Novel Artificial Intelligence Systems in Detecting Adenomas in Colonoscopy: A Systemic Review and Network Meta-Analysis

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INTRODUCTION: **Artificial intelligence (AI) has the potential to improve adenoma detection rates (ADRs) during colonoscopy, but the efficacy of various AI-assisted systems remains unclear. To evaluate and compare the effectiveness of different AI-assisted systems for detecting colorectal neoplasia during colonoscopy.**

METHODS: **A systematic literature search of PubMed, Scopus, and Google Scholar databases was conducted up to March 4, 2025, to identify randomized controlled trials comparing AI-assisted colonoscopy with conventional colonoscopy. The analysis included AI systems such as GI Genius (Medtronic, Dublin, Ireland), CAD EYE (Fujifilm, Tokyo, Japan), ENDOANGEL, EndoScreener, and EndoAID. The primary outcome was ADR, analyzed using random-effects models to calculate pooled odds ratios (OR) and 95% confidence intervals (CI). Surface under the cumulative ranking curve (SUCRA) rankings and subgroup analyses were also performed.**

RESULTS: **Seventeen randomized controlled trials with 10,547 participants were included. ENDOANGEL showed the highest efficacy (OR 1.84, 95% CI 1.50–2.30; SUCRA 0.9), followed by EndoAID (OR 1.64, 95% CI 1.20–2.26; SUCRA 0.7). CAD EYE and GI Genius were similarly ranked (OR 1.46 and 1.45, respectively). EndoScreener was ranked just above the control group (OR 1.37, 95% CI 1.20–1.56; SUCRA 0.4).**

DISCUSSION: **AI-assisted colonoscopy systems showed improved ADR detection rates compared with traditional colonoscopy. These results suggest that artificial intelligence may help enhance detection during colonoscopy procedures; however, additional large-scale studies are needed to confirm these findings.**

KEYWORDS: artificial intelligence; adenoma detection rate; colorectal neoplasia; colonoscopy

SUPPLEMENTARY MATERIAL accompanies this paper at http://links.lww.com/CTG/B361, http://links.lww.com/CTG/B362.

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INTRODUCTION

Colorectal cancer (CRC) is the third most commonly diagnosed cancer globally and the second leading cause of cancer-related deaths (1). The global burden of CRC has been rising, with an estimated 1.9 million new cases and 935,000 deaths reported in 2020 alone. The disease primarily arises from adenomatous polyps, which, if detected and removed early, significantly reduce CRC incidence and mortality. Early detection plays a critical role in reducing mortality rates associated with this disease, with screening programs proving effective in identifying precancerous adenomas before they progress into malignancy (2).

Colonoscopy remains the gold-standard screening tool for detecting colorectal neoplasia. It allows for direct visualization of the colonic mucosa, facilitating both the detection and removal of adenomas, thereby preventing the development of CRC (3). The

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adenoma detection rate (ADR), defined as the proportion of colonoscopies in which at least one adenoma is detected, is a key performance metric for colonoscopists. Studies have shown that for every 1% increase in ADR, there is a 3% reduction in CRC incidence and a 5% reduction in CRC-related mortality (4). Similarly, the adenomas per colonoscopy (APC) metric provides additional insight into the effectiveness of adenoma detection by quantifying the average number of adenomas identified per procedure. However, despite the effectiveness of colonoscopy, it remains an operator-dependent procedure. Miss rates for adenomas during conventional colonoscopy have been reported to range from 6% to 27%. This variation is influenced by multiple factors including endoscopist experience, lesion morphology (e.g., flat or sessile polyps), withdrawal technique, and bowel preparation quality. Studies such as Zhao et al (2019) emphasize that these variables significantly affect lesion detection and contribute to the heterogeneity observed across trials (5,6). Missed lesions can be caused by various factors such as inadequate bowel preparation, time spent cleaning the mucosa, poor optical diagnostic skills, fatigue, operator fatigue, suboptimal withdrawal techniques, and human error. A recent systematic review and meta-analysis of tandem colonoscopy studies found that colonoscopists with a higher ADR are more effective in protecting patients from postcolonoscopy colorectal cancer development, whereas endoscopists have higher polyp miss rate of 26% for adenomas and 27% for serrated lesions (6,7).

Artificial intelligence (AI) has emerged as a promising adjunct to colonoscopy, offering the potential to enhance detection rates and improve screening outcomes (8). AI-driven computer-aided detection and computer-aided diagnosis systems have been developed to assist endoscopists in real-time polyp detection and characterization. These AI-assisted colonoscopy systems use deep learning algorithms trained on vast image data sets to recognize patterns indicative of adenomas (9). The integration of AI into colonoscopy has been shown to reduce the rate of missed adenomas and improve ADR, which could lead to improved patient outcomes. Multiple AI-assisted colonoscopy systems exist to date, including ENDOANGEL, EndoAID, CAD EYE and GI Genius. Despite the development of these systems, the most effective system for enhancing adenoma detection remains uncertain. Given the growing adoption of AI technologies in clinical practice, understanding the comparative effectiveness of these systems is critical for optimizing their integration into colorectal cancer-screening protocols.

The integration of AI into colonoscopy has been shown to significantly reduce missed adenomas and improve ADRs. Recent meta-analyses have demonstrated that AI assistance can increase ADR by approximately 7–10% compared with standard colonoscopy. For example, Liu et al (10) (2021) reported a pooled absolute ADR increase of 9.8% across randomized controlled trials using AI-based systems. However, real-world effectiveness of AI systems may be influenced by factors such as poor bowel preparation, inadequate mucosal exposure, and operator fatigue. These conditions can compromise image quality and, in turn, reduce the diagnostic accuracy of AI models trained on ideal high-resolution data sets. This explains why AI may not guarantee $<$6% miss rate in practice.

The aim of this network meta-analysis was to evaluate and compare the effectiveness of several AI-assisted colonoscopy systems, ultimately identifying the most reliable system for improving ADR and APC—2 critical measures for the early detection of colorectal cancer. By synthesizing available evidence from randomized controlled trials (RCTs), this study provides a comparative assessment of AI-assisted colonoscopy systems, offering valuable insights into their clinical utility.

