

Unraveling Emerging Trends in AI-Assisted Colorectal Polyp Diagnosis: A Bibliometric Analysis

Yang Yang¹, Liang-Jei Ma², Yu-Xin Han², Shuang-Shuang Ji³, Shu-Xin Zhang^{1,*}

¹ Dongzhimen Hospital, Beijing University of Chinese Medicine, Beijing, China

² Graduate School, Beijing University of Chinese Medicine, Beijing, China

³ Xiyuan Hospital, China Academy of Chinese Medical Sciences, Beijing, China

*Correspondence: Shu-Xin Zhang, Dongzhimen Hospital, Beijing University of Chinese Medicine, Beijing 100700, China.

E-Mail: zhshxincn@126.com

Abstract

Background: Colorectal polyps are the primary precancerous lesions of colorectal cancer (CRC), but the adenoma miss rate associated with manual colonoscopy is relatively high in clinical practice. Although artificial intelligence (AI)-assisted systems have shown substantial potential in improving polyp detection rates, a comprehensive summary of the current research landscape is still lacking.

Methods: This study conducted a literature search of publications indexed in the Web of Science Core Collection (WOSCC) from January 1, 2016 to December 31, 2025. Bibliometric analyses, including descriptive statistics, co-occurrence analysis, cluster analysis, and burst detection, were applied to the retrieved data.

Results: A total of 570 publications were included. The synchronous growth in publication volume and citation counts reflects the robust development momentum of AI research in colorectal polyps. China and the United States emerged as the core countries in global research. Institutional output was highly concentrated among top-tier academic medical centers. *Gastroenterology* journals and biomedical engineering/computer vision journals serve as complementary knowledge hubs. Mori Y was the most prolific author, with core author groups forming highly cohesive research communities within specific countries. Keyword analysis revealed the developmental trajectory of the field. The early exploration phase focused on traditional machine learning and feasibility validation, while convolutional neural networks (CNNs) and polyp segmentation drove the rapid expansion phase. The current phase emphasizes a clinical orientation toward optical diagnosis, quality indicators, and real-world validation. Citation burst analysis further corroborated this transition.

Conclusion: Research on AI-assisted colorectal polyps has developed rapidly. At present, the research focus in this field is shifting from mere algorithmic performance optimization toward patient-centered clinical validation and application. The literature suggests potential value in reducing interval cancers; however, this potential remains to be confirmed by future prospective studies, as the present bibliometric analysis can only characterize publication trends rather than establish clinical effectiveness.

Keywords: artificial intelligence; colorectal polyps; colonoscopy; deep learning; CiteSpace; VOSviewer

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Introduction

Colorectal cancer (CRC) remains one of the most common malignancies worldwide^[1–3]. According to the Global Cancer Statistics 2024, CRC accounts for 9.9% of all new cancer diagnoses and 9.4% of cancer deaths globally, ranking third in incidence and second in cancer mortality worldwide^[4]. The vast majority of CRC cases arise from colorectal polyps, particularly adenomatous polyps, through the well-established adenoma-carcinoma sequence^[5,6]. This pathological progression provides a unique window of opportunity for cancer prevention, as the detection and removal of precancerous polyps during colonoscopy can effectively interrupt this cascade and reduce both CRC incidence and mortality^[7–9]. Colonoscopy is widely acknowledged as the gold standard for the detection of precancerous polyps^[10,11]. However, despite its established efficacy, conventional colonoscopy is not without limitations^[12–14]. A significant percentage of adenomas and polyps are missed during routine endoscopic examinations, largely due to factors such as lesion morphology, subtle appearance, endoscopist fatigue, and variations in operator experience^[15,16]. These missed lesions contribute to interval cancers and undermine the overall effectiveness of screening programs^[17]. Consequently, there is an urgent and growing need for adjunctive technologies that can enhance the detection and characterization of colorectal polyps, thereby improving the quality and consistency of colonoscopic surveillance^[18].

In recent years, artificial intelligence (AI) has emerged as an important technological advance in gastrointestinal endoscopy, offering promising solutions to the long-standing challenges of polyp detection and diagnosis^[19]. AI technologies, particularly deep learning algorithms and convolutional neural networks (CNNs), have been increasingly integrated into colonoscopic procedures to assist endoscopists in real-time identification and classification of colorectal lesions^[20]. These AI-assisted systems can be broadly categorized into computer-aided detection (CADE) systems, which flag suspicious areas during colonoscopy, and computer-aided diagnosis (CADx) systems, which provide optical characterization of detected polyps^[21]. A growing body of evidence from randomized controlled trials and meta-analyses has demonstrated that AI-assisted colonoscopy significantly

increases adenoma detection rates (ADR) and polyp detection rates (PDR) compared with conventional colonoscopy alone, with some studies reporting detection accuracy as high as 93.7% for colorectal polyps^[22,23]. The accelerating volume and broadening scope of AI-related publications on colorectal polyps necessitate a systematic and quantitative assessment of the research landscape, but such a comprehensive overview is currently lacking. Bibliometric analysis, which employs quantitative methods to evaluate publication patterns, collaboration networks, and emerging research hotspots, offers an ideal approach to map the intellectual structure and evolutionary trajectory of this rapidly expanding field^[24,25]. By providing a macroscopic view of global research productivity, key contributors, and thematic shifts, bibliometric studies can help researchers, clinicians, and policymakers identify gaps, prioritize future directions, and foster interdisciplinary collaborations^[26,27].

Materials and methods

Data sources and literature screening

On July 6, 2026, a systematic literature search was performed in the Web of Science Core Collection (WOSCC), covering publications from January 1, 2016 to December 31, 2025. The search strategy was developed using a combination of controlled vocabulary and free-text terms, built around two core themes: AI and colorectal polyps. Specifically, terms related to AI, such as “artificial intelligence”, “deep learning”, and “machine learning”, were combined with disease-related terms, including “intestinal polyp”, “colorectal polyp”, and “colon polyp”, using Boolean operators. The search was restricted to original articles and reviews published in English. After the initial retrieval, the full records and cited references of all identified publications were exported in plain-text format.

To ensure high relevance to the research topic, two investigators independently conducted a manual screening of the retrieved results. They first evaluated titles and abstracts to exclude clearly irrelevant records, and then read the full texts to determine whether each article met the scope of the study. Any disagreements between the two reviewers were resolved through discussion

or by consultation with a third investigator. Studies were excluded if they mentioned AI only superficially without it being a core component, or if they were conference abstracts, editorials, letters, or lacked essential bibliographic information. The detailed search strategy is presented in Table 1.

Table 1: Construction of search strategy and literature collection

Item	Content
Database	Web of Science Core Collection
Search strategy	TS = (“artificial intelligence” OR “ai” OR “deep learning” OR “machine learning” OR “computer aided” OR “CADe” OR “CADx” OR “neural network” OR “convolutional neural network” OR “CNN” OR “automated” OR “automatic” OR “image recognition” OR “pattern recognition” OR “computational intelligence” OR “machine intelligence”) AND TS = (“intestinal polyp” OR “colorectal polyp” OR “colon polyp” OR “colonic polyp” OR “adenoma**”)
Time period	January 1, 2016 to December 31, 2025
Search date	6 July 2026
Document types	Article and review article
Language	English

Abbreviations: TS, Topic Search.

Data normalization and processing

The retrieved records were imported into CiteSpace (6.2.R4) and VOSviewer (1.6.19) for data cleaning and standardization^[28,29]. To handle variations in terminology among different authors, such as synonyms, abbreviations, and different naming forms, we first unified synonymous concepts to avoid duplicate counting. For example, “CAD” and “CADx” were consolidated into “computer-assisted diagnosis”. Subsequently, we carefully checked each reference to standardize punctuation, capitalization, and DOI information, thereby ensuring the accuracy of the subsequent co-citation analysis.

Statistical analysis and construction of visualization networks

To intuitively illustrate the distribution and evolutionary relationships of research topics, we constructed both

a keyword co-occurrence network and a document co-citation network. For the keyword co-occurrence network, we set a frequency threshold of at least 5. VOSviewer 1.6.19 was used to construct country, institution, author, and journal co-occurrence networks. CiteSpace 6.2.R4 was used for keyword co-occurrence mapping, keyword clustering, betweenness centrality calculation, timeline visualization, document co-citation analysis, burst detection, and pathfinder network pruning. The Louvain community detection algorithm was then applied to automatically partition the network into thematic clusters, with each cluster representing a relatively independent research direction. For the document co-citation network, cited references were treated as nodes and co-citation relationships as edges. The pathfinder network pruning algorithm embedded in CiteSpace was employed to simplify the network structure, thereby highlighting core nodes and major connecting pathways. All networks were visualized using the Kamada-Kawai force-directed layout algorithm. In the resulting visualizations, node size reflects frequency or co-citation count, node color indicates cluster membership, and edge thickness represents the strength of co-occurrence or co-citation. Betweenness centrality was automatically computed by CiteSpace.

Results

Annual publication volume and citation trends

Using the above retrieval strategy, a total of 570 publications were finally included after screening from the WOSCC (Fig. 1). From 2016 to 2025, the annual publication volume and cumulative citation frequency in the field of intestinal polyps and AI exhibited a pronounced upward trajectory, reflecting steadily growing academic attention. The period from 2016 to 2018 represented an initial phase, with annual publications and cumulative citations remaining at a low level. During this stage, only a small number of scholars conducted preliminary explorations of basic algorithms. From 2019 to 2021, both publication volume and citation frequency increased rapidly, with annual publications rising from 32 to 87 and cumulative citations climbing from 423 to 1,853. The widespread adoption of deep learning techniques spurred a surge of studies on polyp detection, while research teams worldwide continued

