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Research article

Visualization analysis of research hotspots and trends in MRI-based artificial intelligence in rectal cancer

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ABSTRACT

Background: Rectal cancer (RC) is one of the most common types of cancer worldwide. With the development of artificial intelligence (AI), the application of AI in preoperative evaluation and follow-up treatment of RC based on magnetic resonance imaging (MRI) has been the focus of research in this field. This review was conducted to develop comprehensive insight into the current research progress, hotspots, and future trends in AI based on MRI in RC, which remains to be studied.
Methods: Literature related to AI based on MRI and RC, as of November 2023, was obtained from the Web of Science Core Collection database. Visualization and bibliometric analyses of publication quantity and content were conducted to explore temporal trends, spatial distribution, collaborative networks, influential articles, keyword co-occurrence, and research directions.
Results: A total of 177 papers (152 original articles and 25 reviews) were identified from 24 countries/regions, 351 institutions, and 81 journals. Since 2019, the number of studies on this topic has rapidly increased. China and the United States have contributed the highest number of publications and institutions, cultivating the most intimate collaborative relationship. The highest number of articles derive from Sun Yat-sen University, while Frontiers in Oncology has published the highest number of relevant articles. Research on MRI-based AI in this field has mainly focused on preoperative diagnosis and prediction of treatment efficacy and prognosis.
Conclusions: This study provides an objective and comprehensive overview of the publications on MRI-based AI in RC and identifies the present research landscape, hotspots, and prospective trends in this field, which can provide valuable guidance for scholars worldwide.

1. Introduction

Colorectal cancer (CRC), one of the most common types of cancer worldwide, ranks as the third most prevalent and second most common cause of mortality among all cancers worldwide. Recent data have indicated that the incidence of new CRC cases is projected

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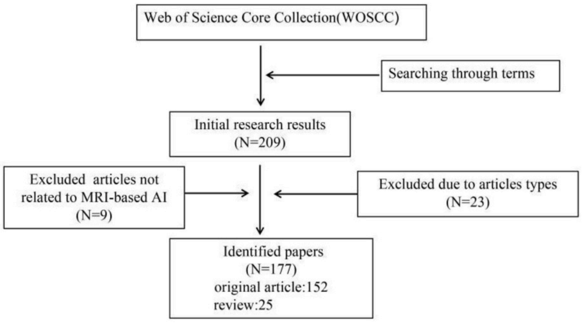

Fig. 1. Flow chart of document screening.

to escalate to 2.5 million by 2035, posing a significant threat to human life and well-being [1,2]. Notably, rectal cancer (RC) accounts for approximately one-third of all CRC cases and its incidence is increasing [3,4]. Given the rising prevalence of RC, timely screening and diagnosis are significant.

Imaging of RC plays a pivotal role in diagnosis and the development of therapeutic strategies. Endoscopic rectal ultrasound may help formulate treatment strategies for early-stage tumors; however, its utility diminishes in cases of locally advanced RC (LARC). A computed tomography scan proves beneficial in detecting metastases but falls short in accurately assessing local tumors due to its restricted soft tissue resolution. The improved soft tissue contrast, non-radioactive nature, and non-invasive evaluation of magnetic resonance imaging (MRI), compared with endoscopic rectal ultrasound and computed tomography scans, show unique advantages, and MRI has been recommended as the preferred choice to manage RC [5,6]. Moreover, an MRI scan can provide detailed information about the tumor, lymph nodes, extramural vascular invasion, mucin content, and involvement of the mesorectal fascia. This information is essential for RC assessment, development of effective treatment plans, and assessment of the response to therapy, during both primary staging and subsequent evaluation following chemoradiotherapy [7]. Unfortunately, the precision of conventional MRI for assessing the morphological features of RC remains insufficient to accurately guide therapeutic strategies, necessitating further refinement. For example, MRI is recommended for assessing the extramural venous invasion (EMVI) status; however, the sensitivity of traditional MRI in evaluating EMVI remains suboptimal [8]. Besides, it remains a challenge for conventional MRI to distinguish minimal residual tumors with fibrotic scars induced

by neoadjuvant chemoradiotherapy (nCRT) and predict treatment effectiveness [9]. Hence, devising a novel and efficacious image-mining approach to attain a precise diagnosis and treatment stands as a formidable challenge in RC.

Recently, artificial intelligence (AI) has achieved notable success in the field of medical image analysis, demonstrating its capability to quantitatively assess radiological features and autonomously identify complex patterns in imaging data [10]. Machine learning, a pivotal branch of AI that includes radiomics and deep learning, has been applied extensively in RC, offering novel opportunities and methodologies to address the challenges associated with diagnosis and treatment. The advancement and use of AI in the field of RC is currently being extensively researched [11,12]; therefore, more attention should be focused on the current research status, hotspots, and frontier trends in this field.

Bibliometric analysis has evolved into a widely employed quantitative method to assess the quality and impact of academic research outcomes in many fields. By analyzing bibliometric data and information, researchers can quantitatively and qualitatively understand the current research status and trends in an academic field and predict future research directions and development trends [13,14]. Currently, bibliometric analysis is widely employed to explore the developmental trajectories of various fields and disciplines, with significant strides also being made in the realm of AI [15,16]. However, no specific bibliometric studies have been undertaken in the field of MRI-based AI applications for individuals with RC. The purpose of this study was to create a knowledge map of MRI-based AI in RC research by collecting and analyzing relevant publications related to MRI-based AI in the field of RC from relevant databases, and thus systematically demonstrate the present research status and predict the future research directions.

2. Materials and methods

2.1. Data source and search strategy

Literature related to the application of AI in RC based on MRI was searched for in the Web of Science Core Collection (WoSCC) database, which is a comprehensive, multidisciplinary database containing leading high-impact journals and publications in various research fields [17,18]. The following keywords were used in the search: “rectal cancer,” “artificial intelligence” and “magnetic resonance imaging.” A detailed search query is provided in the supplementary appendix online. The types of publication were constrained to “article” and “review,” with language limitations set exclusively to English. To avoid potential bias stemming from database updates, all data downloads and literature searches were finalized on November 30, 2023. Two investigators independently screened pertinent articles in the WOSCC database and downloaded the plain-text file format (full records and cited references). In case of divergence, help from a third researcher was required to reach a consensus. The detailed literature screening process is shown in Fig. 1.

Metadata	Description	Missing Counts	Missing %	Status
AB	Abstract	0	0.00	Excellent
C1	Affiliation	0	0.00	Excellent
AU	Author	0	0.00	Excellent
CR	Cited References	0	0.00	Excellent
RP	Corresponding Author	0	0.00	Excellent
DT	Document Type	0	0.00	Excellent
SO	Journal	0	0.00	Excellent
LA	Language	0	0.00	Excellent
PY	Publication Year	0	0.00	Excellent
WC	Science Categories	0	0.00	Excellent
TI	Title	0	0.00	Excellent
TC	Total Citation	0	0.00	Excellent
DI	DOI	1	0.56	Good
ID	Keywords Plus	19	10.73	Acceptable
DE	Keywords	24	13.56	Acceptable

Fig. 2. Overview of publications.
A. Quality evaluation of publications. B. Main information of publications. C. Time trend distribution of publications.