METHODS

Protocol and registration

This network meta-analysis was conducted in accordance with a predefined protocol to ensure methodological transparency and reproducibility. The protocol was prospectively registered in the Open Science Framework before data extraction and analysis. Full details of the protocol, including eligibility criteria, search strategy, and planned statistical methods, are publicly available at the following link: https://doi.org/10.17605/OSF.IO/CP467.

Eligibility criteria and population, intervention, comparision, and outcome

To ensure a high level of evidence, only RCTs were included in the analysis. The inclusion criteria were limited to studies that directly compared the efficacy of AI-assisted colonoscopy with conventional colonoscopy in detecting adenomas. Studies that did not report adequate data on adenoma detection or those focusing on advanced cancer rather than adenoma detection were excluded. The study followed the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) guidelines to maintain transparency and rigor in data collection.

1. Population: Studies enrolling adult patients undergoing screening or diagnostic colonoscopy for the detection of colorectal neoplasia were included. Trials conducted exclusively in pediatric populations or those focusing on advanced colorectal cancer were excluded.
2. Intervention: The intervention of interest was colonoscopy performed with the assistance of AI-based systems, including but not limited to GI Genius, CAD EYE, EndoAID, ENDOANGEL, and EndoScreener.
3. Comparator: The comparator in all included studies was conventional colonoscopy without the use of AI assistance.
4. Outcomes: Studies were required to report on at least one of the following outcomes: ADR, defined as the proportion of procedures in which at least one adenoma was detected, and APC, defined as the average number of adenomas detected per procedure.
5. Study Design: Only RCTs were considered eligible for inclusion to ensure a high level of evidence. Nonrandomized studies, case reports, reviews, editorials, and studies without adequate outcome data were excluded.

Information sources. A comprehensive literature search was conducted across multiple electronic databases to identify relevant randomized controlled trials. The databases searched included PubMed, Scopus, and Google Scholar, covering studies from their inception until March 4, 2025. The search strategy combined Medical Subject Headings (MeSH) and free-text keywords related to artificial intelligence, colonoscopy, and adenoma detection. No language or publication status restrictions were applied. In addition to the database search, reference lists of included studies and relevant reviews were manually screened to identify any additional eligible studies. However, no further records were retrieved through manual searching.

Search strategy. The search strategy was developed to maximize sensitivity in identifying relevant randomized controlled trials comparing AI-assisted colonoscopy with conventional colonoscopy. It used a combination of MeSH and relevant keywords such as "artificial intelligence," "colonoscopy," "adenoma detection," and the names of individual AI systems (e.g., GI Genius, ENDOANGEL). Boolean operators (AND/OR) were applied to optimize the search structure. The full electronic search strategy for each database is provided in Supplementary Digital Content (see Table S3, http://links.lww.com/CTG/B361). The search was conducted by 2 independent reviewers, and all identified citations were imported into EndNote for deduplication and screening.

Study identification and selection

A comprehensive literature search by 2 authors identified a total of 722 records through electronic databases including PubMed, Scopus, and Google Scholar., using a combination of relevant MeSH terms and keywords. The search was designed to identify RCTs comparing AI-assisted colonoscopy with conventional colonoscopy for the detection of colorectal neoplasia, particularly adenomas. The search period extended from the inception of these databases until March 4, 2025. No additional records were found through manual searching or reference lists.

AI systems evaluated

The analysis focused on 5 AI-assisted colonoscopy systems:

1. GI Genius (Medtronic, Dublin, Ireland): A convolutional neural network (CNN) system trained on 1.5 million images and validated on 138 polyps. Approved in Europe (2020), the United States (2021), and Canada (2021) (8).
2. CAD EYE (Fujifilm, Tokyo, Japan): Uses CNN with Skip Connections Net architecture. Trained on 132 polyp images and 94,331 nonpolyp images, validated on 466 polyp images. Approved in Europe and Japan (2020) (9).
3. EndoAID (Olympus Corporation, Tokyo, Japan): CNN-based system, specifics of architecture and validation data sets unspecified. Approved in Europe (2020).
4. ENDOANGEL (Wuhan EndoAngel Medical Technology, Wuhan, China): Uses YOLOv3. Trained on 8,166 polyp images and 11,417 nonpolyp images. Approved in China (2020) (11).
5. EndoScreener (Shanghai Wision, Shanghai, China): Uses SegNet CNN. Trained on 5,545 colonoscopy images, validated on 771,131 images. Approved in China (2020), Europe (2021), and the United States (2021) (12).

These AI systems were compared with conventional colonoscopy (without AI assistance), which served as the control.

Data extraction and management

Data from eligible studies were independently extracted by 2 reviewers using a standardized, prepiloted data extraction form. Extracted variables included study characteristics (author, year, country), participant demographics, type of AI system used, comparator, sample size, and outcome data (ADR and APC). Any disagreements were resolved by consensus or through consultation with a third reviewer. Where necessary, corresponding authors were contacted to obtain missing or unpublished data.

Primary and secondary outcomes

The primary outcome of the meta-analysis was ADR, defined as the proportion of colonoscopies in which at least one adenoma was detected. The secondary outcome was APC, representing the average number of adenomas detected per procedure.

Statistical analysis

All statistical analyses were conducted using Stata software (version 17, StataCorp, College Station, TX). A Bayesian network meta-analysis was performed using a random-effects model to compare AI-assisted endoscopic systems. The results were reported as odds ratios (ORs) with 95% credible intervals (CrIs). The consistency of the network was assessed using node-splitting, and ranking of AI systems was evaluated using the Surface Under the Cumulative Ranking Curve (SUCRA) (Table 1).

Network plot. A network plot was generated to visually represent the geometry of treatment comparisons among the included studies. Each node in the plot corresponds to an intervention (AI-assisted colonoscopy system or conventional colonoscopy), and the size of the node reflects the number of patients assigned to that treatment across all studies. Edges (lines) connecting nodes indicate direct head-to-head comparisons between interventions, with line thickness proportional to the number of studies contributing to that comparison. The plot was created using Stata 17's networkplot command, allowing for a clear visual depiction of both direct and indirect evidence.

