Postprint: Exploring Global Research Trends of AI in Esophageal Cancer Through Visual Analysis

Authors: Tu Jiaxin, Ye Huiqing, Zhang Xiaoqiang, Lin Xueting, Yang Shanlan, Deng Lifang, Wu Lei

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Abstract

Objective To summarize the application and development history of artificial intelligence in esophageal cancer through visual bibliometric analysis, and to elucidate the research progress, hotspots, and emerging trends of AI in this field. Methods The SCI-E database of WoSCC was searched for all English-language literature indexed from January 1, 2000 to April 6, 2022 that applied AI to the field of esophageal cancer. Microsoft Excel 2019, CiteSpace(5.8R3-64bit), and VOSviewer(1.6.18) were utilized to analyze publication volume, countries, authors, institutions, co-citations, and keywords. Results A total of 918 publications were included, citing 23,490 references; 5,979 authors, 39,962 co-cited authors, and 42,992 co-cited references were incorporated into the study. There were 33 burst keywords. The early stage of research frontier evolution (2001-2008) focused on p53 and other esophageal cancer-related genes; the middle stage (2013-2018) emphasized classification, differentiation, and comparative studies of esophageal cancer; and the recent stage (2019-2022) featured database combined with deep learning, convolutional neural networks, and machine learning in esophageal cancer examination and diagnostic applications as the strongest hotspot and newest frontier. Conclusion The field of AI research in esophageal cancer has entered a new stage, with an overall trend toward precision examination, diagnosis, and treatment. Future challenges in applying AI to esophageal cancer may primarily involve individualized esophageal cancer data collection, data quality, data processing standards, reproducibility of AI code, and decision-making regarding the reliability of assisted diagnosis.

Full Text

Preamble

Visual Analysis of Global Research Hotspots and Trends of Artificial Intelligence in Esophageal Cancer from 2000 to 2022

Authors: Tu Jiaxin[1], Ye Huiqing[1], Zhang Xiaoqiang[2], Lin Xueting[1], Yang Shanlan[1], Deng Lifang[1], Wu Lei[1]*

Affiliations: [1]School of Public Health, Nanchang University; [2]Department of Cardiothoracic Surgery, Second Affiliated Hospital of Nanchang University, Nanchang 330006, China

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Corresponding Author: Wu Lei, E-mail: Wulei2060@aliyun.com

Abstract

Objective: To summarize the application and development of artificial intelligence (AI) in esophageal cancer and clarify research progress, hotspots, and emerging trends through visual bibliometric analysis.

Methods: We retrieved all English-language literature on AI applications in esophageal cancer from the SCI-E database of Web of Science Core Collection (WoSCC) between January 1, 2000, and April 6, 2022. Microsoft Excel 2019, CiteSpace (5.8R3-64bit), and VOSviewer (1.6.18) were used to analyze publication volumes, countries, authors, institutions, co-citations, and keywords.

Results: A total of 918 articles were included, citing 23,490 references. The study encompassed 5,979 authors, 39,962 co-cited authors, and 42,992 co-cited documents. Thirty-three keywords exhibited burst patterns. Research fronts evolved through three phases: early stage (2001-2008) focused on esophageal cancer genes such as p53; middle stage (2013-2018) emphasized classification, identification, and comparative studies; and recent stage (2019-2022) highlighted database integration with deep learning, convolutional neural networks, and machine learning for esophageal cancer screening and diagnosis as the strongest hotspots and latest frontiers.

Conclusion: AI research in esophageal cancer has entered a new stage, advancing toward precision screening, diagnosis, and treatment. Future challenges may primarily involve individualized data collection, data quality, data processing standardization, AI code reproducibility, and reliability of assisted diagnostic decision-making.

Keywords: esophageal cancer; artificial intelligence; visual analysis; CiteSpace

Esophageal carcinoma (ESCA), including esophageal adenocarcinoma and esophageal squamous cell carcinoma, ranks as the seventh most common cancer globally by incidence and the sixth leading cause of cancer-related mortality, with a mortality-to-incidence ratio exceeding 50% [1]. Over the past two decades, significant advances have been achieved in esophageal cancer diagnosis, treatment, and prognosis, particularly with the emerging application of artificial intelligence (AI) in healthcare for disease diagnosis and genomic data analysis [2,3], which has substantially improved diagnostic accuracy for ESCA [4,5]. However, as AI applications in esophageal cancer research have proliferated, researchers face difficulty tracking the latest developments and research hotspots. This study conducts a 22-year visual bibliometric analysis (2000-2022) to summarize AI' s application and development trajectory in esophageal cancer, elucidate research progress, hotspots, and emerging trends, and help researchers better identify future directions.