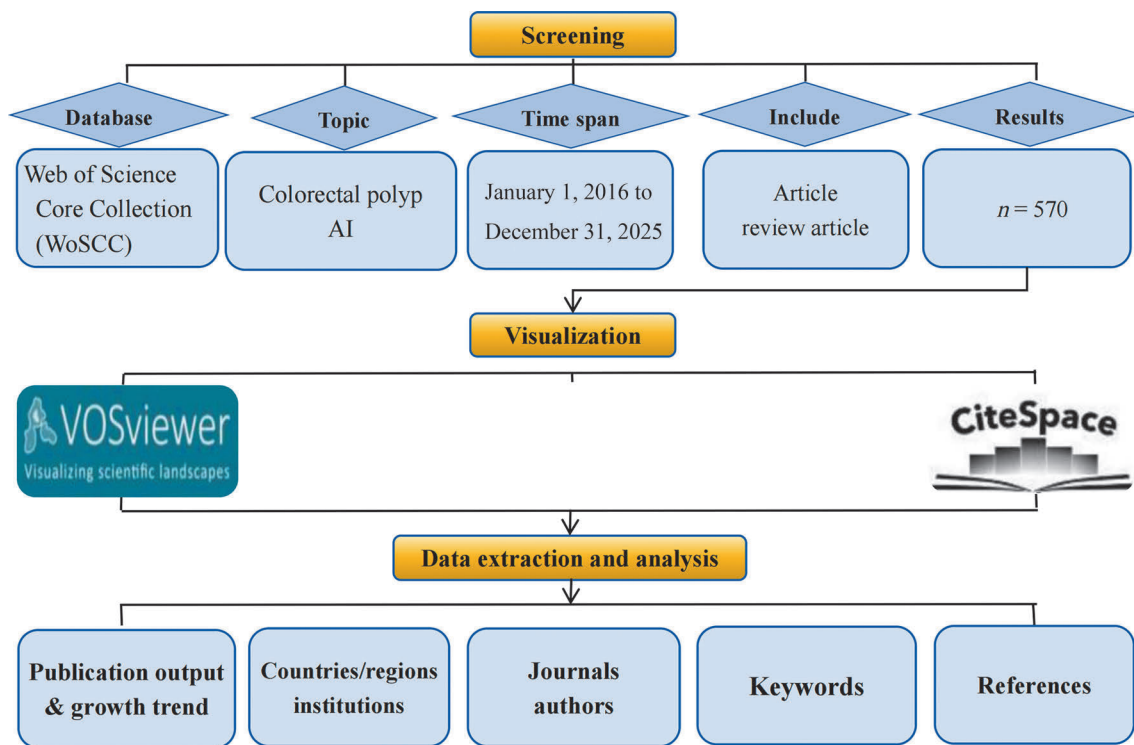


Figure 1: Flow diagram of literature screening and data analysis.
Abbreviations: PRISMA, preferred reporting items for systematic reviews and meta-analyses

to expand, significantly elevating academic interest. In 2022, publication volume experienced a slight decline, which may be related to fluctuations in research cycles and database indexing lag; however, the specific reasons require further investigation. During this period, the citation curve maintained steady growth, indicating that the overall academic influence continued to expand. From 2023 to 2025, both publication output and total citation frequency demonstrated substantial increases, suggesting that research production in this interdisciplinary area continued to grow rapidly. Overall, the application of AI technologies in the intestinal polyp domain shows strong developmental momentum and considerable scholarly influence (Fig. 2).

National academic clusters and international collaboration networks

National academic clusters in the cross-disciplinary field of intestinal polyps and AI exhibit a multipolar distribution pattern, with the United States and China playing dominant dual-core roles (Fig. 3A). Four distinct clustering camps were identified, each with markedly

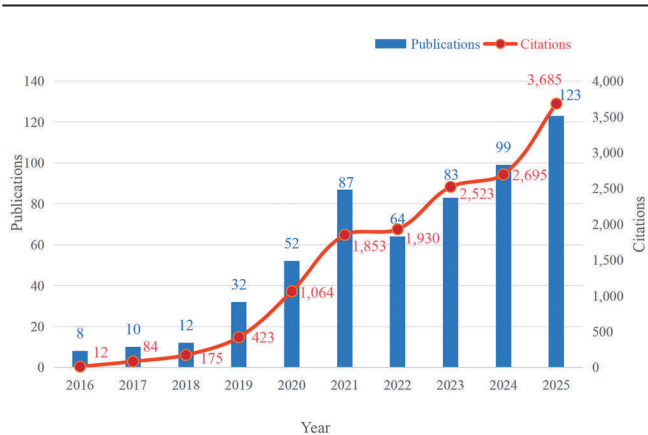


Figure 2: Temporal trends of annual publications and cumulative citation counts in studies on AI for colorectal polyps from 2016 to 2025.

different characteristics. Cluster 1 is centered on China as the dominant core, closely linked with Asia–Pacific countries including India and Australia, forming a substantially large Asia–Pacific academic bloc. Cluster 2 is concentrated in the Iberian Peninsula and South America, primarily comprising Portugal, Spain, and Brazil, reflecting the profound influence of linguistic and

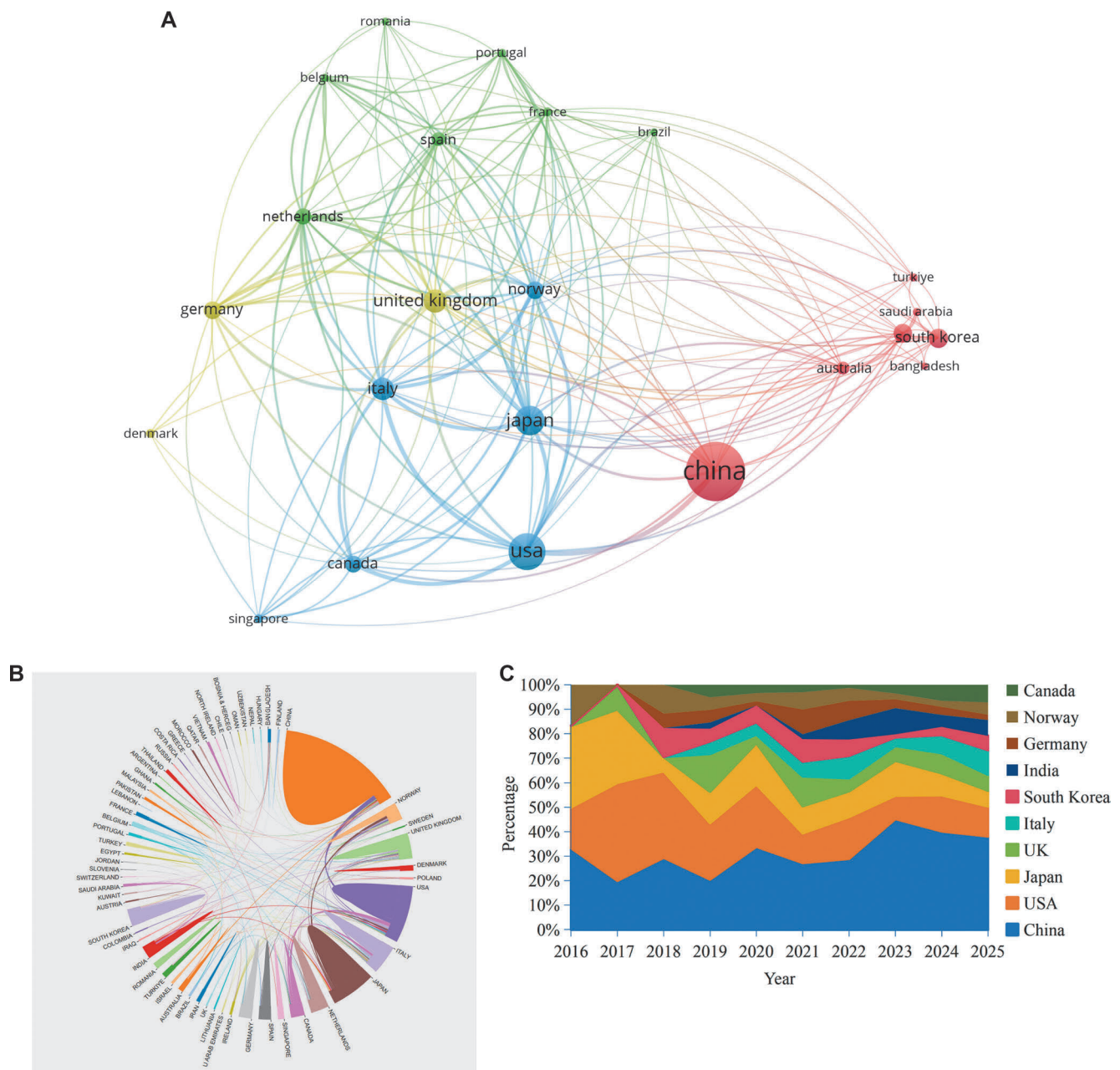


Figure 3: Country-level collaboration network, publication distribution, and temporal contribution map of research on AI for colorectal polyps.

(A) Collaboration network of countries/regions. Node size indicates publication weight of each country, line thickness represents collaboration intensity, and different colors denote distinct clusters. (B) Circular cluster diagram of publications by countries. (C) Stacked area chart showing the proportion of publications contributed by core countries from 2016 to 2025.

cultural affinity on transnational research collaboration. Cluster 3 presents the most distinctive cross-regional composition, encompassing the United States, Norway, Italy, and Turkey, demonstrating a pronounced trans-continental integration across the Americas, Europe, and Asia. Cluster 4 is highly concentrated in the United

Kingdom and its closely collaborating neighboring countries, exhibiting exceptional internal cohesion within a specific academic community. In terms of overall national weights, the United States and China far outrank all other countries in both node counts and aggregate weights. Not only do these two nations share highly

frequent and extensive interconnecting links, but they also serve as pivotal radiation hubs within their respective clusters. This finding underscores that in the cross-disciplinary research on intestinal polyps and AI, the United States and China are not only the highest-producing research and development (R&D) powerhouses but also the crucial nodal connectors that bridge different global collaboration camps.

The transnational collaboration network in this field exhibits a densely interwoven pattern centered on the United States, the United Kingdom, Japan, and Italy as the core tier (Fig. 3B). The United States demonstrates the most prominent weighting and arc length in the global collaboration network, with the United Kingdom, Japan, and Italy also ranking among the forefront of international collaboration. These four nations together form an exceptionally robust and intensive “backbone chain” of cooperation, mutually incorporating and integrating the most essential global research forces in the field. China occupies a comparably substantial arc segment in the chord diagram, not maintaining multidimensional and robust collaborative links not only with the United States, the United Kingdom, and Italy but also with Asian neighbors including Japan, South Korea, and Singapore. This clearly indicates that China is deeply engaged in and connected to the core nodes of global interaction. Beyond the aforementioned countries, Germany, France, Australia, India, and South Korea also participate broadly in the collaboration network through multiple peripheral links, jointly fostering a well-functioning transnational academic ecosystem characterized by strong main trunks and densely distributed branches. Overall, global collaboration in this field has transcended geographic constraints, with European, American, and Asia-Pacific research camps interacting at high frequency, thereby continuously accelerating advances and dissemination at the forefront of this interdisciplinary research.

Examining the annual changes in publication shares among major countries over the past decade, the field has transitioned from an early phase dominated by the United States, China, and Japan to a mature stage characterized by coordinated multi-country advancement (Fig. 3C). From 2016 to 2018, the early exploratory period of this research, the United States and China

accounted for the largest annual publication shares; the United States reached approximately 40% in 2017 and 35% in 2018, while China contributed approximately 20%–33% during this period. Japan also held a notable share, whereas India’s share remained minimal or zero. Starting from 2019, as the application of AI to intestinal polyp research rapidly gained momentum, China’s publication share rose markedly, from approximately 20% in 2019 to around 34% in 2020, and it remained the largest share thereafter, reaching approximately 45% in 2023, 40% in 2024, and 38% in 2025. In contrast, the publication share of the United States declined from its early peak to approximately 12% in 2025. By the most recent observation point in 2025, the global academic landscape had entered a relatively balanced phase of comprehensive development. China became the country with the largest publication share that year, followed by the United States (approximately 12%), Italy (approximately 10%), and Canada (approximately 7%), while Japan, the United Kingdom, and India each accounted for approximately 6%–7%. In addition, countries including South Korea, Norway, and Germany maintained stable shares. This structural transformation clearly indicates that cross-disciplinary research on intestinal polyps and AI has moved beyond reliance on a single country’s research capacity and is now entering a new phase co-led by China, the United States, and several other major contributors, with stable participation from multiple nations contributing to synergistic development.