2.2. *Data analysis and visualization*

After rigorous screening, all available data were imported into Microsoft Excel 2021, CiteSpace (version 6.2.R6), online bibliometric analysis platform (http://bibliometric.com/), VOSviewer (1.6.20), SCImago Graphica (1.0.37), and R (4.3.2) for performing bibliometric and visual analysis [19–21]. Data, including country or region, authors, keywords, institutions, citations, references, and journals, were analyzed separately. In addition, the strongest citation bursts, based on keywords and references, were analyzed using CiteSpace to illustrate the developing trend in research hotspots over time. Two researchers independently completed and checked the data analysis to ensure the accuracy and reproducibility of the data.

3. Results

3.1. *Annual publications and trends*

A total of 177 papers were identified, including 152 original articles and 25 reviews. All articles were published in English between 2016 and 2023. The overall quality of the studies was good (Fig. 2A). The papers originated from 81 journals, had 1233 authors, and cited 5074 references. Documents related to international cooperation accounted for approximately 19.77 % of the publications. Fig. 2B presents the characteristics of the included studies. Fig. 2C shows that the number of articles related to AI in RC increased gradually each year. After 2020, a further increase in the number of publications was observed. The number of papers published by 2023 is expected to exceed 60. These findings suggest that the study of AI applications based on MRI in RC has attracted increasing interest and is poised to remain a focal point for future research.

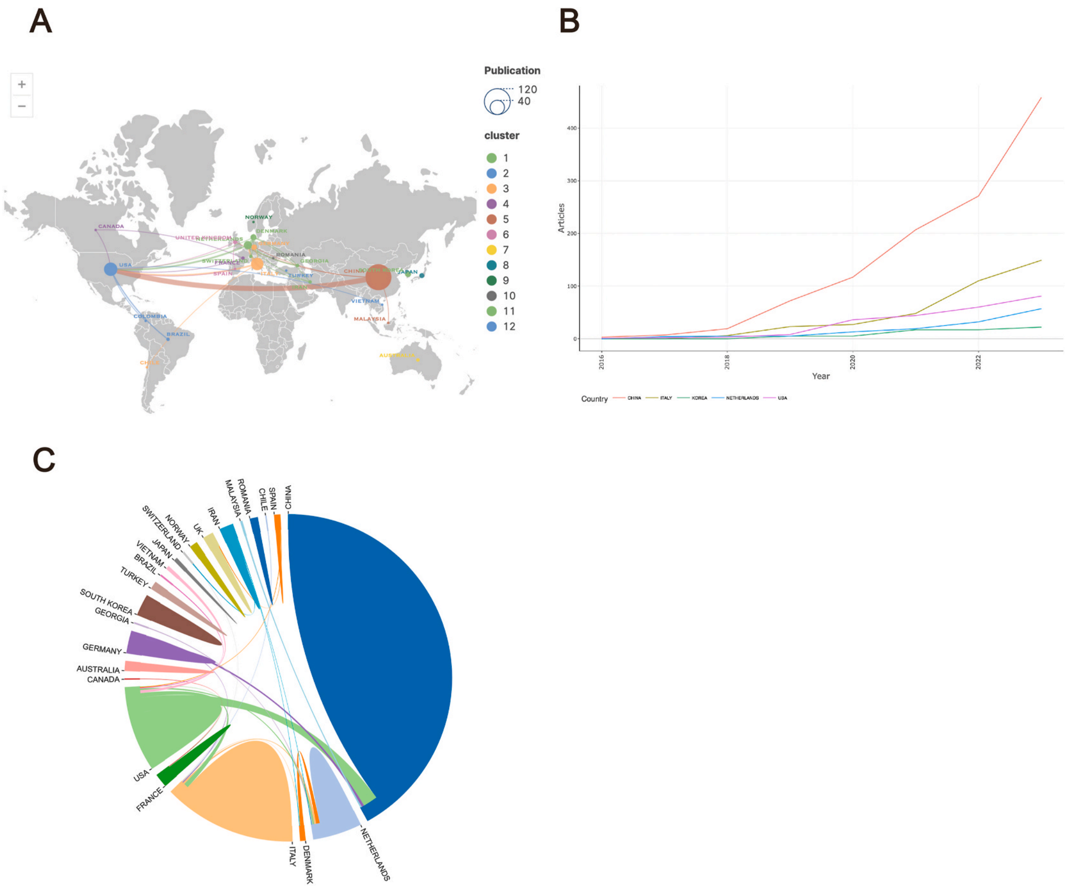

Fig. 3. Publications and collaborations of countries/regions related to artificial intelligence (AI) in rectal cancer (RC) magnetic resonance imaging (MRI) research.
A. Map of country/region collaborations. B. Countries'/regions' production changes with time. C. International cooperation between countries/regions and publications.

Table 1
Top 10 most productive institutions.

Rank	Institution	Documents	Country
1	Sun Yat Sen University	17	China
2	Chinese Academy of Sciences	12	China
3	Beihang University	10	China
4	Maastricht University	9	Netherlands
5	Qingdao University	9	China
6	University of Chinese Academy of Sciences	9	China
7	Shanxi Medical University	8	China
8	GE HealthCare	7	United States
9	Netherlands Cancer Institute	7	Netherlands
10	Sapienza University of Rome	7	Italy

3.2. Countries/regions cooperation analysis

Publications in the field of AI based on MRI in RC were published from 24 countries or regions, with the most publications from China (n = 109), trailed by the United States (n = 29), and Italy (n = 25); the cumulative citations for the three countries were 2288, 1057, and 497, respectively. A map of cooperation distribution is shown in Fig. 3A. Fig. 3B depicts the cumulative number of times the top five countries appeared in publications over time and indicates that China has remained in first place. International cooperation among countries/regions is shown in Fig. 3C. China has fostered the most extensive collaborations with various nations, notably the United States, Italy, and the Netherlands.