Table 1. Treatments are ranked from highest to lowest along the leading diagonal for the outcome ADR

Comparator	ENDOANGEL	EndoAID	CAD EYE	GI Genius	EndoScreener	Control
ENDOANGEL	ENDOANGEL	N/A	N/A	N/A	N/A	1.84 [1.32; 2.56]
EndoAID	1.12 [0.70; 1.77]	EndoAID	N/A	N/A	N/A	1.64 [1.20; 2.26]
CAD EYE	1.26 [0.86; 1.84]	1.13 [0.78; 1.63]	CAD_EYE	N/A	N/A	1.46 [1.21; 1.75]
GI Genius	1.27 [0.87; 1.84]	1.14 [0.79; 1.63]	1.00 [0.78; 1.30]	GI_GENIUS	N/A	1.45 [1.22; 1.73]
EndoScreener	1.34 [0.94; 1.92]	1.20 [0.85; 1.70]	1.06 [0.85; 1.33]	1.06 [0.85; 1.32]	EndoScreener	1.37 [1.20; 1.56]
Control	1.84 [1.32; 2.56]	1.64 [1.20; 2.26]	1.46 [1.21; 1.75]	1.45 [1.22; 1.73]	1.37 [1.20; 1.56]	Control

Above the leading diagonal are estimates from pairwise meta-analyses, below the leading diagonal are estimates from network meta-analyses. Relative treatment effects in ranked order for all studies. Values are given as odds ratio (OR) and 95% confidence intervals.
ADR, adenoma detection rate; N/A, data not available.

Forest plot. Forest plots were constructed to display the pairwise and network effect estimates for each intervention comparison. Each plot shows the OR and 95% CrI for ADR or APC, allowing for interpretation of both the direction and precision of effects. The network forestplot command in Stata 17 was used to generate these plots, enabling the presentation of results from the Bayesian random-effects model for both direct and network estimates.

Rank plot. Rank plots were developed to show the probability of each intervention being ranked at each possible position (e.g., best, second-best, etc.) based on its relative effectiveness. These plots were generated using SUCRA values derived from the network meta-analysis. The network rankplot command in Stata was used to produce these plots, providing a visual summary of the relative rankings of all AI systems and the control group for ADR and APC outcomes.

League table. A league table was generated to summarize all pairwise comparisons among the included interventions. The table presents estimated ORs and 95% CrIs for each possible treatment pair, using the results of the Bayesian network meta-analysis. Comparisons below the diagonal reflect the estimated effects of the treatment in the row versus the column, whereas values above the diagonal may represent inverse comparisons or additional outcome summaries. This matrix format was created using Stata's network league table function and allows for quick reference and interpretation of comparative efficacy across interventions.

Inconsistency table. To assess the consistency of the network, an inconsistency table was generated using node-splitting analysis. This method compares direct and indirect estimates for the same treatment comparisons to detect potential inconsistencies in the network. The results are presented in tabular form, showing *P*-values and effect estimates for each comparison where both direct and indirect evidence are available. This analysis was conducted in Stata 17 using the network nodesplit command, and the resulting table provides key information to judge the validity of the consistency assumption underlying the network meta-analysis.

Assessment of heterogeneity

Heterogeneity among the included studies was assessed using the I^2 statistic, as recommended by the Cochrane Handbook for Systematic Reviews of Interventions. According to Cochrane guidance, an I^2 value of 30%–50% was interpreted as moderate heterogeneity, 50%–75% as substantial, and >75% as considerable heterogeneity. These thresholds were used to interpret the consistency of effects across studies and to inform decisions regarding the appropriateness of pooling data. In the presence of substantial or considerable heterogeneity, potential sources were explored through subgroup and sensitivity analyses.

Summary measures and data synthesis. The primary summary measure was the OR with corresponding 95% CrIs for binary outcomes such as ADR and APC. A Bayesian network meta-analysis was performed using a random-effects model to account for between-study variability. All analyses were conducted using Stata version 17.0. A network plot was constructed to display the geometry of treatment comparisons. Treatment ranking was evaluated using SUCRA scores to determine the probability that each intervention was the most effective.

Assessment of inconsistency and transitivity. As the network consisted exclusively of comparisons between each AI intervention and the control group, no direct head-to-head comparisons between AI systems were available. Therefore, formal statistical assessment of inconsistency through node-splitting was not feasible. We evaluated the assumption of transitivity by ensuring comparability of study populations, interventions, and outcome definitions across trials. Data for each direct and indirect comparison are given in the Supplementary Digital Content (see Table S1 and S2, http://links.lww.com/CTG/B361).

Treatment ranking. To facilitate comparison among interventions, treatments were ranked based on SUCRA values, which represent the likelihood of each intervention being the most effective in increasing ADR or APC. A SUCRA value closer to 100% indicates a higher probability of being among the best treatments. Ranking probabilities were visually summarized using rank plots.

Assessment of publication bias. Potential small-study effects and publication bias were evaluated through comparison-adjusted funnel plots, constructed separately for each outcome. Visual inspection was used to assess symmetry, and where applicable, Egger's test was used to statistically test for asymmetry. Evidence of publication bias was considered in interpreting the certainty of the results.

Certainty of evidence. The overall certainty of the evidence was assessed using the Confidence in Network Meta-Analysis (CINeMA) framework, which incorporates the GRADE approach adapted for network meta-analysis. CINeMA evaluates 6 domains: within-study bias, reporting bias, indirectness, imprecision, heterogeneity, and incoherence. Each comparison was rated as having high, moderate, low, or very low confidence based on these domains.