Institutional output patterns and collaborative networks

The institutional output landscape in the cross-disciplinary field of intestinal polyps and AI exhibits pronounced concentration (Fig. 4A). The top 10 institutions by publication volume were Showa Univ (29), Humanitas Univ (23), Univ Oslo (21), Oslo Univ Hosp (15), Nagoya Univ (12), Natl Canc Ctr (12), Harvard Med Sch (11), Indiana Univ Sch Med (11), Chinese Univ Hong Kong (10), and Univ Kansas (10) (Fig. 4B). Among them, Showa Univ had the highest total citations (1,789), followed by Univ Oslo (1,173) and Nagoya Univ (1,150) (Fig. 4C). In terms of global publication volume, major academic output is highly concentrated among a group of internationally leading clinical medical centers and comprehensive research

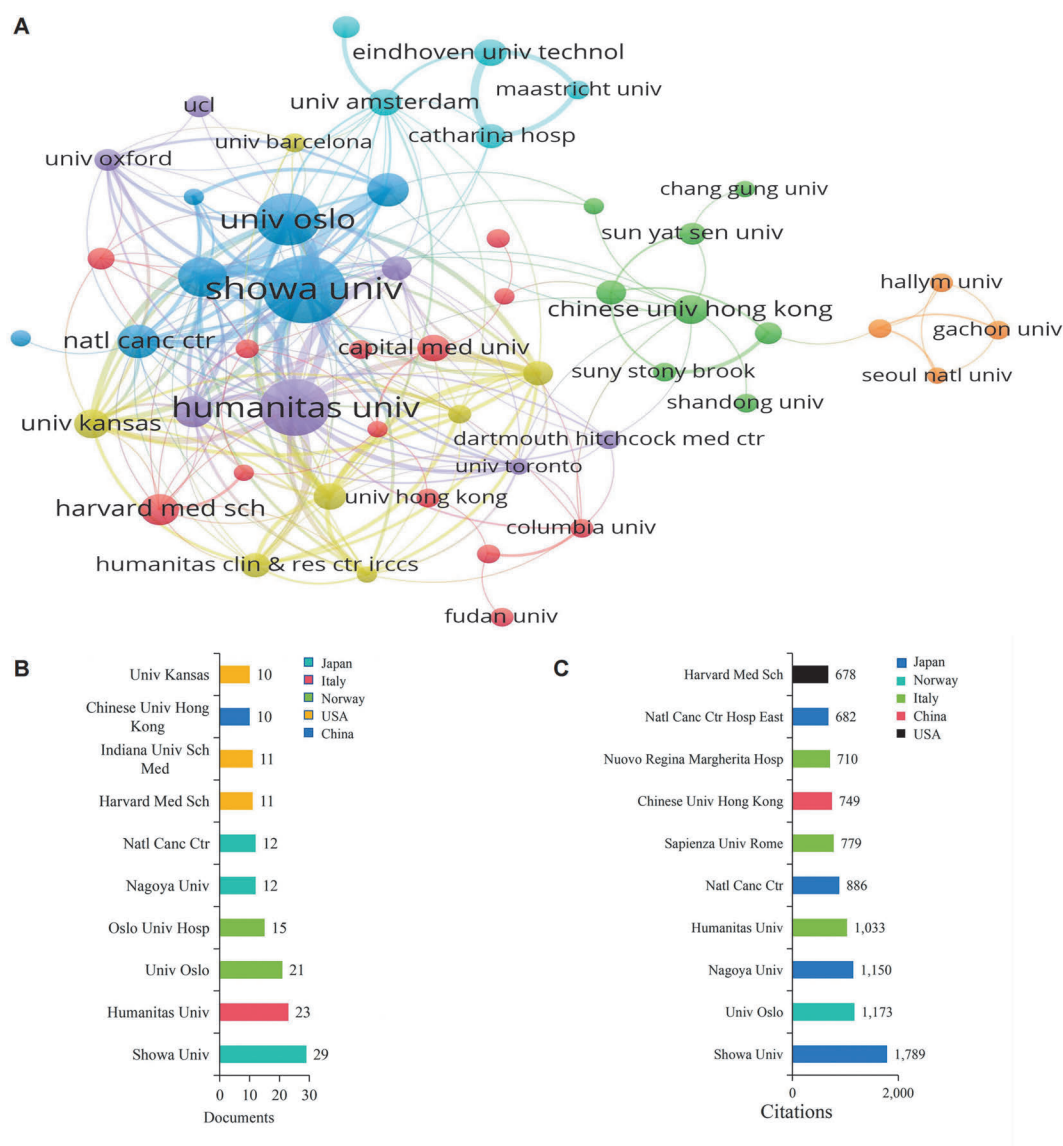


Figure 4: Institutional collaboration network, publication output, and citation contribution map in the field of AI for colorectal polyps.

(A) Global institutional collaboration network; nodes represent research institutions, node size reflects institutional publication volume, line thickness indicates inter-institutional collaboration intensity, and different colors correspond to different institution. (B) Bar chart showing publication outputs of core research institutions. (C) Bar chart showing cumulative citation frequencies of core research institutions.

universities. Among these, the top-tier core medical institutions, leveraging their substantial clinical resources and interdisciplinary research accumulation, constitute the primary driving force steering the field. A considerable number of general hospitals and medical schools with strong specialized capabilities form the second tier; although their total output remains somewhat behind the leading tier, they demonstrate notable focus and activity in specific sub-directions. From a geographic distribution perspective, these high-output institutions are

predominantly located in East Asia, North America, and selected European countries, indicating that the research focus in this field is closely tied to medical centers rich in high-quality case resources and advanced hardware and software facilities, thereby forming highly cohesive medico-engineering clusters with strong endogenous integration.

Institutional collaborations exhibit a multidimensional collaborative network that radiates globally from core

hubs (Fig. 4A). The visualized collaboration relationships intuitively reveal that scientific collaboration in this field has significantly transcended geographical boundaries. The leading core institutions not only play roles of academic leadership and resource aggregation within their respective regions but also serve as critical hub nodes in the global collaboration network, maintaining high-density research exchanges and cooperative ties with renowned medical schools and clinical centers across Europe, Americas, and Asia. The extensive network of intersecting links indicates that these academic frontrunners are not operating in isolation; rather, they effectively integrate global cutting-edge research resources through multiple channels, including data sharing, joint research initiatives, and talent mobility. Meanwhile, a number of emerging institutions have leveraged active participation in transnational collaborative projects led by these core hubs, rapidly overcoming their own geographic and resource limitations through the strong academic radiation of their partners, thereby gaining entry into the globalized research system of the field. This has substantially accelerated the translation of AI-based intestinal polyp diagnostic technologies from theoretical validation to clinical implementation.

Journal co-occurrence networks and publication outlets

The journal co-occurrence network demonstrated significant interdisciplinary characteristics (Fig. 5A). Three major clusters were identified, corresponding to core journals in gastroenterology and digestive endoscopy, core journals in biomedical engineering and computer/information science, and general medical journals, respectively. The gastroenterology specialty journals, centering on classic publications such as *World Journal of Gastroenterology*, *Digestive Endoscopy*, *Gastrointestinal Endoscopy*, and *Digestion*, constituted a clinical research cluster in digestive diseases. The engineering and technology journals, including *IEEE Access*, *Sensors*, *Biomedical Signal Processing and Control*, and *Scientific Reports*, represented a literature cluster in AI, biosignal, and sensing technology directions. Extensive cross-links between these two clusters intuitively reflected the ongoing interdisciplinary integration between digestive endoscopy disease research and AI engineering disciplines.

In terms of the overall distribution of publication output among journals (Fig. 5B), *IEEE Access* and *Biomedical Signal Processing and Control* served as the primary venues for technology and methodology-oriented research, while digestive specialty journals such as *Digestive Endoscopy* and *World Journal of Gastroenterology* also published a substantial number of relevant papers. Leading journals in digestive endoscopy and gastroenterology maintained consistent and stable output of clinical research findings, whereas biomedical engineering and general science journals provided a rich platform for the validation and application of cutting-edge algorithms.

Regarding the academic impact of these journals, most publications appeared in journals ranked in the quartile 1 (Q1) and quartile 2 (Q2) quartiles of the Journal Citation Reports, underscoring that research in this interdisciplinary field not only exhibits strong clinical relevance but also meets high academic quality and publication standards, with broad recognition across mainstream journals in multiple disciplines (Fig. 5C). In terms of total citations, the top clinical journals in gastroenterology established an academic high ground, effectively guiding the theoretical and applied development in the field. Meanwhile, some engineering and technology journals also garnered considerable attention. *Gastroenterology* had the highest co-citation frequency, followed by other leading digestive journals such as *Gastrointestinal Endoscopy*, *Endoscopy*, *The Lancet Gastroenterology & Hepatology*, and *Gut*. Engineering and multidisciplinary journals such as *IEEE Journal of Biomedical and Health Informatics* and *Scientific Reports* also achieved relatively high co-citation counts, further indicating that researchers in this field not only highly recognize authoritative clinical journals in gastroenterology but also continuously refer to publications in biomedical engineering and AI, demonstrating a pronounced interdisciplinary character.

Author co-occurrence networks and leading contributors

The author collaboration network is presented in Figure 6A. The green cluster, centered around Japanese researchers including Mori Y., Misawa M., and Kudo S., formed the largest and most internally cohesive