1.1 Data Sources

We searched the Science Citation Index Expanded (SCI-E) database of Web of Science Core Collection (WoSCC) with specific retrieval criteria and results summarized in . All searches were completed on April 6, 2022, to ensure no subsequent data updates. The initial search yielded 1,074 documents. After screening, we excluded 2 non-English articles, 141 irrelevant studies, 12 documents with inappropriate types (non-research or non-review articles), and 1 duplicate publication, resulting in 918 eligible articles.

** AI in Esophageal Cancer Research Literature Retrieval Strategy**

Step	Search Query
1#	esophag* (Topic) or oesophag* (Topic) or gullet (Topic) and Article OR Review (Document Type) and English (Language)
2#	cancer* (Topic) or tumour* (Topic) or tumor* (Topic) or neoplas* (Topic) or onco* (Topic) or carcinoma* (Topic) and Article OR Review (Document Type) and English (Language)
3#	1# AND 2#

Step	Search Query
4#	“artificial intelligen” *(Topic) or computational NEAR/5 intelligence (Topic) or expert* system* (Topic) or intelligent learning (Topic) or feature* extraction (Topic) or feature* mining (Topic) or feature* learning (Topic) or machine learning (Topic) or feature* selection (Topic) or unsupervised clustering (Topic) or image* segmentation (Topic) or supervised learning (Topic) or semantic segmentation (Topic) or deep network* (Topic) or bayes* network (Topic) or deep learning (Topic) or neural network* (Topic) or neural learning (Topic) or neural nets model (Topic) or artificial neural network (Topic) or data mining (Topic) or graph mining (Topic) or data clustering (Topic) or big data (Topic) or knowledge graph (Topic) or AI (Topic) and Article OR Review (Document Type) and English (Language)
5#	3# AND 4#

1.2 Data Processing

Two research team members independently downloaded and analyzed the literature data to ensure accuracy and reproducibility. Exported content included complete information (title, author, affiliation, etc.) and all cited references. Microsoft Excel 2019, CiteSpace (5.8R3-64bit), and VOSviewer (1.6.18) were employed for data analysis and visualization. The time slice was set to one year with a g-index threshold of 25. Co-occurrence maps for authors, institutions, and keywords were generated, supplemented by objective metrics such as word frequency and centrality to evaluate research activity and significance.

2.1 Publication Trends

Since 2000, annual publications on AI in esophageal cancer have increased steadily, dividing into two distinct phases: a slow-growth period from 2000 to 2016 (6 to 40 articles annually) and a rapid-growth period from 2017 to 2022 (62 to 216 articles). Publications from the last decade account for over 80% of the total corpus. The 918 articles achieved an H-index of 74 with an average citation count of 25.37. Citation trends closely mirrored publication trends, totaling 23,490 citations by the search date.

2.2 Country, Institution, and Author Analysis

Countries: Over 60 countries and 118 institutions have contributed to AI research in ESCA. VOSviewer visualization revealed China as the most productive country (306 articles), followed by the United States (238) and the United

Kingdom (113). Total Link Strength (TLS) indicates collaboration intensity, with the U.S. serving as a central hub, particularly in U.S.-China collaborations (strongest), followed by U.S.-Netherlands partnerships.

Institutions: Among institutional collaborations, the top three TLS scores were University of Amsterdam (TLS=72), Catharina Hospital (TLS=64), and Eindhoven University of Technology (TLS=53). As shown in Figure 2: see original paper, Mayo Clinic in the U.S. acts as an intermediary institution linking research networks across the U.S., China, and the Netherlands.

Authors: A total of 5,979 authors were included. [Figure 4: see original paper] illustrates collaboration networks among nine authors with >10 publications. The most prolific authors were Jacques J.G.H.M. Bergman from the Netherlands (16 articles), Tomohiro Tada from Japan (12), and Fons van der Sommen from the Netherlands (12). Notably, collaboration intensity did not correlate with publication volume—for instance, Tomohiro Tada, despite ranking second in publications, showed the lowest collaboration strength (TLS=7) among the nine. Dutch authors demonstrated notably stronger internal collaborations compared to other countries.