RESULTS

Study characteristics

The study selection process is illustrated in the PRISMA flow diagram (Figure 1). A total of 722 records were initially identified through database searches (PubMed, Scopus, and Google Scholar), with no additional records retrieved from other sources. After the removal of 3 duplicate entries, 719 records were screened based on titles and abstracts. Of these, 342 records were excluded, and the remaining 377 articles underwent full-text review for eligibility. Subsequently, 360 articles were excluded for the following reasons: wrong population (n = 354), unavailability of detailed data (n = 3), and incorrect document type (n = 3). Ultimately, 17 studies met the inclusion criteria and were included in the final synthesis (Figure 1). A total of 17 RCTs involving 10,539 participants were included in the meta-analysis. These studies investigated the impact of 5 AI-assisted colonoscopy systems on adenoma detection compared with conventional colonoscopy. Four studies reported the use of GI Genius (Medtronic, Dublin, Ireland) with 1,080 patients (13–16), 3 studies (17–19) reported the use of CAD EYE (FujiFilm, Tokyo, Japan) with 924 patients, 5 studies reported the use of EndoScreener (12,20–23) (Shanghai Wision AI, Shanghai, China) with 2,332 patients, 2 studies reported the use of ENDOANGEL

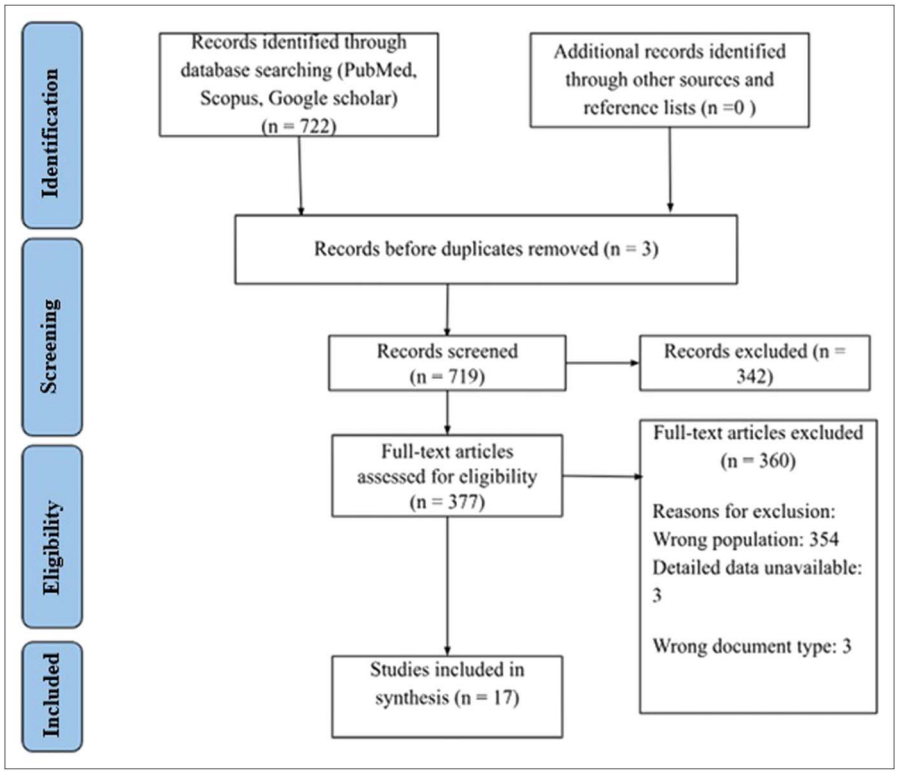

Figure 1. Prisma flowchart.

(Wuhan EndoAngel Medical Technology, Wuhan, China) (24,25) and EndoAID (Olympus Corporation, Tokyo, Japan) (26,27) with 592 and 249 patients, respectively. All studies had standard colonoscopy as control, with 5,262 patients. Comparison details of different models of colonoscopies are shown in the network plot in Figure 2. The studies varied regarding design, patient populations, and the specific AI systems evaluated. Most studies reported relatively low risk of bias, although some studies were limited by small sample sizes or unclear reporting. Details of the study characteristics are provided in Table 2.

Risk of bias assessment

The risk of bias for each included study was assessed using the Cochrane Risk of Bias 2.0 tool. This tool evaluates bias across 5

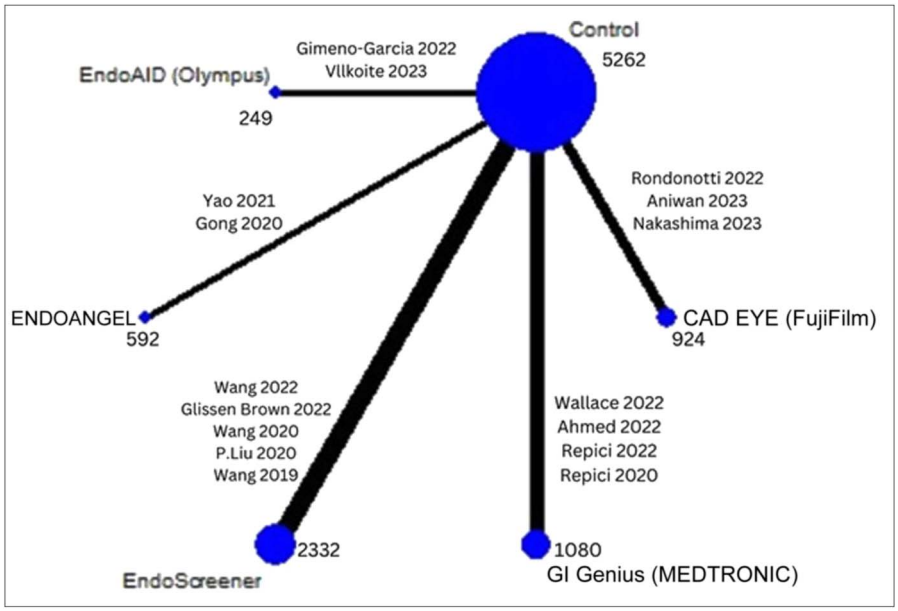

Figure 2. Network diagram illustrating the total number of patients analyzed in each treatment arm. The thickness of the lines corresponds to the number of studies comparing each pair of interventions, and the size of each node reflects the number of participants (sample size). CI, confidence interval; OR, odds ratio.