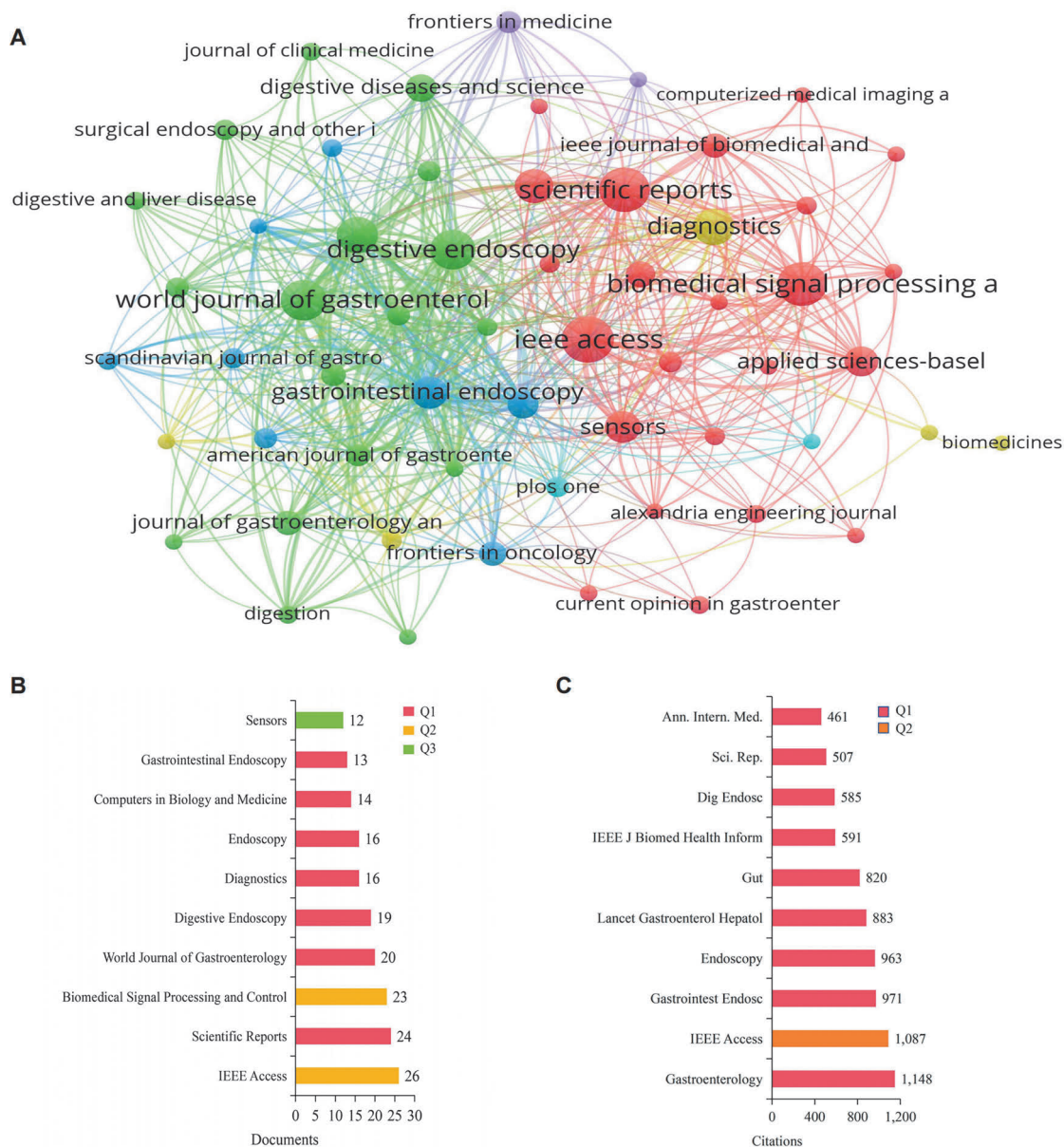


Figure 5: Journal co-occurrence network, publication quantity and citation distribution of literature on AI for colorectal polyps.

(A) Journal co-occurrence network map; node size represents the number of published articles of each journal, the thickness of connecting lines stands for the co-citation strength between journals, and different color clusters distinguish journal groups with similar research positioning. (B) Bar chart showing the annual document quantity of core journals, with color blocks marking journal partition (Q1, Q2, Q3). (C) Bar chart displaying cumulative citation counts of high-impact core journals, with colors indicating journal partition (Q1, Q2). Abbreviations: Q1, quartile 1; Q2, quartile 2; Q3, quartile 3.

collaborative research group. The red cluster comprised Italian scholars such as Repici A., Hassan C., and Antonelli G., representing another core research team. Additionally, small independent collaborative subgroups composed of researchers from the United States and the Netherlands were also observed. Although cross-cluster links indicated some degree of interregional academic

exchange among research teams, overall collaboration remained predominantly intranational.

Figure 6B illustrates the distribution of highly productive authors. Mori Y. ranked first with 22 publications, followed by Hassan C. (19) and Misawa M. (19). The most prolific authors were primarily from Japan and

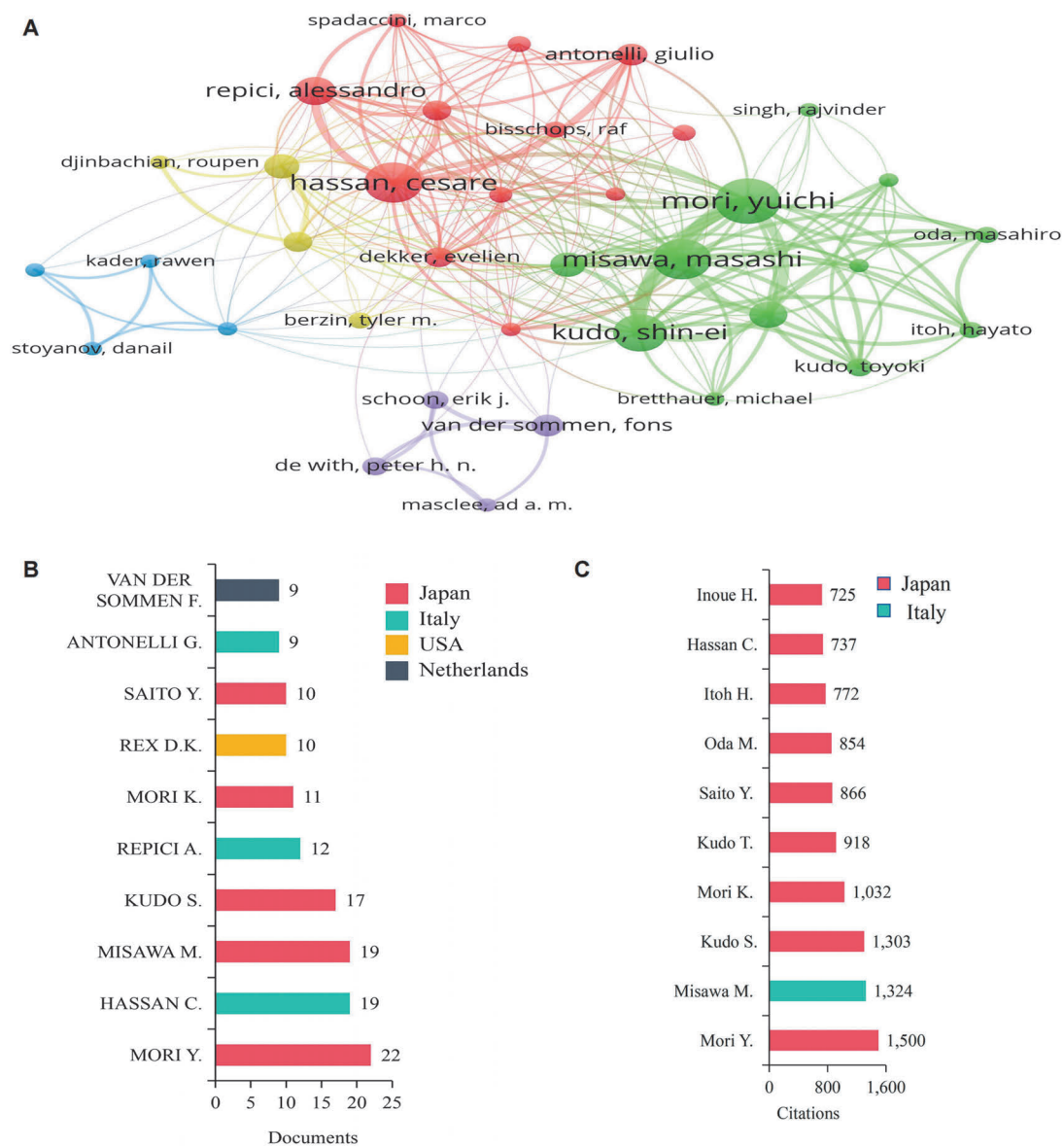


Figure 6: Author collaboration network, publication output, and citation distribution of research on AI for colorectal polyps.

(A) Global author collaboration network; node size reflects each author's total publications, line thickness represents the collaboration intensity between scholars, and distinct colors represent author clusters from different countries. (B) Bar chart of total publications for core productive authors, color-coded by national affiliation. (C) Bar chart of cumulative citation counts for highly cited core authors, color-coded by national affiliation.

Italy, while researchers from the United States and the Netherlands contributed relatively fewer publications, corroborating the geographical clustering patterns observed in the collaboration network. Figure 6C ranks authors by citation counts of their publications. Mori Y. had the highest total citations (1,500), followed by Misawa M. (1,324) and Kudo S. (1,303). Highly cited scholars were predominantly Japanese, with Italian researcher Hassan C. also demonstrating notable academic

impact. These findings indicate that Japanese research teams hold a leading position in both overall output and academic influence in this field, while Italian research teams serve as another significant contributor of high-value contributions. Although independent research groups exist in other regions of Europe and the United States, their overall academic volume and influence remain comparatively lower than those of Japanese and Italian authors.

High-frequency keyword analysis and thematic clusters

The keyword co-occurrence network is shown in Figure 7A. Prominent large nodes including “colonoscopy”,

“polyp detection”, “colorectal polyps”, “computer-aided detection”, “convolutional neural network”, and “capsule endoscopy” serve as core hotspots, demonstrating that existing studies mainly focus on computer-aided detection technologies applied in colorectal polyp

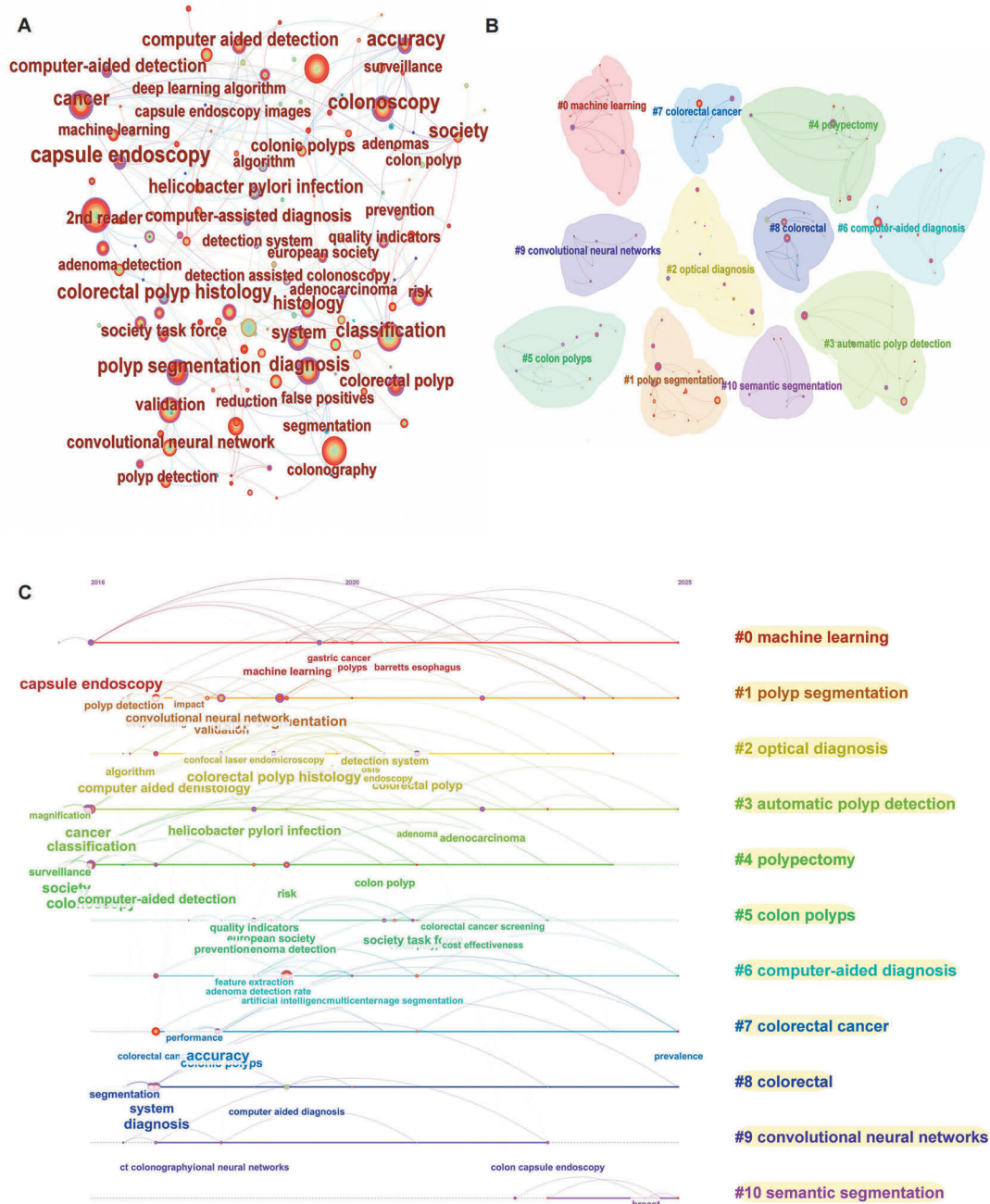


Figure 7: Keyword co-occurrence network, clustering map, and temporal evolution timeline of AI research on colorectal polyps.