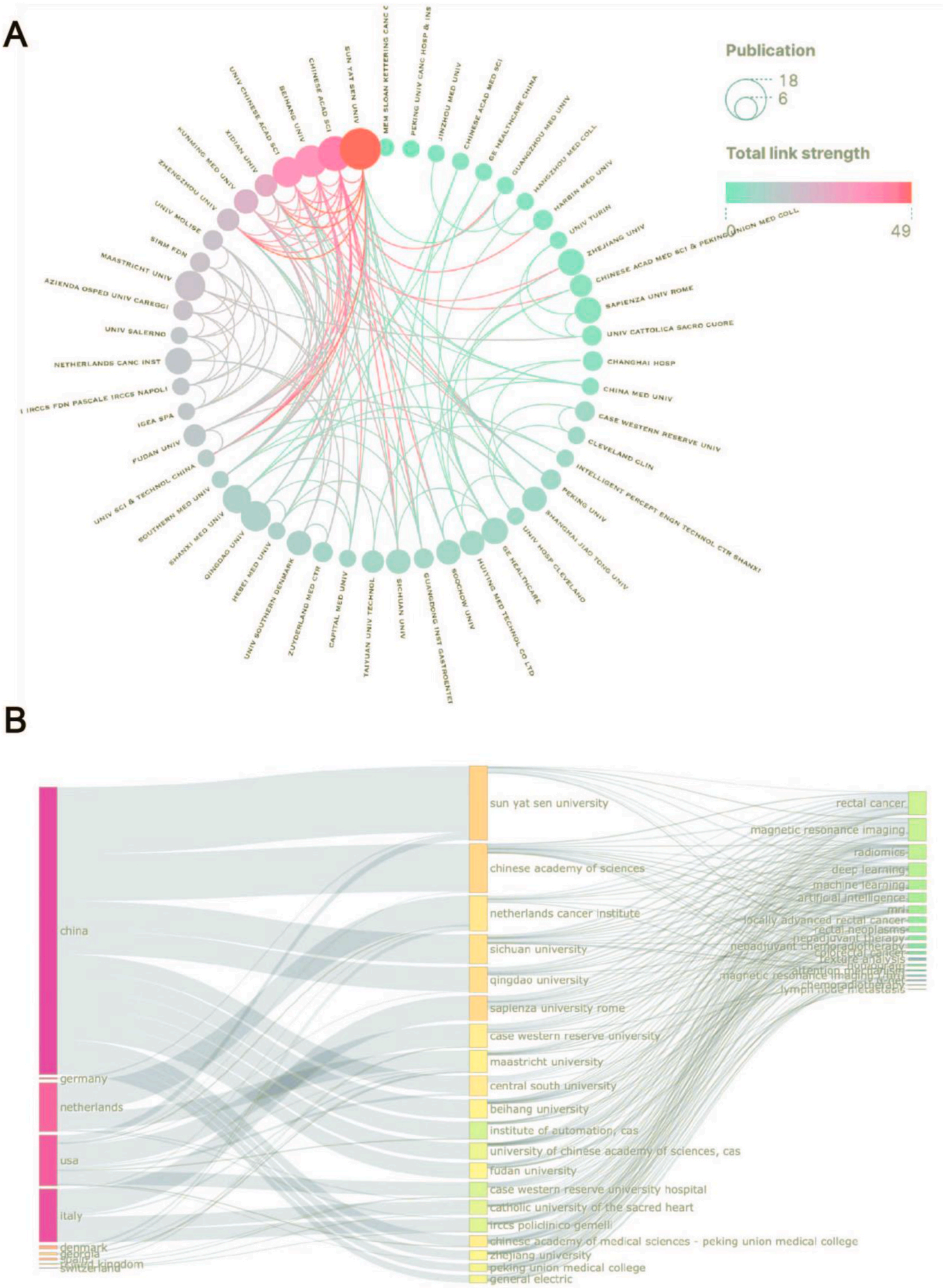

Fig. 4. Cooperation analysis of institutions.

A. Circular graph of cooperation between institutions. The larger the circle, the more publications issued; the thicker the line, the more collaboration between institutions. B. The three fields plot. The left column represents countries, the middle column represents institutions, and the right column represents keywords.

Table 2
Top 15 authors by publications.

Rank	Author	Documents	Country
1	BeetsTan, Regina G. H.	8	Netherlands
2	Zhenyu Liu	7	China
3	Jie Tian	7	China
4	Yanfen Cui	6	China
5	Yingshi Sun	6	China
6	Xiaotang Yang	6	China
7	Xiaoyan Zhang	6	China
8	Lambregts, Doenja M. J.	5	Netherlands
9	Xiaoting Li	5	China
10	Yun Lu	5	China
11	XiaoChun Meng	5	China
12	Fu Shen	5	China
13	Yanjie Shi	5	China
14	Peiyi Xie	5	China
15	Haitao Zhu	5	China

3.3. Statistical analysis of institutions

A total of 351 institutions have published on AI research in RC. The most productive institution was Sun Yat-sen University, followed by the Chinese Academy of Sciences, Beihang University, Maastricht University, and Qingdao University. The top 10 institutions with the highest number of publications are listed in Table 1. Many research institutions have embarked on wide-ranging and in-depth collaborations in this field. The collaboration map and interconnections among these institutions are displayed in Fig. 4A. Fig. 4B presents a three-field plot illustrating the relationship between high-output countries, institutions, and high-frequency keywords. These findings indicate that institutional collaboration within each country is more prevalent than cooperation among institutions across different countries.

3.4. Bibliometric analysis of authors

A total of 1300 authors and 3891 co-cited authors contributed to the relevant research. The 15 most productive authors are listed in Table 2. The most published articles were by the Netherlands scholars Beets-Tan and Regina, while the most cited authors were Chinese scholars Zhenyu Liu and Jie Tian; this suggests that these authors have significant influence in the field. The information pertaining to authors who contributed to more than three articles was imported into VOSviewer to generate a co-authorship visualization graph (Fig. 5A). As seen from the figure, compared to the close connections displayed in the network of countries and institutions, the network of authors is relatively dispersed, with only a select few scholars appearing to maintain close collaborative relationships. Co-citation analysis among the authors identified Natally Horvat, Vincenza Granata, and Zhenyu Liu as the three most cited authors (Fig. 5B).

3.5. Analysis of journals

A collective of 81 journals disseminated articles in this field, and the top 10 most productive journals, with their impact factors and citations, are listed in Table 3. The top three journals were *Frontiers in Oncology* (16, Switzerland), *Abdominal Radiology* (14, United States), and *European Radiology* (9, United States). The co-citation and bibliographic couplings between journals were also analyzed and visualized (Fig. 6). The top three most-cited journals were *European Radiology* (400 citations), *Radiology* (383 citations), and *La Radiologia Medica* (266 citations).

