is vital during development to ensure that AI tools are aligned with real-world clinical needs and contribute to improved patient outcomes. Integrating continuous learning capabilities into these models is necessary for maintaining their accuracy over time, as they can be updated with new data. Further research and development in this field are crucial for refining current models and developing innovative solutions for GI diagnosis and management.

In addition, many studies included in this review evaluated AI retrospectively, meaning the algorithms were tested on stored endoscopic images rather than being actively integrated into live procedures. While retrospective studies demonstrate AI's potential, they do not account for real-time variables such as endoscopist interaction, procedural duration, or clinical decision-making. In contrast, real-time AI integration in endoscopy has been shown to improve ADR and reduce miss rates. Lou et al. found that AIAC significantly reduced polyp miss rates (RR: 0.475) and adenoma miss rates (RR: 0.495), while increasing polyp and ADRs per colonoscopy.[25] However, real-time AI implementation remains limited due to logistical challenges, including hardware requirements, latency issues, and the need for seamless integration with existing endoscopic systems.

Ethical and legal considerations are essential in the development of AI models for endoscopy or any health-care field. The World Health Organization highlights key principles for the ethical and responsible use of AI, emphasizing that these systems must respect human dignity, fundamental rights, and values.[38] AI in health care should actively promote equity, fairness, inclusiveness, and accountability. Prior to integrating AI with health-care systems, it is crucial that medical professionals adhere to the four core principles of medical ethics: autonomy, beneficence, nonmaleficence, and justice.[39] To unlock AI's full potential in health care, four major ethical concerns must be addressed: informed consent for data usage, safety and transparency of AI systems, algorithmic fairness to avoid biases, and data privacy protection.[40] Besides World Health Organization, several international bodies have established codes of conduct to promote the responsible use of AI in health care. For example, the FUTURE-AI international consortium developed consensus guidelines based on six key principles: fairness, universality, traceability, usability, robustness, and explainability.[41] These principles span the entire AI lifecycle and emphasize transparency, bias reduction, data privacy, and ongoing risk evaluation, which are essential for safe and effective AIAC.

Conclusion

The application of AI in endoscopy shows promising potential, particularly in the early detection of GI tumors, due to its high diagnostic accuracy. However, despite these advantages, AI systems must undergo rigorous evaluation to ensure their robustness and reliability before clinical implementation. It is essential that AI functions as a tool to assist, rather than replace, clinicians in decision-making processes. In addition, ethical and legal considerations, such as data privacy, algorithmic fairness, and patient consent, must be addressed in the integration of AI into health care. Further research and development are necessary to optimize AI models, improving their accuracy and ensuring their safe and effective contribution to enhancing patient care.

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