(A) Keyword co-occurrence network; node size indicates the occurrence frequency of each keyword, connecting lines represent the co-occurrence correlation strength between keywords. (B) Keyword clustering map based on Log Likelihood Ratio (LLR) algorithm, with different colored regions representing independent research clusters labeled by serial numbers. (C) Keyword temporal evolution timeline spanning 2016–2025, illustrating the rise and shift of each research cluster over years.

examination under colonoscopy and capsule endoscopy. Meanwhile, closely linked keywords such as “adenoma”, “histology”, “prevention”, “surveillance”, and “reduction false positives” can be observed, revealing that apart from algorithm construction, researchers also attach importance to clinical challenges including adenoma pathological classification, CRC prevention, endoscopic surveillance and false positive optimization (Tables 2 and 3).

Table 2: Top 10 high-frequency keywords in the analyzed literature

Rank	Keyword	Frequency	Proportion (%)	Year
1	Artificial intelligence	158	14	2019
2	Colorectal cancer	142	5	2017
3	Deep learning	134	8	2017
4	Classification	114	18	2016
5	Cancer	104	27	2016
6	Colonoscopy	92	20	2016
7	Diagnosis	81	26	2017
8	Validation	78	15	2018
9	Colorectal polyps	76	3	2019
10	System	70	24	2017

Note: Year indicates the year in which the keyword first appeared in the included publications.

Table 3: Top 10 keywords with highest betweenness centrality

Rank	Keyword	Frequency	Betweenness centrality	Year
1	Capsule endoscopy	19	0.52	2016
2	Helicobacter pylori infection	13	0.32	2019
3	Colorectal polyp	27	0.31	2021
4	Polyp segmentation	61	0.29	2019
5	Accuracy	25	0.28	2018
6	Cancer	104	0.27	2016
7	Diagnosis	81	0.26	2017
8	System	70	0.24	2017
9	Computer-assisted diagnosis	2	0.24	2020
10	Adenocarcinoma	2	0.23	2022

The cluster map based on modularity analysis is displayed in Figure 7B. All research topics are divided into 11 clusters, namely #0 machine learning, #1 polyp segmentation, #2 optical diagnosis, #3 automatic polyp detection, #4 polypectomy, #5 colon polyps, #6 computer-aided diagnosis, #7 colorectal cancer, #8 colorectal, #9 convolutional neural networks, and #10 semantic segmentation. Two interwoven research threads can be summarized: the technical thread consists of AI algorithms including “convolutional neural networks”, “machine learning”, and “semantic segmentation”, while the clinical thread covers “colon polyps”, “colorectal cancer”, optical diagnosis and endoscopic treatment of polyps, strongly proving the interdisciplinary integration of AI and clinical digestive endoscopy.

The timeline visualization of keywords is presented in Figure 7C, which reflects the evolutionary trajectory of research themes across years. Early studies centered on “capsule endoscopy”, “computer-aided detection” and the evaluation of polyp detection performance. In subsequent periods, deep learning-related themes such as “convolutional neural networks”, image segmentation, and “semantic segmentation” gained growing attention. Recent research pays more attention to CRC screening, feature extraction of algorithms, clinical performance of models, and epidemiological characteristics of diseases. The evolutionary trend indicates that the research paradigm has shifted from preliminary exploration of basic detection models to the development of refined image segmentation algorithms, and further extended toward clinical screening practice and real-world performance verification.

Reference co-citation analysis and intellectual base

The reference analysis revealed that the knowledge base of the interdisciplinary field of colorectal polyps and AI exhibits a co-citation network characteristic of a close integration between clinical digestive endoscopy and deep learning technologies (Fig. 8A and 8B). In terms of clustering distribution (Fig. 8B), the field was partitioned into several thematic clusters, with representative clusters including #0 polyp segmentation, #1 artificial intelligence, #2 polyp detection, #6 cnn, and #7 optical diagnosis. Research directions centered on

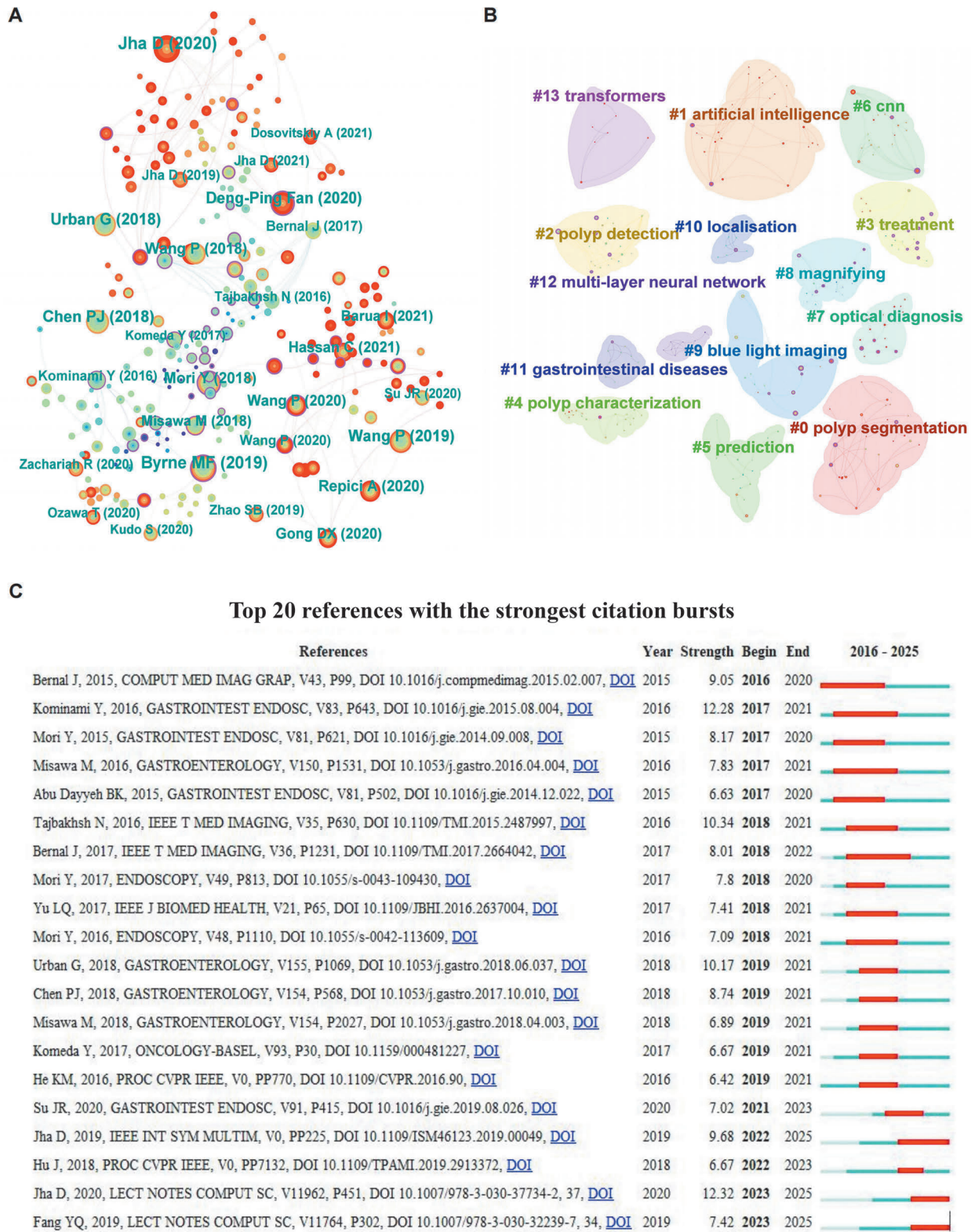


Figure 8: Reference co-citation network, reference clustering map, and top burst references of AI research on colorectal polyps.

(A) Reference co-citation network; node size represents co-citation frequency of each publication, and node labels mark representative pivotal references. (B) Reference clustering map categorized by LLR algorithm, where distinct color zones denote independent citation clusters with serial number labels for thematic topics. (C) Top 20 references with the strongest citation bursts from 2016 to 2025; "Strength" indicates burst intensity, while horizontal bars visualize the time interval of citation burst for each core literature.

AI, polyp segmentation, and polyp detection were closely interconnected, with dense cross-linking among them. Clusters pertaining to foundational algorithm models, clinical translation, and standardized diagnostic and therapeutic protocols were mutually interpenetrating, collectively constituting the academic knowledge foundation of this field.

Highly cited publications were predominantly published between 2018 and 2020 (Tables 4 and 5). These studies established critical algorithmic benchmarks and clinical validation evidence for AI-assisted polyp recognition. Publications with high betweenness centrality were mostly derived from foundational algorithm development in computer vision and standardization research for

clinical applications. These works served as important academic “bridges”, effectively facilitating the translation of underlying algorithmic frameworks into practical clinical demands in digestive endoscopy.