3.6. Analysis of articles and references

Paper citation frequency is a pivotal metric for assessing the caliber of research outcomes; an increased citation frequency implies a more pronounced impact of a publication within a specific field. From the relevant articles, the top 10 were identified based on their citation frequencies, including 9 original articles and 1 review(Table 4).Liu et al. [22] conducted an extensive study in 2019, reviewing the applications of radiomics in the precision diagnosis and treatment of oncology, and this article stands out as the most frequently cited (total citations = 415). The second- and third-most cited articles were by Liu et al. [23], with 347 citations, and Nie et al. [24], with 248 citations. These two original articles included 222 and 48 patients, respectively, and both focused on MRI-based AI in predicting treatment response after nCRT in patients with LARC. The 177 relevant articles cited 5065 references, and the 10 publications most often cited by others in the list of relevant articles are presented in Table 5. The most extensively cited article was by Liu et al. [23], with 50 citations. These authors scrutinized the pathological complete response (pCR) to nCRT in LARC via radiomics analysis. Fig. 7 illustrates the co-citation analysis of the publications. The focus of the publications formed three primary clusters; the prevalence, diagnosis, and treatment of RC, the specific applications of AI in RC; and MRI in RC.

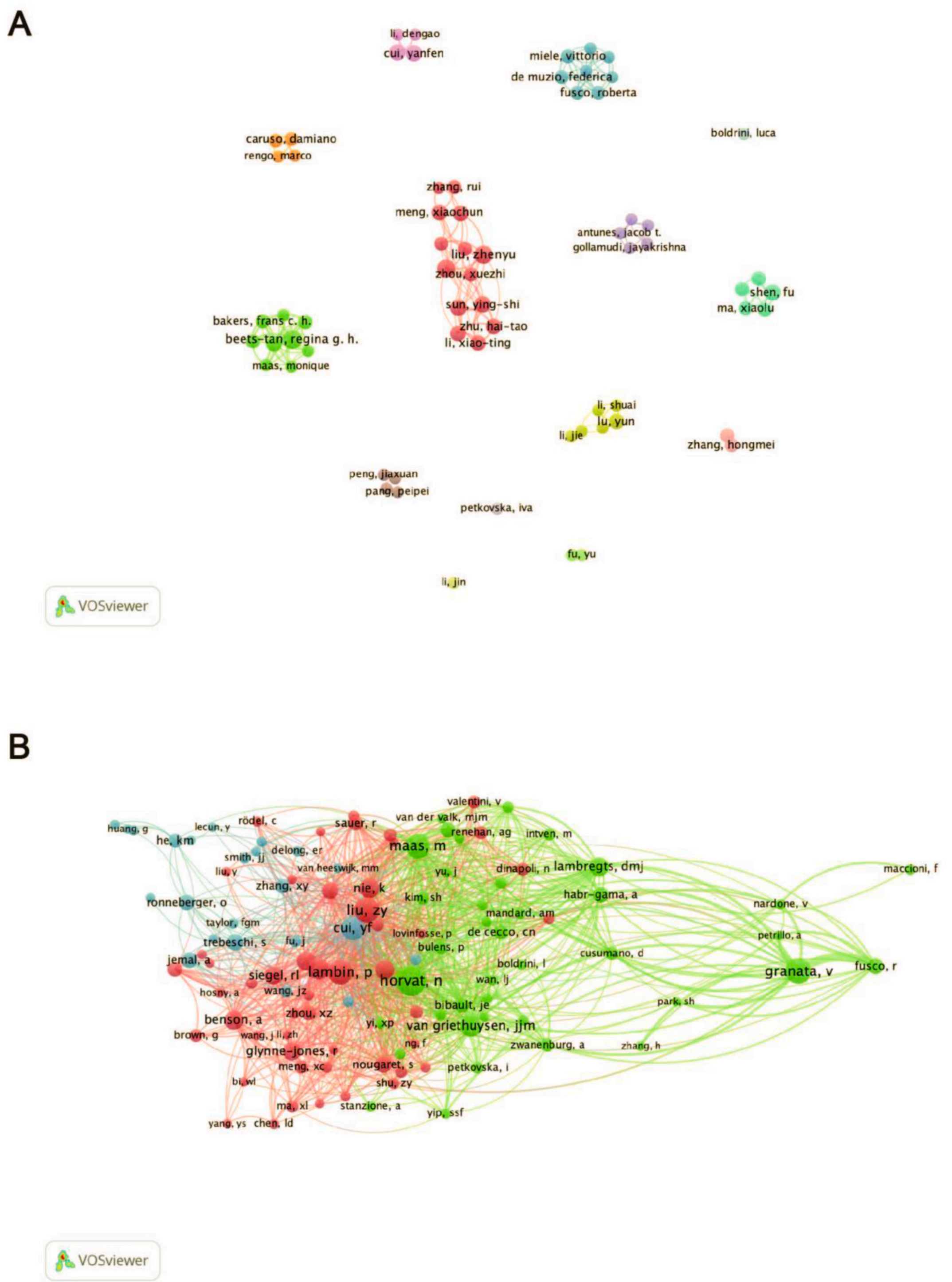

Fig. 5. Visualization analysis graph of authors.
Co-authorship (A) and co-citation (B) analyses among authors.

3.7. Analysis of keywords

A total of 586 keywords were extracted from the 177 publications, including author keywords and KeyWords Plus. KeyWords Plus are index words automatically generated according to the article title. Fig. 8A shows the word clouds of the most frequently used KeyWords Plus. Keywords such as rectal cancer, radiomics, and magnetic resonance imaging appeared the most frequently. A keyword

Table 3
Top 10 productive journals.

Rank	Source	Documents	Citations	2022 IF
1	Frontiers in Oncology	16	156	4.7
2	Abdominal Radiology	14	179	2.4
3	European Radiology	9	147	5.9
4	Diagnostics	8	72	3.6
5	Cancers	6	89	5.2
6	Journal of Magnetic Resonance Imaging	5	58	4.4
7	Medical Physics	5	105	3.8
8	Radiotherapy and Oncology	5	52	5.7
9	Bmc Cancer	4	37	3.8
10	Radiologia Medica	4	173	8.9

co-occurrence network and visual density maps were built using VOSviewer (Fig. 8B and C). Several other high-frequency keywords, including neoadjuvant chemoradiotherapy, prediction, and pathological complete response, were also closely linked to research on RC. If certain keywords are concentrated within a specific period, they are referred to as burst words. Burst words indicate distinct phases of advancement in a particular field. Fig. 8D illustrates the top 10 keywords exhibiting the most notable bursts in citations. The findings suggested that the scholarly works in this investigation were most prevalent during the period spanning from 2016 to 2021, with the keyword chemoradiotherapy exhibiting the highest burst intensity. Furthermore, it is worth noting that some early emergent keywords have faded since 2020.

4. Discussion

In this study, a bibliometric analysis was conducted to explore the characteristics of publications, encompassing metrics such as number, geographic distribution, institutions, journals, references, authors, and keywords, to objectively uncover the current research landscape, future research trends, and hotspots of research on MRI-based AI in RC. A total of 177 publications focusing on MRI-based AI in RC were collected from the WoSCC database and analyzed. China and the United States have made the greatest academic contributions to this field, as reflected in the number of publications, researchers, institutions, and the closest cooperation between the two countries. However, most studies conducted in China exhibited restricted impacts, suggesting the necessity for further enhancement in both topic selection and research implementation. In terms of journals, *Frontiers in Oncology* published the most articles in this field, and most of the productive journals had high Journal Citation Report scores, indicating that the quality of published articles in this field is generally recognized.