Table 2. Study characteristics

Article	Study design	Country	Outcomes available	No. of patients	Mean age, y	Female, %	AI system		ADR				APC					
									AI		Control		AI			Control		
							Name	Developer	Diagnosed	Total	Diagnosed	Total	Mean	SD	N	Mean	SD	N
Ahmad et al, 2022	Parallel	United Kingdom	ADR and APC	579	66.3	66.1	GI Genius	Medtronic	216	293	196	286	2.5	3	293	2.3	2.7	286
Aniwan et al, 2023	Parallel	Thailand	ADR and APC	622	62.4	57	CAD-EYE	FujiFilm	163	312	130	310	1.11	1.62	312	0.76	1.22	310
Gimeno-garcía, 2022	Parallel	Spain	ADR and APC	312	63.9	47.1	Endo-AID	Olympus	88	155	70	157	1.54	2.17	155	0.92	1.34	157
Glissen brown et al, 2022	Tandem	United States	ADR and APC	223	60.9	45.3	EndoScreener	Shanghai Wision AI	57	113	48	110	1.19	2.03	113	0.9	1.55	110
Gong et al, 2020	Parallel	China	ADR and APC	642	49.5	51	EndoAngel	Wuhan EndoAngel Medical Technology	54	324	26	318	0.18	0.43	324	0.08	0.27	318
Liu et al, 2020	Parallel	China	ADR and APC	790	49.3	52.7	EndoScreener	Shanghai Wision AI	123	207	99	200	1.21	1.36	207	1.01	1.5	208
Nakashima et al, 2023	Tandem	Japan	ADR and APC	415	55.4	28.2	CAD-EYE	FujiFilm	114	393	83	397	0.48	0.69	393	0.29	0.54	397
Repici et al, 2020	Parallel	Italy	ADR and APC	685	61.3	50.8	GI Genius	Medtronic	187	341	139	344	1.07	1.54	155	0.92	1.34	157
Repici et al, 2022	Parallel	Italy, Switzerland	ADR and APC	660	62.3	50	GI Genius	Medtronic	176	330	147	330	1.26	1.82	330	1.04	1.75	330
Rondonotti et al, 2022	Parallel	Italy	ADR and APC	800	61	48.8	CAD-EYE	FujiFilm	217	405	179	395	1.13	1.06	405	0.9	0.95	395
Vilkoite et al, 2023	Parallel	Latvia	ADR	400	50.7	51.8	Endo-AID	Olympus	59	194	43	206	N/A	N/A	N/A	N/A	N/A	N/A
Wallace et al, 2022	Tandem	Italy, United Kingdom, United States	ADR and APC	213	63.8	31.7	GI Genius	Medtronic	72	116	70	114	1.79	2.63	116	1.46	1.7	114
Wang et al, 2019	Parallel	China	ADR and APC	1,058	50.5	51.6	EndoScreener	Shanghai Wision AI	152	522	109	536	0.53	0.73	522	0.31	0.56	536
Wang et al, 2020a	Parallel	China	ADR and APC	962	49	48.5	EndoScreener	Shanghai Wision AI	229	668	181	663	0.58	0.76	484	0.38	0.62	478
Wang et al, 2020b	Tandem	China	ADR and APC	369	47.5	51.5	EndoScreener	Shanghai Wision AI	64	184	49	185	0.67	0.82	184	0.39	0.62	185
Wang et al, 2022	Parallel	China	ADR and APC	1,261	46	45.3	EndoScreener	Shanghai Wision AI	164	636	150	625	0.42	0.65	636	0.35	0.59	625
Yao et al, 2021	Parallel	China	ADR and APC	539	50.8	56	EndoAngel	Wuhan EndoAngel Medical Technology	57	268	40	271	0.24	0.49	268	0.17	0.41	271

ADR, adenoma detection rate; AI, artificial intelligence; APC, adenomas per colonoscopy; N/A, not available.

domains: randomization process, deviations from intended interventions, missing outcome data, measurement of the outcome, and selection of the reported result. Two reviewers independently assessed the risk of bias, and disagreements were resolved through discussion.

The methodological quality of the included studies was evaluated using the Cochrane Risk of Bias 2.0 tool. Overall, the studies demonstrated a low risk of bias across most domains. The randomization process, adherence to intended interventions, outcome measurement, and completeness of outcome data were well reported and appropriately conducted in most trials. No serious concerns were noted regarding selective reporting, and trial protocols or registrations were available for most studies. As a result, the overall risk of bias in the included studies was considered low, supporting the validity and robustness of the findings from the network meta-analysis (see Figure S8, Supplementary Digital Content, http://links.lww.com/CTG/B362).

Efficacy of AI systems

Adenoma detection rate. ENDOANGEL (Wuhan EndoAngel Medical Technology, Wuhan, China) was the most effective AI system, with a pooled OR of 1.84 (SUCRA = 0.9), significantly improving ADR compared with conventional colonoscopy. EndoAID (Olympus Corporation, Tokyo, Japan) ranked second, with an OR of 1.64 (SUCRA = 0.7), demonstrating a substantial improvement in ADR. CAD EYE (Fujifilm, Tokyo, Japan) and GI Genius (Medtronic, Dublin, Ireland) shared third place, with similar ORs of 1.46 and 1.45, respectively (SUCRA = 0.5). EndoScreener ranked second last, with an OR of 1.37 (SUCRA = 0.4), still showing a moderate improvement in ADR. The control group (conventional colonoscopy) ranked last, with the lowest ADR. Relative Ranks of AI systems for ADR outcome are given in the Supplementary Digital Content (see Figure S4, http://links.lww.com/CTG/B362). SUCRA values are mentioned in Table 3. Direct comparison of ADR of different AI systems with control group through a network meta-analysis is shown in Figure 3.

The results from pairwise and network meta analyses for ADR outcome are summarized in the league table in Table 1. Treatments are ranked from best to worst along the leading diagonal. Values above the diagonal are derived from pairwise meta-analyses, whereas those below are from network meta-analyses, providing a comparative analysis of treatment effects.