The temporal sequence of citation bursts clearly mapped the periodic shifts in research perspectives within this field (Fig. 8C). Early burst documents tended to explore the feasibility of AI applications in colorectal polyps and CRC screening, whereas recent strong bursts have focused on more granular technical challenges, including optimization of polyp segmentation algorithms, construction of clinical evaluation metrics, and evidence-based assessment of auxiliary diagnostic and therapeutic tools. The burst periods of some of the

Table 4: Top 10 cited references in the co-citation network

Rank	Cited reference (first author, year, journal)	Frequency	DOI
1	Jha D, 2020, <i>Lect Notes Comput Sc</i>	98	10.1007/978-3-030-37734-2
2	Byrne MF, 2019, <i>Gut</i>	93	10.1136/gutjnl-2017-314547
3	Chen PJ, 2018, <i>Gastroenterology</i>	75	10.1053/j.gastro.2017.10.010
4	Urban G, 2018, <i>Gastroenterology</i>	75	10.1053/j.gastro.2018.06.037
5	Wang P, 2019, <i>Gut</i>	75	10.1136/gutjnl-2018-317500
6	Deng-Ping Fan, 2020, <i>MICCAI (LNCS)</i>	66	10.1007/978-3-030-59725-2
7	Mori Y, 2018, <i>Ann Intern Med</i>	64	10.7326/M18-0249
8	Sung H, 2021, <i>CA-Cancer J Clin</i>	63	10.3322/caac.21660
9	Wang P, 2018, <i>Nat Biomed Eng</i>	61	10.1038/s41551-018-0301-3
10	Repici A, 2020, <i>Gastroenterology</i>	60	10.1053/j.gastro.2020.04.062

Table 5: Top 10 cited references with the highest betweenness centrality

Rank	Cited reference (first author, year, journal)	Centrality	Frequency
1	Yu LQ, 2017, <i>IEEE J Biomed Health</i>	0.67	23
2	He KM, 2016, <i>CVPR</i>	0.54	19
3	Shen DG, 2017, <i>Annu Rev Biomed Eng</i>	0.54	5
4	Zhang RK, 2018, <i>Pattern Recogn</i>	0.53	24
5	Deng-Ping Fan, 2020, <i>MICCAI (LNCS)</i>	0.51	66
6	Mori Y, 2018, <i>Ann Intern Med</i>	0.51	64
7	Vázquez D, 2017, <i>J Healthc Eng</i>	0.51	16
8	Rondonotti E, 2023, <i>Endoscopy</i>	0.45	27
9	Rex DK, 2024, <i>Ann Intern Med</i>	0.45	9
10	Tajbakhsh N, 2016, <i>IEEE T Med Imaging</i>	0.42	18

most recent emergent publications extended continuously into 2025, suggesting that segmentation models and Transformer-related architectures remain persistently active frontier research directions.

Discussion

As the predominant precursor lesions of CRC, colorectal polyps are histologically classified into hyperplastic polyps, inflammatory polyps, adenomatous polyps, and sessile serrated lesions (SSLs)^[30]. Among these, adenomatous polyps are highly prevalent and carry a well-established risk of malignant transformation, while SSLs are increasingly recognized as clinically significant precursors with a distinct and considerable neoplastic potential^[31,32]. The malignant potential of these lesions is closely correlated with lesion size, endoscopic morphological features, and the depth of submucosal invasion. The foremost advantage of colonoscopy lies in its ability to simultaneously detect and resect precancerous lesions in a single procedure. During the endoscopic examination, accurate real-time differentiation between neoplastic and non-neoplastic polyps is critical for guiding immediate resection decisions and determining appropriate surveillance intervals. However, conventional endoscopic diagnosis and treatment are inherently dependent on the operator's technical skill, visual attention, ability to inspect blind areas behind colonic folds, and consistency of subjective judgment, factors that inevitably contribute to a non-negligible polyp miss rate, thereby undermining the overall effectiveness of screening programs^[33]. AI-assisted tools, capable of marking suspicious lesions in real time and providing instantaneous optical biopsy predictions, hold the potential to assist endoscopists in achieving more consistent and higher-quality polyp management across diverse clinical settings, potentially contributing to reduced incidence of malignant outcomes^[34].

This study conducted a systematic bibliometric analysis of research literature on AI in the field of colorectal polyps from 2016 to 2025, based on the WOSCC. It comprehensively revealed the knowledge structure and development trajectory of this field from multiple dimensions, including annual output, countries/regions, institutions, journals, authors, keywords, and references.

The results indicate that research in this field has undergone a significant transformation from sporadic exploration to rapid growth over the past decade, with a concurrent sharp increase in both publication volume and citation counts after 2019. The substantial expansion of research output can be attributed to multiple driving factors: the global promotion of colonoscopy-based cancer screening, the continuous accumulation of high-quality endoscopic polyp image databases, the iterative optimization of computer vision and convolutional neural network (CNN) algorithms, and the clinical demands for reducing polyp miss rates and standardizing endoscopic judgment criteria^[35,36]. The synchronous growth in citations suggests that research findings in this field have gained extensive attention and been adopted by the academic community. Overall, the field of AI-assisted diagnosis and treatment of colorectal polyps is experiencing not only an expansion in scale but also a concurrent accumulation of academic influence, and is currently on a steady upward trajectory.

At the national level, this study reveals a complex collaborative network driven by the United States and China, with multipolar collaboration pattern. The United States, leveraging its dual strengths in foundational AI algorithms and clinical research in digestive endoscopy, is among the most influential contributors. China, in turn, has become the major hub of the Asia-Pacific region, underpinned by its vast clinical case resources and rapidly advancing technological R&D capabilities, and has established the most intensive collaborative links with the United States^[37,38]. This configuration suggests that major breakthroughs in this field increasingly depend on cross-national and cross-regional resource integration and coordinated research efforts. Notably, Japan once held a dominant role in the early pioneering phase; however, with the deepening engagement of a growing number of countries, the global academic landscape has evolved into a mature stage characterized by balanced development among multiple nations. This structural shift indicates that the field has transitioned from reliance on the first-mover advantages of individual countries toward a multi-centric and benignly competitive collaborative pattern, which holds positive implications for the diverse validation and global translation of these technologies.

At the institutional level, the analysis reveals that the total publication output is highly concentrated among top-tier comprehensive universities and large clinical medical centers, which have formed a leading first tier by leveraging their abundant endoscopic case resources and well-established interdisciplinary platforms in medical engineering. The second tier consists of specialized hospitals and medical schools with targeted research outputs. Geographically, high-output institutions are predominantly located in East Asia, North America, and Europe, forming close medical-industrial collaborative clusters around resource-rich advanced medical centers. In terms of collaborative networks, research institutions have transcended geographical boundaries, integrating global cutting-edge resources through joint research, data sharing, and talent exchange, thereby accelerating the clinical translation of AI-based polyp diagnostic technologies. At the current stage, however, a notable imbalance in institutional research capabilities persists. Japanese core institutions hold a leading position in both publication volume and citation impact, whereas institutions in some regions have more limited independent research capacity and mostly rely on collaborative projects with top-tier centers to conduct their studies. Future research should foster deeper collaboration between core institutions and emerging regional medical centers, so as to further advance the standardization and multi-center clinical validation of AI-assisted diagnostic systems.

Bibliometric analysis of journal co-occurrence, publication volume, and citation metrics further elucidates the interdisciplinary development characteristics of AI-assisted colorectal polyp research. *Gastroenterology* and digestive endoscopy journals, as traditional bastions of clinical medicine, focus on publishing prospective validation studies of AI-assisted technologies in real-world clinical settings, multicenter randomized controlled trial results, and cost-effectiveness analyses, with their editorial emphasis placed on clinical feasibility of methodologies and patient outcome-oriented evaluation metrics. In contrast, biomedical engineering and computer vision journals serve as the breeding ground for algorithmic innovation, giving greater attention to innovations in deep learning model architecture design, performance optimization of image segmentation and object detection algorithms, and technical solutions addressing

the specific limitations of endoscopic imaging, with evaluation standards centering on technical novelty, computational efficiency, and performance on public benchmark datasets. This journal distribution pattern, characterized by the integration of medicine and engineering, reflects the continuous translation of algorithmic innovations into the clinical diagnosis and treatment of colorectal polyps.

Author co-occurrence analysis reveals that core author groups have formed tightly-knit research communities within specific countries, while extensive cross-national and cross-regional collaborative links also exist, indicating that research efforts in this field are anchored by core teams that drive the participation of scholars worldwide. In terms of overall publication output, the literature in this field is predominantly contributed by core teams from Asia and Europe. Japanese scholar Mori Y. stands as one of the most prolific authors in this domain, with his research tracing a complete pathway from proof-of-concept to clinical translation of AI-assisted colonoscopy. Mori's group initially focused on the application of deep learning-based CADx systems in therapeutic decision-making for colorectal polyps, and subsequently expanded into evaluating the intervention effectiveness of AI in cancer screening programs, its preventive benefits against CRC mortality, and its clinical application in endoscopic surveillance of ulcerative colitis^[39,40]. European scholars such as Repici A. and Antonelli G. have also made significant contributions to the integrated evaluation of CADe/CADx systems. Repici, as a core author of multiple high-impact systematic reviews and meta-analyses, has investigated not only the detection and characterization accuracy of AI systems but also the enhancement effect of AI assistance on the diagnostic performance of non-expert endoscopists^[41]. Antonelli, in his reviews, explicitly stated that CADe and CADx represent the most evidence-based clinical applications of AI in gastroenterology, and emphasized that the transformative potential of AI in colonoscopy lies in achieving standardization of practice^[42]. In terms of academic influence, current high-impact research is heavily dependent on Japanese authors. Future efforts should further strengthen in-depth transnational collaboration to promote the universal development of AI-based diagnostic technologies for colorectal polyps.

Keyword co-occurrence analysis enables the identification of research hotspots and the evolution of research themes^[43]. The strong associations among high-frequency keywords such as “deep learning”, “validation”, “colonoscopy”, “colorectal polyps”, and “colorectal cancer” indicate that the core driving force of this field consistently originates from clinical needs, with algorithmic innovations ultimately serving to improve polyp detection rates and neoplastic polyp recognition rates^[44]. Keywords including “adenoma detection”, “polyp segmentation”, and “optical diagnosis” reflect research hotspots focused on differentiating benign from malignant polyps and screening diminutive polyps, corresponding to the central clinical goal of enhancing ADR^[45,46]. From a technical perspective, “computer-aided detection” and “computer-aided diagnosis (CADx)” represent the prevailing general paradigms in the field, bridging traditional computer vision and deep learning^[47]. “Machine learning”, “convolutional neural network”, and “deep learning algorithm” constitute the main algorithmic backbone, while a substantial number of secondary keywords such as “segmentation”, “classification”, and “semantic segmentation” have emerged as derivatives built upon deep learning architectures^[48]. Furthermore, keywords including “surveillance”, “quality indicators”, “prevention”, and “capsule endoscopy” indicate that the research scope has expanded from isolated polyp image recognition to broader domains such as CRC screening, endoscopic quality control, and intelligent recognition in non-invasive capsule endoscopy scenarios^[49,50].