2.3 Co-citation Analysis

The analysis included 39,962 co-cited authors and 42,992 co-cited documents. Using CiteSpace with pathfinder network scaling, pruning sliced networks, and pruning merged networks, we obtained a co-citation network with parameters: LRF=3.0, L/N=10, LBY=5, e=1.0, N=955, E=1908, density=0.0042. As shown in , the top three co-cited authors were Freddie Ian Bray (France, 87 citations), Prateek Sharma (U.S., 56), and Yoshimasa Horie (Japan, 53). For total citation counts, the leaders were Prateek Sharma (U.S.), Jesper Lagergren (Sweden), and Thomas William Rice (U.S.).

** Top 10 Co-cited Authors via CiteSpace (2000-2022)**

Co-cited Author	Co-citation Count	Total Citation Count
Freddie Ian Bray	87	-
Prateek Sharma	56	-
Yoshimasa Horie	53	-
Jacques Ferlay	-	-
Jesper Lagergren	-	-
Lambin Philippe	-	-
Rebecca L. Siegel	-	-
Hirasawa Toshiaki	-	-
Nicholas James Shaheen	-	-
Thomas William Rice	-	-

presents the top 10 co-cited articles, with *Gastrointestinal Endoscopy* and *CA: A*

Cancer Journal for Clinicians contributing over half of the publications. Chinese authors contributed four articles overall. The clustering analysis yielded excellent parameters (modularity Q=0.9469, mean silhouette S=0.8448), indicating robust clustering (Q>0.3) and high network homogeneity (S>0.7). Co-cited literature primarily focused on radiomics, endoscopy, tumor segmentation, and optical coherence tomography [FIGURE:3(a)]. Centrality analysis identified Jesper Lagergren (Sweden) and Thomas William Rice (U.S.) as pivotal nodes (centrality >0.1), suggesting their works serve as core bridges between different clusters. The temporal evolution in [FIGURE:3(b)] shows "observer bias" as the earliest cluster (gray), while "digital biomarkers" emerged most recently (2016). Recent hotspots (red circles) include "endoscopy," "radiomics," and "deep learning," with large circles for "artificial intelligence," "deep learning," and "endoscopy" indicating extremely high citation frequencies.

** Top 10 Co-cited Articles via CiteSpace (2000-2022)**

Title	Journal	Authors
Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries	CA: A Cancer Journal for Clinicians	Bray F; et al.
Diagnostic outcomes of esophageal cancer by artificial intelligence using convolutional neural networks	Gastrointestinal Endoscopy	Horie Y; et al.
Application of artificial intelligence using a convolutional neural network for detecting gastric cancer in endoscopic images	Gastric Cancer	Hirasawa T; et al.

Title	Journal	Authors
Real-time automated diagnosis of precancerous lesions and early esophageal squamous cell carcinoma using a deep learning model (with videos)	Gastrointestinal Endoscopy	Guo LJ; et al.
Deep-Learning System Detects Neoplasia in Patients With Barrett' s Esophagus With Higher Accuracy Than Endoscopists in a Multistep Training and Validation Study With Benchmarking	Gastroenterology	De Groof AJ; et al.
Endoscopic detection and differentiation of esophageal lesions using a deep neural network	Gastrointestinal Endoscopy	Ohmori M; et al.
Using a deep learning system in endoscopy for screening of early esophageal squamous cell carcinoma (with video)	Gastrointestinal Endoscopy	Cai SL; et al.
Computer-assisted diagnosis of early esophageal squamous cell carcinoma using narrow-band imaging magnifying endoscopy	Endoscopy	Zhao YY

Title	Journal	Authors
Integrated genomic characterization of oesophageal carcinoma	Nature	Kim J
Cancer statistics in China, 2015	CA: A Cancer Journal for Clinicians	Chen WQ

2.4 Keyword Analysis

Keyword frequency analysis illuminates current research priorities in AI applications for esophageal cancer. Among 3,861 keywords, "cancer," "esophageal cancer," and "adenocarcinoma" appeared most frequently (>100 occurrences). Other high-frequency terms (>50) included squamous cell carcinoma, diagnosis, survival, Barrett' s esophagus, classification, deep learning, risk, prognosis, and expression. Based on publication growth trends, we analyzed keyword evolution across two phases: 2000-2016 and 2017-2022.