Currently, radiomics and deep learning are the primary methods of AI. Radiomics endeavors to create models for enhancing the precision of diagnosis, prognosis, and prediction by extracting and analyzing both first-order and high-order image features from medical images. Radiomics boasts certain advantages, including well-explained features and superior performance in small datasets. However, due to the limited number of model parameters, it may not be as effective as neural networks in large datasets [40]. Deep learning commonly denotes neural networks characterized by a significant number of hidden layers. A convolutional neural network is the most utilized in medical imaging and contributes significantly to medical image research for tasks such as distinguishing types of tumors, segmenting tumors, detecting lesions, and enhancing imaging speed [41,42]. The application of AI in RC has emerged as a current hotspot.

Hotspots denote specific scientific themes within a particular research field within a certain period and constitute a pivotal method in bibliometric analysis. The analysis of keywords and highly cited papers can highlight the direction of research hotspots and reflect research frontiers and trends. This analysis indicated that researchers are most interested in the clinical applications of MRI-based AI, including diagnosis, treatment efficacy, and prognosis in RC. The most-cited article was published by Liu et al. [22] in *Theranostics*. This study reviewed the latest methodological developments in radiomics, as well as the primary applications and challenges of radiomics in the realms of diagnosis, treatment planning, and evaluation within the expansive field of oncology. Recently, LARC and nCRT have become popular research topics. Currently, nCRT followed by total mesorectal excision is the recommended standard treatment for LARC [5]. However, owing to the complexity and heterogeneity of LARC, the response to nCRT exhibits significant variability, ranging from no tumor regression to pCR. Importantly, a watch-and-wait strategy can be suggested for patients who achieve pCR to avoid surgical complications while realizing satisfactory long-term survival outcomes [43]. Thus, there is a growing need for preoperative evaluation of predictors for pCR to determine individuals eligible for the organ-preserving approach. In the current analysis, 7 of the 10 most-cited articles developed MRI-based radiomics models showing high accuracy and reliability in predicting pCR in patients with LARC after nCRT. For example, Liu et al. [23] devised a radiomics model utilizing T2-weighted images (T2WI) and diffusion-weighted images in a cohort of 222 patients with LARC and achieved excellent performance in predicting pCR, with the area under the receiver operating characteristic curve (AUC) reaching 0.9756 in the validation cohort. Zhou et al. [30] developed a multiparametric, MRI-based radiomics model employing 16 features to forecast non-response to nCRT in 425 patients with LARC and showed excellent predictive performance (AUC = 0.822). Zhang et al. [44] proposed the first deep-learning model based on T2WI and diffusion kurtosis images in 383 patients with LARC to predict pCR. The results showed that the AUC of the training set was 0.99, which was significantly higher than the AUC values of the two imaging physicians (0.66 and 0.72) ($P < 0.001$). Furthermore, several investigations have used T2WI of the mesorectal fat and established radiomics models to predict pCR after nCRT

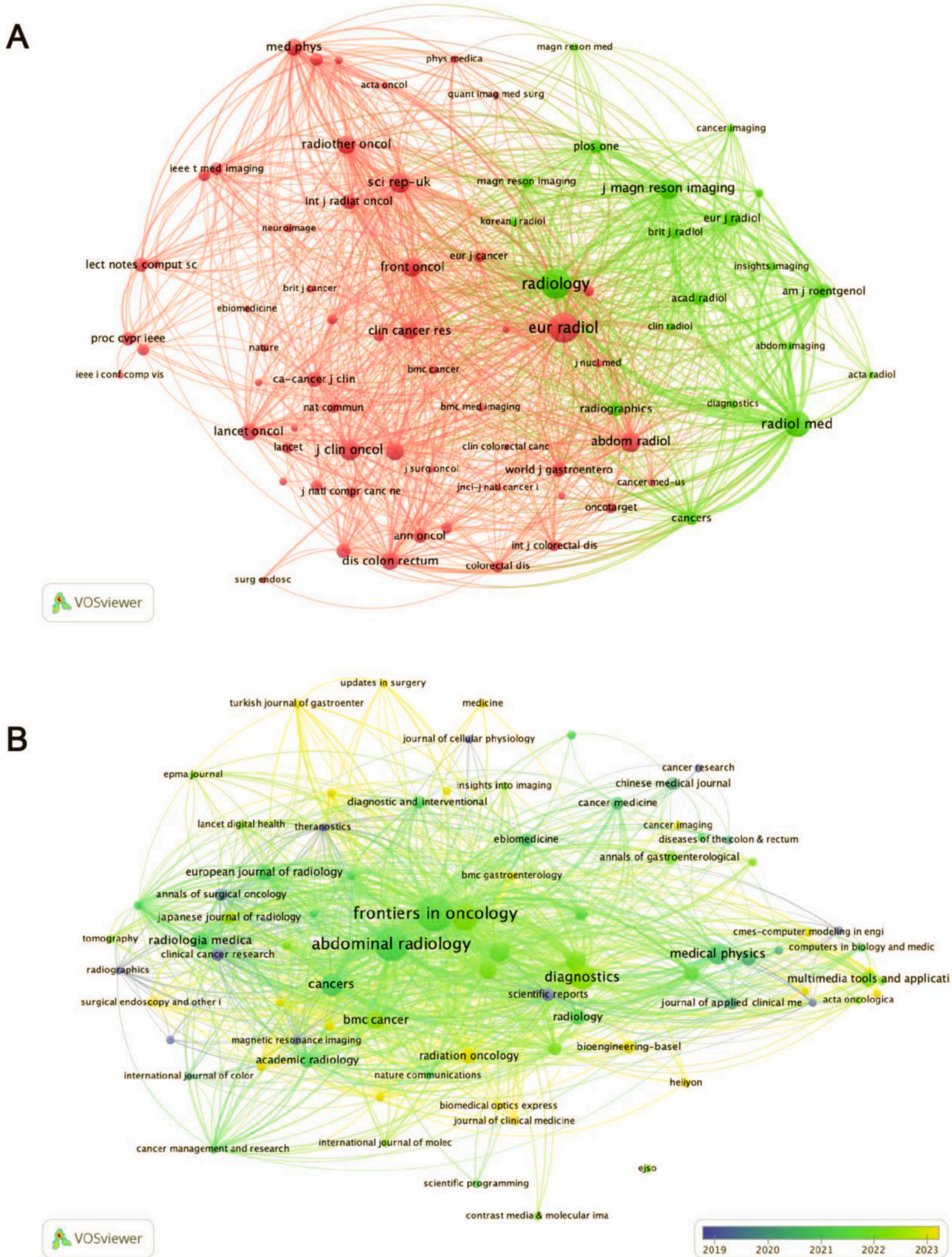

Fig. 6. Visualization analysis graph of journals.
Co-citation (A) and bibliographic coupling (B) analyses between journals.