Timeline analysis reveals that in the early developmental stage, research concentrated on directions such as “computer-aided detection”, “virtual colonography”, and “polyp histology”, primarily relying on traditional digital image processing and shallow machine learning approaches. During this phase, only coarse detection of polyps in static images was feasible, with low model accuracy and no capability for real-time endoscopic application. This period was paralleled by the emergence of foundational algorithmic studies that later experienced strong citation bursts, such as Bernal *et al.* (2017)^[51], which proposed a robust polyp detection method in colonoscopy videos and served as an early benchmark in the field, and Tajbakhsh *et al.* (2016)^[52], which introduced automated polyp detection in colonoscopy images using CNNs and became one of the most intensively

cited methodological references during 2018–2021^[51,52]. With the widespread adoption of CNNs, keywords such as “convolutional neural networks”, “deep learning”, “polyp segmentation”, and “semantic segmentation” experienced a concentrated surge. This period marked a breakthrough beyond the limitations of traditional image algorithms, shifting research emphasis toward the construction of standardized endoscopic datasets for colorectal polyps and the development of dedicated deep learning models targeting diminutive adenomas and flat polyps^[53]. The citation burst analysis corroborates this technological transition: Urban *et al.* (2018)^[53], which demonstrated that a deep learning system could achieve gastroenterologist-level adenoma detection, and Chen *et al.* (2018)^[54], who developed a real-time CNN-based polyp detection system, both exhibited strong citation bursts starting in 2019, reflecting the academic community’s rapid recognition of deep learning’s transformative potential in this domain^[54]. Concurrently, a series of studies by Mori and Misawa, published between 2015 and 2018, which systematically validated CADe/CADx systems in clinical settings, registered citation bursts spanning from 2017 to 2021, indicating that the field’s knowledge base was being simultaneously shaped by both algorithmic breakthroughs and clinical validation efforts^[39,40,55].

In recent years, hotspot keywords have exhibited a pronounced clinical orientation, with the frequencies of “optical diagnosis”, “capsule endoscopy”, “quality indicators”, “surveillance”, and “risk” continuing to rise, and new terms persistently emerging from clusters #2 (optical diagnosis), #4 (polypectomy), and #5 (colon polyps). This indicates that current research is no longer confined to algorithmic performance improvement, but has shifted toward the validation of clinical utility and effectiveness of AI systems^[42,44,56]. This shift in research focus is specifically projected onto a number of rapidly evolving research hotspots in recent years. The improvement effects of AI on adenoma detection rate and miss rate, the application of AI in non-invasive screening settings such as capsule endoscopy and virtual colonoscopy, AI-based monitoring of endoscopic procedural quality, as well as prediction of postoperative polyp recurrence risk and optimization of population-based CRC screening strategies, have emerged as further hot topics for future investigation^[56,57].

The evolution of keywords also reveals a series of unresolved structural deficiencies that have accompanied the rapid development of this field. From the keyword timeline, terms such as “polyp detection” and “convolutional neural network” have long occupied a central position. A substantial body of research has focused on demonstrating that AI can improve polyp detection rates, yet the long-term benefits in terms of CRC incidence and mortality remain unconfirmed by high-quality prospective studies^[48]. The widespread use of CADE is accompanied by potential risks of false-positive alarms, unnecessary polypectomies, and endoscopist skill degradation. More critically, some studies suggest that the diagnostic accuracy of CADx systems may be lower in the proximal colon than in the distal colon, a region that is a predilection site for interval CRC^[58,59]. In addition, the effectiveness of AI assistance is fundamentally contingent upon the image quality provided by the endoscopist; any evaluation of AI performance that is detached from operator-related factors is likely to overestimate its true clinical value^[60]. These noteworthy issues are rarely mentioned within the keyword network.

Therefore, the findings of this study carry multiple implications for both clinical practice and future research. From the perspective of clinical translation, the systematic evidence for AI-assisted polyp detection and diagnosis has become increasingly robust; the future challenge no longer lies solely in further improving algorithmic accuracy in the laboratory, but rather in ensuring its stability and generalizability in real-world settings, and in achieving optimal efficiency of human–machine collaboration^[61]. The lack of unified benchmarking standards and common clinical endpoints across different CADE/CADx systems hinders cross-study comparisons and the synthesis of evidence for clinical decision-making^[62]. Future research should place greater emphasis on clinical endpoints beyond adenoma detection rate, incorporating more substantive outcome measures such as interval cancer incidence and health economic benefits, so as to provide higher-level evidence for the widespread implementation of AI-assisted colonoscopy^[63]. From the perspective of algorithmic design, research priorities should be redirected from the development of single-task polyp recognition technologies toward full-chain clinical value validation

and risk optimization, thereby mitigating the potential for erosion of diagnostic skills induced by over-reliance on automation^[64]. From the perspective of the overall academic landscape, subsequent investigations should be more oriented toward addressing real-world clinical pain points, including false-positive risks, suboptimal recognition in the proximal colon, difficulties in SSL discrimination, and the negative aspects of human–machine interaction, in order to redress the current imbalance in research directions within the field^[65].

Conclusion

This study employs bibliometric methods to systematically review the research progress on AI in the field of colorectal polyps from 2016 to 2025, revealing the complete development trajectory of this field from initial exploration to rapid growth. The findings indicate that academic output and impact have grown rapidly over the past decade, with the United States and China serving as global research hubs, leading a multidisciplinary research landscape driven by clinical needs and supported by deep learning technologies. Keyword evolution and citation burst analyses demonstrate that research hotspots have shifted from macro-level feasibility validation to micro-level precision tackling, with refined topics such as polyp segmentation, optical diagnosis, risk assessment, and clinical quality evaluation emerging as current frontiers. The journal ecosystem and knowledge base of this field exhibit a deep integration of clinical medicine and engineering, forming a productive and collaborative academic environment. Overall, the application of AI in the diagnosis and treatment of colorectal polyps has moved beyond the early exploratory phase and is advancing toward clinical practicality and precision. The literature suggests potential value in improving the efficiency of early CRC screening and reducing the incidence of interval cancer; however, this potential remains to be confirmed by future prospective studies, as the present bibliometric analysis can only characterize publication trends rather than establish clinical effectiveness.

Limitations

Although this study has systematically delineated the research landscape and evolutionary trajectory of AI in the field of colorectal polyps through bibliometric

methods, several limitations should be carefully considered when interpreting the findings. The data source was restricted to the WOSCC, without inclusion of other databases or preprint platforms, which may lead to systematic underestimation of non-English literature, regional journals, and the latest algorithmic breakthroughs. Citation counts as an indicator of impact are subject to multiple non-quality-related factors: review articles tend to attract more citations by nature, the time-lag effect in citation accumulation may distort assessments of true influence, and positive citations and critical comments are statistically equivalent, further complicating the interpretation of citation metrics. Furthermore, this study employed two complementary tools, VOSviewer and CiteSpace, differences in their clustering algorithms and visualization layouts may introduce minor discrepancies in the resulting structural maps. Bibliometric analysis is adept at revealing macro-level trends but cannot provide granular evaluations of scientific quality or clinical translational value on a study-by-study basis. Future research could further extend the depth and breadth of such analyses by integrating multi-source data, incorporating semantic analysis, and leveraging multi-dimensional evidence.

Author contributions

Yang Yang conceptualized the study, developed the methodology, performed formal analysis, produced visualizations, and wrote the original draft. Liang-Jei Ma curated the data, conducted the investigation, implemented the software, validated the results, and reviewed and edited the manuscript. Yu-Xin Han participated in data curation, formal analysis, software development, visualization, and writing of the original draft. Shuang-Shuang Ji contributed to investigation, validation, resource provision, and reviewing and editing the manuscript. Shu-Xin Zhang contributed to conceptualization and methodology, administered the project, and reviewed and edited the manuscript. All authors reviewed, edited, and approved the final version of the manuscript and agreed to its publication.

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Ethics statement

All figures are either original to this work or properly attributed. No original images have been previously published, and all images comply with research integrity standards without inappropriate manipulation or misrepresentation.

Data availability statement

The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

AI statement

The AI tool was not used for data analysis, data generation, image processing, or scientific content creation. All outputs were carefully reviewed and verified by the authors, who take full responsibility for the final content.

Conflicts of interest

The authors declare no conflicts of interest.

References

1. Morgan E, Arnold M, Gini A, et al. Global burden of colorectal cancer in 2020 and 2040: incidence and mortality estimates from GLOBOCAN. *Gut*. 2023;72(2):338-344.
2. GBD 2019 Colorectal Cancer Collaborators. Global, regional, and national burden of colorectal cancer and its risk factors, 1990–2019: a systematic analysis for the Global Burden of Disease Study 2019. *Lancet Gastroenterol Hepatol*. 2022;7(7):627-647.
3. Song M. Global epidemiology and prevention of colorectal cancer. *Lancet Gastroenterol Hepatol*. 2022;7(7):588-590.
4. Sung H, Filho AM, Laversanne M, et al. Global cancer