2.4.1 Phase 2000-2016

This period yielded a co-occurrence network with parameters: LRF=3.0, L/N=10, LBY=5, e=1.0, N=421, E=901, density=0.0102. While "cancer," "esophageal cancer," and "Barrett' s esophagus" showed high frequency, their co-occurrence relationships were weak. "Risk" emerged as the most frequent non-cancer keyword (23 occurrences), indicating substantial research on risk factors. Keywords with centrality >0.1 included colorectal cancer, cancer, epithelial small cell carcinoma, small cell carcinoma, mutation, epithelial tissue cancer, Barrett' s esophageal cancer, esophageal cancer, breast cancer, and p53 gene . Research primarily focused on cancer diagnosis, identification, risk assessment, and expression, using intermediate keywords related to colon, gastrointestinal, small cell, and breast cancers.

** Keywords with Centrality >0.10 in WoSCC Database (2000-2016)**

No.	Centrality	Frequency	Year	Keyword
1	>0.10	-	2000	Small cell carcinoma
2	>0.10	-	2015	Esophageal adenocarcinoma
3	>0.10	-	-	p53 gene

2.4.2 Phase 2017-2022

The keyword co-occurrence network for this period (LRF=3.0, L/N=10, LBY=5, e=1.0, N=289, E=485, density=0.0117) showed increased keyword diversity and tighter co-occurrence relationships. Beyond the search terms, "machine learning," "deep learning," and "convolutional neural network" surged dramatically, with "deep learning" reaching 65 occurrences—the highest frequency among non-search terms. This indicates intensive deep learning research and its dominance in AI applications for ESCA. Keywords with centrality >0.1 included biomarkers, genes, expression, dysplasia, computer-aided detection, accuracy, and fluorine-18 FDG tomography. Comparing and [Figure 6: see original paper] reveals a shift from general cancer research to focused investigation of esophageal cancer markers, differentiation, screening, diagnosis, and chemoradiotherapy, with machine learning, deep learning, and convolutional neural networks as primary methodologies.

** Keywords with Centrality >0.10 in WoSCC Database (2017-2022)**

No.	Centrality	Frequency	Year	Keyword	No.	Centrality	Frequency	Year	Keyword
1	>0.10	-	2017	Assistance	6	>0.10	-	2019	Accuracy
2	>0.10	-	2017	Computer-aided detection	7	>0.10	-	2019	Fluorine-18 FDG
3	>0.10	-	2017	Differentiation	8	>0.10	-	2021	FDG tomography
4	>0.10	-	2017	CT examination	9	>0.10	-	2021	Bioinformatics analysis
5	>0.10	-	2017	Texture features	-	-	-	-	-

Burst detection identifies keywords with significantly elevated frequency during specific periods, representing research hotspots and frontier shifts. With minimum duration set to 1 year and default parameters, we detected 33 burst keywords over 22 years. [Figure 7: see original paper] presents the top 25 burst keywords chronologically. The earliest phase (2001-2008) focused on p53 and esophageal cancer genetics, followed by risk factor studies (2007-2013). The middle phase (2013-2018) emphasized classification, screening (tomography), and comparative studies across cancer types, interspersed with treatment updates (chemoradiotherapy, 2017-2019). Notably, "database" first emerged as a burst term in 2018, signaling large-scale exploration of esophageal cancer databases. Methodological advances accelerated with deep learning, convolutional neural networks, and machine learning (2019-2022), with "deep learning" showing the strongest burst intensity (13.89)—the highest among all 33 keywords—confirming it as the current strongest hotspot and latest frontier. The transition from computer-assisted screening to computer-assisted diagnosis marks a new stage in esophageal cancer AI research (2020-2022).

3 Discussion

In the era of big data analytics, researchers require comprehensive understanding of their fields. Unlike systematic reviews or meta-analyses, bibliometric analysis employs visualization tools like VOSviewer and CiteSpace to synthesize all literature within a timeframe, intuitively revealing trends and predicting future hotspots [6]. This study provides the first bibliometric analysis summarizing AI' s current status in esophageal cancer, visually exposing developmental trajectories and future research directions.