The league table for ADR outcome showed the treatments ranking from best to worst based on OR with 95% confidence intervals. ENDOANGEL demonstrated the highest odds ratio (OR) (1.84 [1.32; 2.56]), suggesting it might be the most effective treatment for improving ADR. This was followed by EndoAID (OR = 1.64 [1.20; 2.26]), ENDOEYE (OR = 1.46 [1.21; 1.75]), ENDOFREE (OR = 1.45 [1.22; 1.73]), and both EndoGenius and EndoScreener, which shared the same OR (1.37 [1.20; 1.56]). These results provide a comparative understanding of the relative effectiveness of each treatment in enhancing ADR (Table 1).

APC. Regarding APC, EndoAID showed the highest mean difference of 0.62, indicating that it detected more adenomas per colonoscopy than conventional colonoscopy. ENDOANGEL followed with a mean difference of 0.09, which, although the smallest, still showed a notable improvement in adenoma detection over conventional colonoscopy. Relative ranks of AI systems for APC outcome are given in the Supplementary Digital Content (see Figure S5, http://links.lww.com/CTG/B362). Direct comparison of APC of different AI systems with control group through a network meta-analysis is shown in Figure 4.

The results from pairwise and network meta analyses for APC outcome are summarized in the league table in Table 4. Treatments are ranked from best to worst along the leading diagonal. Values above the diagonal are derived from pairwise meta-analyses, whereas those below are from network meta-analyses, providing a comparative analysis of treatment effects.

The league table for APC outcome demonstrated AI-assisted systems to have lower odds ratios compared with the control group, with ENDOANGEL (OR = 0.54, 95% CI: 0.39–0.76) exhibiting the lowest OR, followed by EndoAID (OR = 0.61, 95% CI: 0.44–0.84). However, pairwise comparisons between different AI systems showed overlapping confidence intervals, indicating no statistically significant differences among them. For instance, the comparison between GI GENIUS and EndoScreener resulted in an OR of 0.94 (95% CI: 0.76–1.17), whereas CAD EYE vs GI GENIUS yielded an OR of 1.00 (95% CI: 0.77–1.28), suggesting comparable effectiveness (Table 4).

The leverage plot (see Figure S1, Supplementary Digital Content, http://links.lww.com/CTG/B362) was examined to assess the influence of each direct comparison on the network meta-analysis results. The plot revealed that Ahmed et al 2022 had the

Table 3. Probabilities are given for each AI system to occupy different ranks, along with mean rank

	Treatment				
Rank	CAD EYE (Fujifilm)	EndoAID (Olympus)	ENDOANGEL	EndoScreener	GI Genius (Medtronic)
Highest	0	3.8	29.1	0.6	3.3
2nd	0	18.3	38.8	5	15.9
3rd	0	32.2	13.8	16.4	30.8
4th	0	26.2	9.2	32.3	28.2
5th	0.1	19.6	9.7	45.7	21.8
Lowest	99.9	0	0.1	0	0
Mean rank	6	3.4	2.3	4.2	3.5
SUCRA	0	0.5	0.7	0.4	0.5

SUCRA (surface under the cumulative ranking curve) values are calculated as per ADR, outcome.
AI, artificial intelligence.

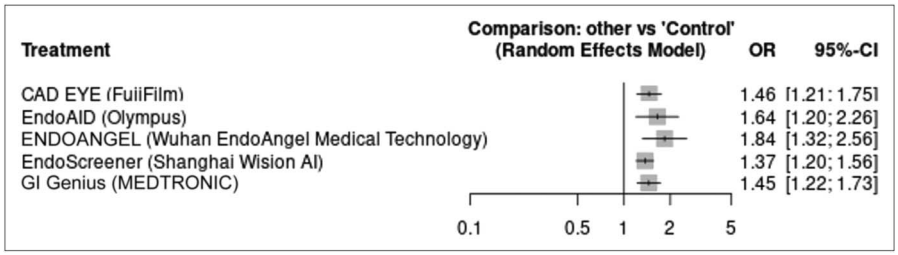

Figure 3. Forest plot of direct comparison of different pairs of various AI systems through a network meta-analysis in assessing adenoma detection rate (ADR). AI, artificial intelligence; CI, confidence interval; OR, odds ratio.

most influence on the results. This suggests that overall, all the studies had similar influence on the network meta-analysis result.

The residual deviance plot was examined to assess the model's fit to the data (see Figure S3, Supplementary Digital Content, http://links.lww.com/CTG/B362). The plot revealed no major deviations. This suggests that the model adequately captured the patterns and relationships in the data. The stem plot (see Figure S2, Supplementary Digital Content, http://links.lww.com/CTG/B362) further testified this result.

Heterogeneity and publication bias assessment

The analysis showed low heterogeneity across most groups, with an I^2 of less than 50%. A funnel plot (see Figure S6 and S7, Supplementary Digital Content, http://links.lww.com/CTG/B362) was generated to assess potential publication bias among the included studies. The plot displays the log-transformed odds ratios (log ORs) of each study against their standard errors. A symmetrical distribution of studies within the triangular region—bounded by 95% confidence limits—suggests a low likelihood of publication bias. In this analysis, the plot for ADR outcome seems reasonably symmetrical, whereas for APC outcome, there is a slight asymmetry. However, due to the limited number of included studies (n = 5), the interpretive power of the funnel plot remains constrained, and the results should be viewed with caution.

Certainty of evidence

A CINeMA-based risk of bias assessment was conducted across 6 key domains for all included AI-assisted colonoscopy interventions. The evaluation revealed that all AI-assisted colonoscopy interventions demonstrated a low risk of within-study bias, reporting bias, and indirectness, with the exception of ENDOANGEL, which showed moderate concerns for both reporting bias and indirectness. Imprecision was rated as moderate to high across the interventions, largely attributable to small sample sizes in several included studies, which limited the precision of effect estimates. Importantly, heterogeneity was consistently low across all comparisons, suggesting reliable consistency in study outcomes. The domain of incoherence was marked as not applicable, as no direct head-to-head trials were available between the AI systems; all effect estimates were derived from indirect comparisons through conventional colonoscopy arms. Overall, the risk of bias assessment supports a moderate level of confidence in the evidence base, with the primary limitations stemming from small study sizes and the absence of direct AI-vs-AI comparisons. This is provided in Supplementary Digital Content (see Figure S9, http://links.lww.com/CTG/B362).