Table 4
Top 10 most cited publications.

Rank	Title	First Author	Journals	Year	Citations
1	The applications of radiomics in precision diagnosis and treatment of oncology: opportunities and challenges [22]	Zhenyu Liu	Theranostics	2019	415
2	Radiomics analysis for evaluation of pathological complete response to neoadjuvant chemoradiotherapy in locally advanced rectal cancer [23]	Zhenyu Liu	Clinical Cancer Research	2017	347
3	Rectal Cancer: Assessment of neoadjuvant chemoradiation outcome based on radiomics of multiparametric MRI [24]	Nie, K	Clinical Cancer Research	2016	278
4	Deep learning for fully-automated localization and segmentation of rectal cancer on multiparametric MR [25]	Trebeschi, S	Scientific reports	2017	171
5	Fractal-based radiomic approach to predict complete pathological response after chemo-radiotherapy in rectal cancer [26]	Cusumano, D	Radiologia Medica	2018	76
6	Machine learning for prediction of chemoradiation therapy response in rectal cancer using pre-treatment and mid-radiation multi-parametric MRI [27]	Liming Shi	Magnetic Resonance Imaging	2019	66
7	A field strength independent MR radiomics model to predict pathological complete response in locally advanced rectal cancer [28]	Cusumano, D	Radiologia Medica	2021	65
8	Technical Note:A deep learning-based autosegmentation of rectal tumors in MR images [29]	Jiazhou Wang	Medical Physics	2018	65
9	Radiomics-based pretherapeutic prediction of non-response to neoadjuvant therapy in locally advanced rectal cancer [30]	Xuezhi Zhou	Annals of Surgical Oncology	2019	63
10	Development and validation of a radiopathomics model to predict pathological complete response to neoadjuvant chemoradiotherapy in locally advanced rectal cancer: a multicentre observational study [31]	Lili Feng	Lancet Digit Health	2022	57

Table 5
Top 10 frequently co-cited references.

Rank	Title	First Author	Journals	Year	Citations
1	Radiomics analysis for evaluation of pathological complete response to neoadjuvant chemoradiotherapy in locally advanced rectal cancer [23]	Zhenyu Liu	Clinical Cancer Research	2017	50
2	Rectal Cancer: Assessment of neoadjuvant chemoradiation outcome based on radiomics of multiparametric MRI [24]	Nie, K	Clinical Cancer Research	2016	42
3	MR imaging of rectal cancer: Radiomics analysis to assess treatment response after neoadjuvant therapy [32]	Horvat N	Radiology	2018	41
4	Radiomics:Images are more than pictures, they are data [33]	Gillies RJ	Radiology	2016	40
5	Radiomics analysis of multiparametric MRI for prediction of pathological complete response to neoadjuvant chemoradiotherapy in locally advanced rectal cancer [34]	Yanfen Cui	European Radiology	2019	38
6	Long-term outcome in patients with a pathological complete response after chemoradiation for rectal cancer: a pooled analysis of individual patient data [35]	Maas M	Lancet Oncology	2010	36
7	Radiomics: the bridge between medical imaging and personalized medicine [36]	Lambin P	Nature Reviews Clinical Oncology	2017	33
8	Computational radiomics system to decode the radiographic phenotype [37]	van Griethuysen	Cancer Research	2017	33
9	Development and validation of a radiomics nomogram for preoperative prediction of lymph node metastasis in colorectal cancer [38]	Yanqi Huang	Journal of Clinical Oncology	2016	32
10	Magnetic resonance imaging for clinical management of rectal cancer: Updated recommendations from the 2016 European Society of Gastrointestinal and Abdominal Radiology (ESGAR) consensus meeting [39]	Beets Tan	European Radiology	2018	31

in LARC, achieving good predictive efficacy [45]. Combining radiomics and pathomics to amplify the effectiveness of AI models for predicting pCR in RC has garnered significant attention as a research hotspot in recent years. Feng et al. [31] established and validated a radiopathomics integrated model using machine learning based on pretreatment MRI and biopsy whole-slide images to predict pCR after nCRT, which showed high accuracy and robustness. These results indicate that the research field of MRI-based AI in RC appears highly cohesive and focuses on the assessment of treatment efficacy, which could potentially be implemented in clinical practice to personalize perioperative management for patients with RC. Further exploration and validation are required in future studies to achieve wide applicability of the model.

In addition to assessing treatment efficacy, preoperative diagnosis and prognosis prediction of RC using medical imaging remain major research priorities. Preoperative diagnosis, including preoperative T stage and lymph node involvement in RC, is pivotal for clinical treatment decisions, prognostic predictions, and assessment of treatment responses. However, the diagnostic accuracy of MRI and the experience of radiologists are unsatisfactory. Thus, AI has been applied in the use of MRI to T staging and identifying lymph node metastasis in RC. Wu et al. [46] established an automatic diagnostic platform for T staging of RC through the study of MRI of 183 patients via a faster region-based convolutional neural network, suggesting that this model might be an effective and objective method for predicting RC T-staging. A recent investigation by Hou et al. [47] revealed that a deep learning-based three-dimensional super-resolution MRI radiomics model had superior performance in predicting preoperative T staging in RC, compared with high-resolution T2WI-based AI models and visual assessment by radiologists. Li et al. applied deep transfer learning based on MRI to