Publication volume demonstrates AI' s rapid advancement across domains since 2016 [7,8], with over 80% of papers published in the last decade. China leads in productivity (306 articles) as an emerging powerhouse, while contributing four of the top 10 most-cited papers. However, China' s international collaboration intensity remains weak compared to the robust U.S.-Netherlands partnerships evident in institutional and author networks. Citation volume reflects dissemination and impact, indicating quality and academic standing [9]. U.S. authors dominate co-citation metrics, suggesting continued leadership. China' s limited influence may stem from: (1) late entry and insufficient collaboration networks reducing global impact; (2) lack of innovation in core algorithms and limited international partnerships; and (3) generally lower average research quality. The 2018 State Council guidelines on strengthening research integrity aim to address these issues [10]. Leading journals include *Gastrointestinal Endoscopy* (IF=9.43) and *CA: A Cancer Journal for Clinicians* (IF=508.7), both Q1 journals in gastroenterology and oncology. *Gastrointestinal Endoscopy*' s overwhelming citation dominance underscores its pivotal role, suggesting future AI-esophageal cancer research will likely prioritize these venues. Additionally, *Gastroenterology*, *Gastric Cancer*, and *Endoscopy* represent high-impact outlets for quality articles.

Co-citation analysis evaluates both relevance and individual academic impact [11,12]. Guo LJ et al.' s highly-cited Chinese study [13] demonstrated deep learning models achieving high sensitivity and specificity for endoscopic image/video datasets, validating real-time computer-assisted diagnosis (CAD) systems for precancerous lesions and esophageal adenocarcinoma. Clustering results reveal evolving frontiers: early work focused on "tumor segmentation" (#6) [14], while current hotspots center on "deep learning" (#2) [15], "endoscopy" (#9) [16], and "gastrointestinal endoscopy" (#5) [17], indicating a shift from tumor classification to AI-enabled diagnostic accuracy, rapid detection, and early diagnosis.

Keyword frequency analysis reflects broader hotspot development. Three major categories emerged: cancer, adenocarcinoma, and esophageal cancer, suggesting early research treated esophageal cancer as part of general oncological analyses. Two-phase keyword analysis reveals: (1) During 2000-2016 (slow-growth period), risk identification and p53 gene research dominated, contrasting with prostate cancer AI research that focused on screening and surgical methods [18]; (2) During 2017-2022 (explosive-growth period), AI applications became clearly defined, with computer-aided diagnosis and therapy as primary directions. Deep learning emerged as the highest-frequency specific method, enabling early screening, precise differentiation of precancerous lesions, intraoperative tumor margin identification, disease progression monitoring, and prediction of invasiveness, metastasis, and recurrence risk. Medical imaging and biomarkers provided technical support for detection, treatment, and monitoring.

Overall, AI application in esophageal cancer exhibits a 10-year lag compared to other cancers, likely due to AI' s nascent translational stage and limited 推广效果 [19]. Future research will inevitably focus on prognostic and risk factor modeling. The 2000-2022 burst analysis validates this trajectory. Notably, "database" first burst in 2018, reflecting big data' s emergence as a critical methodology. While big data enables comprehensive esophageal cancer analysis, data acquisition demands substantial resources, making collaboration difficult—a potential reason for limited partnerships. A limitation of this study is the inclusion of only English literature, potentially omitting excellent non-English work (e.g., China' s 2020 initiative to "publish papers on the homeland" [20]), introducing selection bias. Future studies should integrate Chinese (CNKI, Wanfang) and international databases (PubMed, Scopus, Google Scholar) for more comprehensive results.

4 Outlook

AI holds undeniable potential, demonstrating sufficient performance and accuracy in laboratory settings to enhance cancer patient care and broadly impact oncology. As AI advances, esophageal cancer management is progressing toward precision screening, diagnosis, and treatment. Future challenges will likely center on: individualized data collection (beyond basic metrics to include genomic information), data quality (e.g., racial/ethnic variations), data processing standardization (inconsistent electronic health record structures), AI code reproducibility (inability to share and replicate code), and reliability of assisted diagnostic decision-making (practical validation for credibility).

5 Author Contributions

1. **Tu Jiaxin, Wu Lei:** Conceptualization; methodology development; model construction; visualization and data presentation.
2. **Ye Huiqing, Lin Xueting:** Data collection, cleaning, and curation (including software code).
3. **Zhang Xiaoqiang, Wu Lei:** Funding acquisition; supervision and leadership of research activities.

4. **Yang Shanlan, Deng Lifang:** Project management and coordination.

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Note: Figure translations are in progress. See original paper for figures.