- statistics 2024: GLOBOCAN estimates of incidence and mortality worldwide for 34 cancers in 186 countries. *CA Cancer J Clin*. 2026;76(4):e70090.
5. IJspeert JEG, Bretthauer M, Jover R, Dekker E. Balancing benefit and burden: rethinking post-polypectomy colonoscopy surveillance strategies. *Lancet Gastroenterol Hepatol*. 2026;11(8):720-726.
 6. Gupta S, Demb J, Qin J, et al. Impact of guideline-concordant post-polypectomy colonoscopy surveillance on colorectal cancer incidence and mortality. *Clin Gastroenterol Hepatol*. 2026;24(6):1709-1719.
 7. Kaminski MF, Kalager M, Løberg M, et al. Long-term effects of colonoscopy screening on colorectal cancer incidence and mortality: a multicountry, population-based randomised controlled trial. *Lancet*. 2026;407(10541):1787-1795.
 8. Wang L, Knudsen MD, Lo CH, et al. Adherence to a healthy lifestyle in relation to colorectal cancer incidence and all-cause mortality after endoscopic polypectomy: a prospective study in three U.S. cohorts. *Int J Cancer*. 2022;151(9):1523-1534.
 9. van Toledo DEFW, IJspeert JEG, Spaander MCW, et al. Colorectal cancer risk after removal of polyps in fecal immunochemical test based screening. *EClinicalMedicine*. 2023;61:102066.
 10. Bretthauer M, Løberg M, Wieszcy P, et al. Effect of colonoscopy screening on risks of colorectal cancer and related death. *N Engl J Med*. 2022;387(17):1547-1556.
 11. Wieszcy P, Bugajski M, Januszewicz W, et al. Comparison of quality measures for detection of neoplasia at screening colonoscopy. *Clin Gastroenterol Hepatol*. 2023;21(1):200-209.e6.
 12. Rath T. Missed lesions and artificial intelligence during colonoscopy: the tireless working expert in the room. *Endoscopy*. 2022;54(5):473-474.
 13. Jiang W, Xin L, Zhu S, et al. Risk factors related to polyp miss rate of short-term repeated colonoscopy. *Dig Dis Sci*. 2023;68(5):2040-2049.
 14. van Keulen KE, Papanikolaou IS, Mak TWC, et al. Comparison of adenoma miss rate and adenoma detection rate between conventional colonoscopy and colonoscopy with second-generation distal attachment cuff: a multicenter, randomized, back-to-back trial. *Gastrointest Endosc*. 2024;99(5):798-808.e3.
 15. Nayar KD, Yakout A, Bakheet N, et al. Outcomes of artificial intelligence-enhanced colonoscopy in a tertiary clinical setting. *Am J Gastroenterol*. 2026;121(4):974-981.
 16. Biscaglia G, Cocomazzi F, Gentile M, et al. Real-time, computer-aided, detection-assisted colonoscopy eliminates differences in adenoma detection rate between trainee and experienced endoscopists. *Endosc Int Open*. 2022;10(5):616-621.
 17. Segura A, Mehta SJ. Postcolonoscopy colorectal cancer as a quality metric-identifying opportunities to improve outcomes. *JAMA Netw Open*. 2023;6(4):e236680.
 18. Maida M, Marasco G, Maas MHJ, et al. Effectiveness of artificial intelligence assisted colonoscopy on adenoma and polyp miss rate: a meta-analysis of tandem RCTs. *Dig Liver Dis*. 2025;57(1):169-175.
 19. Boland PA, Hardy NP, Moynihan A, et al. Intraoperative near infrared functional imaging of rectal cancer using artificial intelligence methods—now and near future state of the art. *Eur J Nucl Med Mol Imaging*. 2024;51(10):3135-3148.
 20. Kim KO, Kim EY. Application of artificial intelligence in the detection and characterization of colorectal neoplasm. *Gut Liver*. 2021;15(3):346-353.
 21. Gimeno-García AZ, Hernández-Pérez A, Nicolás-Pérez D, Hernández-Guerra M. Artificial intelligence applied to colonoscopy: is it time to take a step forward? *Cancers*. 2023;15(8):2193.
 22. Makar J, Abdelmalak J, Con D, Hafeez B, Garg M. Use of artificial intelligence improves colonoscopy performance in adenoma detection: a systematic review and meta-analysis. *Gastrointest Endosc*. 2025;101(1):68-81.e8.
 23. Tan S, Zeng P, Liu S, et al. Effectiveness of artificial intelligence-assisted colonoscopy in detecting and diagnosing colorectal tumors: a systematic review and network meta-analysis. *Int J Colorectal Dis*. 2025;40(1):218.
 24. Wang YF, Ma LJ, Han YX, Chen GY, Ma X. Global trends and hotspots of artificial intelligence in pain management: a bibliometric analysis. *Digit Health*. 2026;12:20552076261460708.
 25. Han Y, Wang Z, Lan M, et al. Tongue feature-based model for assessing disease activity in patients with rheumatoid arthritis. *Front Pharmacol*. 2025;16:1651557.
 26. Wang Y, Wang Z, Lou P, et al. Research trends and hotspots in jak inhibitors for ulcerative colitis: a bibliometric analysis from 2015 to 2024. *J Multidiscip Healthc*. 2025;18:6755-6771.
 27. Chen G, Yan Z, Wang Y, Tao Q. Rheumatoid arthritis and fibromyalgia syndrome: a bibliometric and bioinformatics perspective on comorbidity research. *J Multidiscip Healthc*. 2025;18:6811-6827.
 28. Chen C. Citespace II: detecting and visualizing emerging trends and transient patterns in scientific literature. *J Am Soc Inf Sci Technol*. 2006;57(3):359-377.
 29. van Eck NJ, Waltman L. Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics*. 2010;84(2):523-538.
 30. Rosty C, Hewett DG, Brown IS, Leggett BA, Whitehall VL. Serrated polyps of the large intestine: current understanding of diagnosis, pathogenesis, and clinical management. *J Gastroenterol*. 2013;48(3):287-302.
 31. Yang N, Jin S. Study on the diagnostic value of lipid and systemic inflammatory markers in colorectal adenomatous polyps and the construction of a diagnostic model.

- BMC Gastroenterol.* 2026;26(1):551.
32. IJspeert JE, Vermeulen L, Meijer GA, Dekker E. Ser-rated neoplasia-role in colorectal carcinogenesis and clinical implications. *Nat Rev Gastroenterol Hepatol.* 2015;12(7):401-409.
 33. Ahmad OF, Mazomenos E, Chadebecq F, et al. Identifying key mechanisms leading to visual recognition errors for missed colorectal polyps using eye-tracking technology. *J Gastroenterol Hepatol.* 2023;38(5):768-774.
 34. Ham DY, Lee JG, Ahn CI, Kae SH, Jang HJ. Artificial intelligence-assisted colonoscopy improves adenoma detection rates in routine colonoscopy practice: a single-center, retrospective, propensity score-matched study with concurrent controls. *BMC Gastroenterol.* 2025;25(1):755.
 35. Nie MY, An XW, Xing YC, Wang Z, Wang YQ, Lü JQ. Artificial intelligence algorithms for real-time detection of colorectal polyps during colonoscopy: a review. *Am J Cancer Res.* 2024;14(11):5456-5470.
 36. Nazarian S, Glover B, Ashrafian H, Darzi A, Teare J. Diagnostic accuracy of artificial intelligence and computer-aided diagnosis for the detection and characterization of colorectal polyps: systematic review and meta-analysis. *J Med Internet Res.* 2021;23(7):e27370.
 37. Letafatkar N, El-Sehrawy AAMA, Prasad K, et al. Artificial intelligence in endoscopy and colonoscopy: a comprehensive bibliometric analysis of global research trends. *Front Med (Lausanne).* 2025;12:1532640.
 38. Peng Z, Wang X, Li J, et al. Comparative bibliometric analysis of artificial intelligence-assisted polyp diagnosis and AI-assisted digestive endoscopy: trends and growth in AI gastroenterology (2003–2023). *Front Med.* 2024;11:1438979.
 39. Mori Y, Kudo SE, East JE, et al. Cost savings in colonoscopy with artificial intelligence-aided polyp diagnosis: an add-on analysis of a clinical trial (with video). *Gastrointest Endosc.* 2020;92(4):905-911.e1.
 40. Mori Y, Misawa M, Kudo SE. Challenges in artificial intelligence for polyp detection. *Dig Endosc.* 2022;34(4):870-871.
 41. Repici A, Spadaccini M, Antonelli G, et al. Artificial intelligence and colonoscopy experience: lessons from two randomised trials. *Gut.* 2022;71(4):757-765.
 42. Hassan C, Misawa M, Rizkala T, et al. Computer-aided diagnosis for leaving colorectal polyps *in situ*: a systematic review and meta-analysis. *Ann Intern Med.* 2024;177(7):919-928.
 43. Wu T, Duan Y, Zhang T, Tian W, Liu H, Deng Y. Research trends in the application of artificial intelligence in oncology: a bibliometric and network visualization study. *Front Biosci.* 2022;27(9):254.
 44. Hassan C, Spadaccini M, Iannone A, et al. Performance of artificial intelligence in colonoscopy for adenoma and polyp detection: a systematic review and meta-analysis. *Gastrointest Endosc.* 2021;93(1):77-85.e6.
 45. Leung FW, Hsieh YH. Artificial intelligence (computer-assisted detection) is the most recent novel approach to increase adenoma detection. *Gastrointest Endosc.* 2021;93(1):86-88.
 46. Spadaccini M, Iannone A, Maselli R, et al. Computer-aided detection versus advanced imaging for detection of colorectal neoplasia: a systematic review and network meta-analysis. *Lancet Gastroenterol Hepatol.* 2021;6(10):793-802.
 47. Chen J, Zhu M, Shen Z, Xia K, Xu X, Wang G. Development of a convolutional neural network-based ai-assisted multi-task colonoscopy withdrawal quality control system (with video). *Front Physiol.* 2025;16:1666311.
 48. Misawa M, Kudo SE. Current status of artificial intelligence use in colonoscopy. *Digestion.* 2025;106(2):138-145.
 49. Foroutan F, Vandvik PO, Helsingen LM, et al. Computer aided detection and diagnosis of polyps in adult patients undergoing colonoscopy: a living clinical practice guideline. *BMJ.* 2025;388:e082656.
 50. Sultan S, Shung DL, Kolb JM, et al. Aga living clinical practice guideline on computer-aided detection-assisted colonoscopy. *Gastroenterology.* 2025;168(4):691-700.
 51. Bernal J, Tajkbaksh N, Sanchez FJ, et al. Comparative validation of polyp detection methods in video colonoscopy: results from the MICCAI 2015 endoscopic vision challenge. *IEEE Trans Med Imaging.* 2017;36(6):1231-1249.
 52. Tajbakhsh N, Gurudu SR, Liang J. Automated polyp detection in colonoscopy videos using shape and context information. *IEEE Trans Med Imaging.* 2016;35(2):630-644.
 53. Urban G, Tripathi P, Alkayali T, et al. Deep learning localizes and identifies polyps in real time with 96% accuracy in screening colonoscopy. *Gastroenterology.* 2018;155(4):1069-1078.e8.
 54. Chen PJ, Lin MC, Lai MJ, Lin JC, Lu HH, Tseng VS. Accurate classification of diminutive colorectal polyps using computer-aided analysis. *Gastroenterology.* 2018;154(3):568-575.
 55. Mori Y, Kudo SE, Misawa M, et al. Real-time use of artificial intelligence in identification of diminutive polyps during colonoscopy: a prospective study. *Ann Intern Med.* 2018;169(6):357-366.
 56. Hassan C, Spadaccini M, Mori Y, et al. Real-time computer-aided detection of colorectal neoplasia during colonoscopy: a systematic review and meta-analysis. *Ann Intern Med.* 2023;176(9):1209-1220.
 57. Chen ELY, Li JW. Computer-aided quality control in colonoscopy: clinical applications and limitations. *Clin Endosc.* 2025.
 58. Li JW, Lai WY, Lin KW, et al. Artificial intelligence in colonoscopy: where are we now in 2024? *Digestion.* 2025;106(5):480-494.
 59. Rizkala T, Hassan C, Mori Y, et al. Accuracy of computer-

- aided diagnosis in colonoscopy varies according to polyp location: a systematic review and meta-analysis. *Clin Gastroenterol Hepatol*. 2025;23:531-541.
60. Amirmohammadi E, Shalbaf A, Esteki A, et al. Application of artificial intelligence in colonoscopy imaging for polyp analysis-a systematic review. *Comput Methods Programs Biomed*. 2026;277:109239.
 61. Ahmad OF. Human-artificial intelligence adaptation in colonoscopy: beyond deskilling and upskilling. *Endoscopy*. 2026;58(9):1015-1016.
 62. Shinozaki S, Watanabe J, Kanno T, Nakazawa K, Yano T. Comparative performance of artificial intelligence-based computer-aided detection systems for colorectal polyps: a systematic review and network meta-analysis. *Dig Endosc*. 2026;38(4):e70138.
 63. Gadi SRV, Mori Y, Misawa M, et al. Creating a standardized tool for the evaluation and comparison of artificial intelligence-based computer-aided detection programs in colonoscopy: a modified delphi approach. *Gastrointest Endosc*. 2025;102(1):109-116.e2.
 64. Hassan C, Bisschops R, Sharma P, Mori Y. Colon cancer screening, surveillance, and treatment: novel artificial intelligence driving strategies in the management of colon lesions. *Gastroenterology*. 2025;169(3):444-455.
 65. Halvorsen N, Hassan C, Correale L, et al. Benefits, burden, and harms of computer aided polyp detection with artificial intelligence in colorectal cancer screening: microsimulation modelling study. *BMJ Med*. 2025;4(1):e001446.