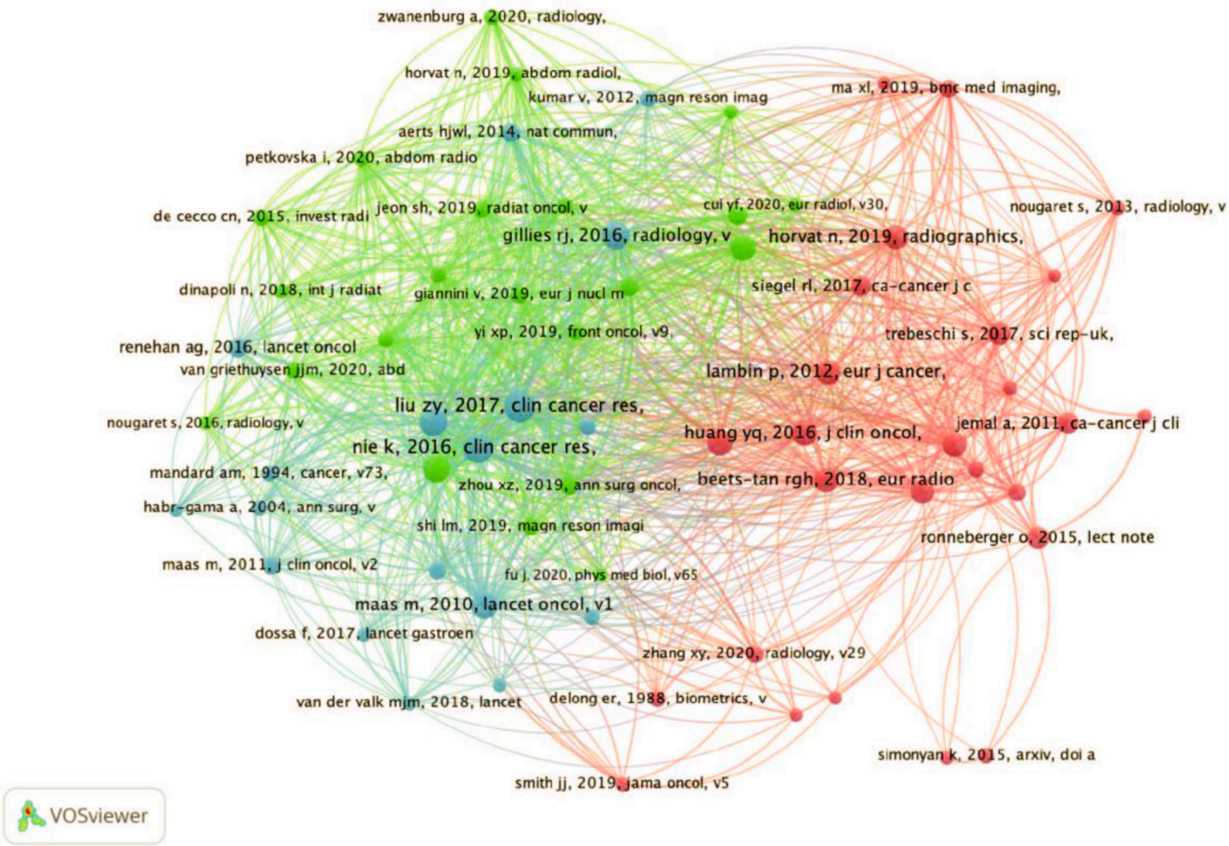

Fig. 7. Co-citation analysis of references.
Colors represent the clustering of references. Articles in the blue cluster predominantly focus on the prevalence, diagnosis, and treatment of RC; the red and green clusters focus on the specific applications of AI and MRI in RC.

identify the lymph node status in patients with RC to improve N staging accuracy, which reflected a notably better performance than that of radiologists [48]. Kasai et al. [49] developed a practical prediction model for lateral lymph node metastasis in RC using machine learning by integrating preoperative information of 267 patients, which helped make reasonable medical decisions for lateral lymph node dissection. In terms of prognosis, MRI-based AI has gathered increasing attention from researchers because of its remarkable predictive prognostic ability. Tibermacine et al. [50] conducted a multicenter study to evaluate and compare the ability of various radiomics models to predict disease-free survival in 98 patients with LARC, and all showed good performance, with AUC values ranging from 0.77 to 0.89. Another retrospective study identified an outstanding performance in predicting disease-free survival in patients with LARC by constructing a multiparametric MRI-based radiomics model [51]. In addition, Liu et al. [52] conducted a retrospective multicenter study to construct a deep-learning radiomics signature based on MRI for predicting distant metastasis in 235 patients with LARC receiving nCRT, with an AUC of 0.894. Consequently, the deep-learning radiomics signature can help evaluate the risk of distant metastasis in patients with different responses to nCRT. These studies demonstrate that MRI-based AI can help clinicians predict patient diagnosis and prognosis information and provide more accurate medical decisions for patients.

MRI-based AI research on RC remains challenging. First, the necessity for superior-quality images in AI research is undeniable, while the inherent tubular structure and peristaltic motion of the rectum present formidable challenges for rectal MRI. Therefore, the amalgamation of AI and RC imaging has emerged as a crucial avenue for expediting imaging processes and enhancing image quality. Second, owing to the complex anatomical structures, diverse medical scenarios, and inconsistent image quality, the current algorithms still fall short of meeting the stringent medical standards essential for high-precision, fully automatic workflows, and require further improvement. Furthermore, while deep learning exhibits superior performance in extensive datasets, it grapples with the challenge of inadequate interpretation of features and is incapable of providing a qualitative explanation of the essence of deep learning features. This limitation is a critical factor influencing the clinical application of AI and can be solved in the future by fusing radiomics and deep learning features. In addition, especially for deep learning methods, the majority of studies have relied on a limited volume of data from a single source, and more data are required to train and verify the model. An MRI-based AI model needs to be universally validated in large multicenter datasets [53]. Hence, future researchers conducting studies on the advancement of AI in RC should prioritize increasing the amount of research data and standardizing the AI workflow to ensure the robustness and generality of the model. Despite these challenges, the potential applications of MRI-based AI in RC are substantial. In the near future, by standardizing