DISCUSSION

Traditionally, colonoscopies relied on the manual identification of polyps by clinicians, who assessed whether lesions were benign or precursors to malignancy. However, this approach is prone to human error and variability in detection rates because of differences in operator experience, fatigue, or visualization technique (28). Even with advancements in colonoscopy technology, missed lesions remain a significant challenge, with studies reporting miss rates as high as 25% for adenomas (29). This underscores the need for supplementary tools, such as AI-assisted detection systems, to enhance ADR and APC and reduce CRC-related mortality.

AI-assisted colonoscopy systems have demonstrated the ability to improve ADR by providing real-time visual alerts for suspected lesions, thereby reducing human error and enhancing detection rates. The results of this network meta-analysis suggest that ENDOANGEL had the highest estimated effect size for improving ADR and a notable impact on APC compared with conventional colonoscopy (30). However, the differences between systems were modest, and the confidence intervals for many estimates overlapped, indicating that the comparative effectiveness of these systems should be interpreted with caution. Although SUCRA values suggested a higher probability of effectiveness for ENDOANGEL, followed by EndoAID, CAD EYE, GI Genius, and EndoScreener, these values represent relative probabilities rather than definitive rankings. These findings are

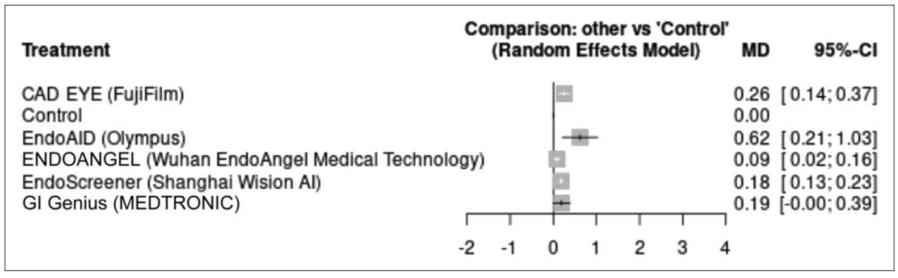

Figure 4. Forest plot of direct comparison of different pairs of various AI systems through a network meta-analysis in assessing adenoma per colonoscopy (APC). 95% CI, confidence interval; AI, artificial intelligence; MD, mean difference.

Table 4. Treatments are ranked from highest to lowest along the leading diagonal for the outcome APC

Comparator	EndoAID	CAD EYE	GI Genius	EndoScreener	ENDOANGEL	Control
EndoAID	EndoAID	N/A	N/A	N/A	N/A	0.62 [0.21; 1.03]
CAD EYE	0.37 [−0.06; 0.79]	CAD_EYE	N/A	N/A	N/A	0.25 [0.14; 0.37]
GI Genius	0.41 [−0.03; 0.86]	0.05 [−0.17; 0.27]	GI_GENIUS_MEDTRONIC_	N/A	N/A	0.21 [0.02; 0.39]
EndoScreener	0.44 [0.04; 0.85]	0.08 [−0.05; 0.21]	0.03 [−0.16; 0.22]	EndoScreener	N/A	0.18 [0.13; 0.22]
ENDOANGEL	0.53 [0.12; 0.94]	0.17 [0.03; 0.30]	0.12 [−0.08; 0.31]	0.09 [0.01; 0.17]	ENDOANGEL	0.09 [0.02; 0.15]
Control	0.62 [0.21; 1.03]	0.25 [0.14; 0.37]	0.21 [0.02; 0.39]	0.18 [0.13; 0.22]	0.09 [0.02; 0.15]	Control

Above the leading diagonal are estimates from pairwise meta-analyses, below the leading diagonal are estimates from network meta-analyses. Relative treatment effects in ranked order for all studies. Values are given as mean difference (MD) and 95% confidence intervals.
APC, adenomas per colonoscopy; N/A, data not available.

consistent with previous meta-analyses, which have reported that AI assistance can significantly improve ADR compared with standard colonoscopy (7).

One possible explanation for ENDOANGEL's relative superior performance is its advanced deep-learning architecture, which incorporates robust image recognition and classification algorithms. By leveraging CNNs trained on extensive data sets, ENDOANGEL is capable of identifying a wide range of adenomas, including flat and diminutive lesions that are often missed by human observers (6). In addition, the system's real-time feedback mechanism enables endoscopists to focus on potential lesions more effectively, reducing cognitive burden and enhancing procedural efficiency.

The comparative analysis of AI-assisted colonoscopy systems revealed notable differences in both architecture and clinical performance, which may influence their efficacy in practice. All included systems use CNNs but with varying architectural designs and training data sets.

ENDOANGEL uses YOLOv3, a CNN-based object detection model optimized for real-time identification of polyps using semantic segmentation. EndoScreener, in contrast, is built on a SegNet-based CNN with similar segmentation capabilities. While both systems share a semantic segmentation foundation, their performance differs—ENDOANGEL ranked highest in ADR (OR 1.84), whereas EndoScreener showed only modest improvement (OR 1.37). This discrepancy may be explained by differences in training data volume, real-time feedback design, and system integration with endoscopy workflows. In addition, ENDOANGEL's training data set was substantially larger and more diverse, which may contribute to its superior lesion recognition and generalization.

CAD EYE uses a CNN with skip connection architecture, and GI Genius uses a CNN trained on over a million polyp images. Both performed similarly in ADR outcomes, suggesting that architectural differences may have less impact when data sets are robust and clinical integration is consistent. EndoAID, developed by Olympus, has an unspecified CNN structure but demonstrated strong performance in APC, suggesting its algorithm may be optimized for identifying multiple adenomas per procedure rather than just detecting at least one.

An important observation from our analysis is that ENDOANGEL demonstrated the highest estimated ADR but showed only a modest mean difference in APC (0.09). This pattern may suggest that the system is effective at detecting at least one adenoma per procedure but does not necessarily increase the total number of adenomas detected. By contrast, EndoAID was associated with the greatest improvement in APC (0.62) and also showed a notable increase in ADR. These differing patterns highlight an important clinical consideration—whether systems that improve overall detection (ADR) or those that contribute to a higher number of APC offer more value. As ADR remains the primary benchmark linked to reduced colorectal cancer risk, it continues to serve as the most robust outcome measure, though APC may offer complementary insights into detection performance.

Overall, while CNN-based semantic segmentation seems to be a valuable feature, its effectiveness depends on more than just model architecture—it is also shaped by training data quality, real-time latency, and user interface. Thus, performance variation among AI systems should be interpreted in the context of both technical and clinical factors.

Although AI-assisted systems show promising results, their effectiveness is influenced by multiple factors, including variations in study design, patient populations, and endoscopist experience levels. Standardizing training protocols for AI use and ensuring high-quality data inputs could help mitigate variability in performance and improve generalizability across diverse healthcare settings (10).

Another critical consideration is the clinical adoption and cost-effectiveness of AI-assisted colonoscopy. Although AI systems enhance detection rates, their widespread implementation requires assessment of cost-benefit ratios, resource allocation, and potential workflow disruptions. Future studies should explore the economic feasibility of integrating AI into routine colonoscopy programs, particularly in resource-limited settings where cost constraints may limit access to advanced technologies.

In addition, the long-term impact of AI-assisted colonoscopy on CRC prevention and mortality remains to be fully elucidated. While improvements in ADR and APC are promising, future research should focus on longitudinal studies that evaluate how AI-enhanced detection translates into real-world reductions in CRC incidence and mortality. Large-scale, multicenter trials will be essential to validate these findings and assess whether AI-assisted systems can sustain their performance over extended periods and across diverse patient populations.

Despite these challenges, AI-assisted colonoscopy represents a significant advancement in colorectal cancer screening. The integration of AI into endoscopic practice has the potential to standardize adenoma detection, minimize interoperator

variability, and improve overall screening efficacy. This study provides strong evidence supporting the adoption of AI-assisted systems, particularly ENDOANGEL, as an effective tool for enhancing adenoma detection. However, continued research and technological refinements will be necessary to optimize AI performance and maximize its clinical benefits.

Limitations

Despite the strengths of this network meta-analysis, several limitations must be acknowledged. First, the analysis included a relatively small number of randomized controlled trials (n = 17), and certain AI-assisted colonoscopy systems—such as EndoAID and ENDOANGEL—were evaluated in only a few studies, potentially limiting the statistical power and generalizability of the findings. In addition, many of the comparisons between AI systems relied on indirect evidence because of the absence of head-to-head trials, which may introduce bias. The variability in training data sets and proprietary algorithms across AI systems also complicates direct comparisons. Moreover, although most included studies were at low risk of bias, some lacked detailed reporting on randomization or blinding methods. Finally, while improvements in ADR and APC were demonstrated, the analysis did not assess long-term clinical outcomes such as colorectal cancer incidence or mortality, nor did it evaluate the cost-effectiveness or implementation barriers associated with AI adoption in diverse healthcare settings. These factors warrant further investigation in future large-scale, multicenter studies.

Although all included RCTs used a conventional colonoscopy group as the comparator, there were methodological differences across studies that may introduce clinical heterogeneity. These included variations in the models and manufacturers of endoscopes used, quality of bowel preparation (as assessed by scoring systems such as the Boston Bowel Preparation Scale), and differences in endoscopist training, skill level, and fatigue. While individual randomization within each study minimizes internal bias, these variations across trials may act as confounding factors, potentially influencing the pooled effect estimates in the network meta-analysis. These findings should be interpreted cautiously, as differences in system performance were small and based on indirect comparisons. Further direct head-to-head trials are warranted to confirm comparative effectiveness.

This network meta-analysis provides comprehensive evidence on the comparative effectiveness of various AI-assisted colonoscopy systems in enhancing adenoma detection. Among the evaluated systems, ENDOANGEL, EndoAID, CAD EYE, and GI Genius were all associated with improvements in ADR and APC compared with conventional colonoscopy. Although ENDOANGEL demonstrated the highest estimated effect sizes in our analysis, the overlapping confidence intervals between systems and variability across studies suggest that differences in performance may be modest and should be interpreted cautiously.

These findings support the broader value of incorporating AI technologies into endoscopic practice to enhance colorectal cancer screening. However, given the indirect nature of the comparisons and the evolving landscape of AI development, further head-to-head trials are needed to clarify comparative effectiveness. Future research should also explore cost-effectiveness and real-world implementation to guide clinical decision making and optimize the role of AI in colorectal cancer prevention.

CONFLICTS OF INTEREST

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Financial support: None to report.
Potential competing interests: None to report.
Ethical statement: This study is a meta-analysis of previously published randomized controlled trials and did not involve the direct collection of new data from human participants. As such, ethical approval and informed consent were not required. All included studies had obtained appropriate ethical approval from their respective institutional review boards.
IRB approval: No IRB approval required for this manuscript as no human subjects were involved.
Data availability statement: The authors confirm that the studies included in this research are publicly available on PubMed Central. Data supporting the findings of this study are available within the article and Supplementary material files. Further information can be requested by the corresponding author if needed.

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Study Highlights

WHAT IS KNOWN

- ✓ Artificial intelligence (AI)-assisted systems have been proposed to enhance adenoma detection rates during colonoscopy, with several technologies already in development. However, the comparative efficacy of different AI systems in improving adenoma detection rates has not been systematically evaluated, leaving uncertainty about their relative performance in clinical practice.

WHAT IS NEW HERE

- ✓ This meta-analysis provides a comprehensive comparison of multiple AI-assisted systems for detecting colorectal neoplasia. The study consolidates data from 17 randomized controlled trials, demonstrating variability in efficacy among AI technologies and offering a clearer understanding of their potential in clinical colonoscopy.
- ✓ The findings suggest that AI-assisted systems could improve colonoscopy outcomes and support further research to optimize these technologies. The results may help guide clinical adoption and inform future guidelines for the use of AI in colorectal cancer screening and prevention.

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