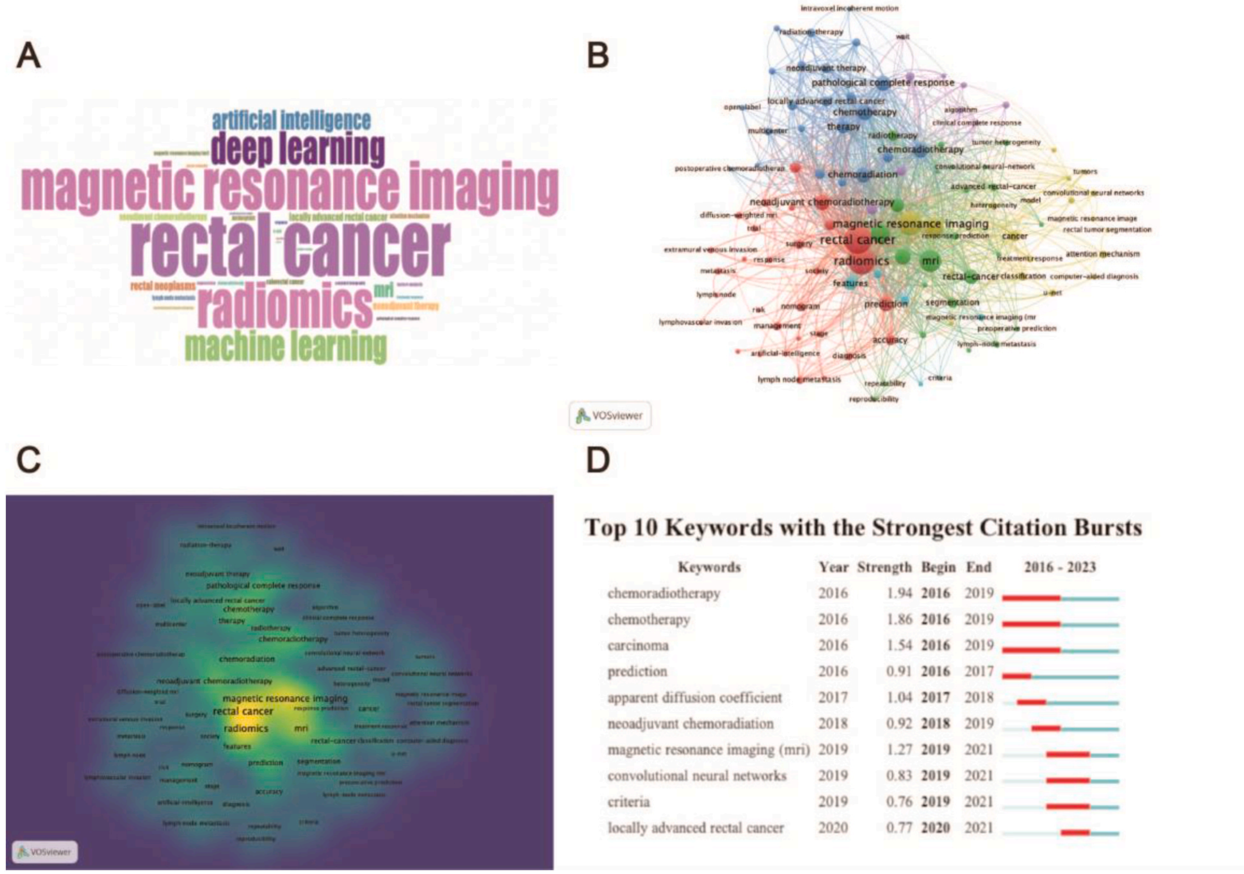

Fig. 8. Visualization analysis of keywords.
A. Word cloud of keywords. B. Co-occurrence network of keywords. C. Density distribution of keywords. D. The top 10 burst keywords. The size of the words is determined based on their frequency. The blue line represents the time period, while the red part indicates the time span of the burst.

the AI processes, breaking down barriers between data, and enhancing model generalization, AI will ultimately be applied in clinical settings. This will significantly advance proctology, delivering more efficient, precise, and personalized healthcare services to a greater number of patients.

Bibliometrics enables the analysis of authors, institutions, countries, and references within literature databases, providing insights into a specific research area and facilitating visualization through various tools, such Citespace and VOSviewer. It offers a more thorough analysis of the literature and presents more intuitive results compared to a typical systematic review. In the present study on MRI-based AI in RC, bibliometrics was used to explore the applications and developments in this field through multiple perspectives, including publication characteristics, contributions from institutional authors, co-citations of authors' work, and keyword trends, utilizing diverse visualization tools, to speculate on future research trends. Nonetheless, this study had some limitations. First, although the WOSCC is regarded as the most commonly used scientometric analysis database, it may not contain all relevant studies; therefore, relevant studies in other databases may have been overlooked. Second, only English-language publications were analyzed, which may have biased the findings. In addition, only publications before November 30, 2023, were included in this study. Owing to citation delays, some recently published high-quality studies may not garner the deserved attention, necessitating timely updates in subsequent research endeavors.

5. Conclusions

This study employed bibliometrics to conduct a comprehensive analysis of the published literature on MRI-based AI in RC. The results indicated that the application of AI to MRI data for the evaluation and prediction of the diagnosis, treatment, and prognosis of RC is a hotspot and at the frontier of current research in this field and has great potential for development. Future research trends in this field will focus on enhancing the image quality, incorporating large-sample, multicenter research data, and standardizing the AI workflow to improve its robustness and generality.

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CRediT authorship contribution statement

Tianming Ma: Writing – original draft, Resources, Methodology, Investigation, Conceptualization. **Jiawen Wang:** Writing – original draft, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Fuhai Ma:** Visualization, Validation, Methodology. **Jinxin Shi:** Writing – review & editing. **Zijian Li:** Writing – review & editing, Validation. **Jian Cui:** Software. **Guoju Wu:** Validation, Supervision, Investigation. **Gang Zhao:** Writing – review & editing, Project administration, Funding acquisition. **Qi An:** Validation, Supervision, Funding acquisition, Conceptualization.

Data availability statement

The data analyzed in this study are included in the article. Further data will be made available on request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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References

[1] R.L. Siegel, K.D. Miller, N.S. Wagle, A. Jemal, Cancer statistics, 2023, CA Cancer J Clin 73 (2023) 17–48, https://doi.org/10.3322/caac.21763.
[2] H. Sung, J. Ferlay, R.L. Siegel, M. Laversanne, I. Soerjomataram, A. Jemal, F. Bray, Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries, CA Cancer J Clin 71 (2021) 209–249, https://doi.org/10.3322/caac.21660.
[3] R.L. Siegel, N.S. Wagle, A. Cercek, R.A. Smith, A. Jemal, Colorectal cancer statistics, 2023, CA Cancer J Clin 73 (2023) 233–254, https://doi.org/10.3322/caac.21772.
[4] R.L. Siegel, L.A. Torre, I. Soerjomataram, R.B. Hayes, F. Bray, T.K. Weber, A. Jemal, Global patterns and trends in colorectal cancer incidence in young adults, Gut 68 (2019) 2179–2185, https://doi.org/10.1136/gutjnl-2019-319511.
[5] A.B. Benson, A.P. Venook, M.M. Al-Hawary, et al., NCCN guidelines insights: rectal cancer. version 6.2020, J Natl Compr Canc Netw 18 (2020) 806–815, https://doi.org/10.6004/jnccn.2020.0032.
[6] R. Glynne-Jones, L. Wyrwicz, E. Tiret, G. Brown, C. Rödel, A. Cervantes, D. Arnold, Rectal cancer: ESMO clinical practice guidelines for diagnosis, treatment and follow-up, Ann. Oncol. 28 (2017) iv22–iv40, https://doi.org/10.1093/annonc/mdx224.
[7] M.C. Fernandes, M.J. Gollub, G. Brown, The importance of MRI for rectal cancer evaluation, Surg Oncol 43 (2022) 101739, https://doi.org/10.1016/j.suronc.2022.101739.
[8] T.H. Kim, S. Woo, S. Han, C.H. Suh, H.A. Vargas, The diagnostic performance of MRI for detection of extramural venous invasion in colorectal cancer: a systematic review and meta-analysis of the literature, Am. J. Roentgenol. 213 (3) (2019) 575–585, https://doi.org/10.2214/AJR.19.21112.
[9] B. Barbaro, C. Fiorucci, C. Tebala, et al., Locally advanced rectal cancer: MR imaging in prediction of response after preoperative chemotherapy and radiation therapy, Radiology 250 (3) (2009) 730–739, https://doi.org/10.1148/radiol.2503080310.
[10] W.L. Bi, A. Hosny, M.B. Schabath, M.L. Giger, N.J. Birkbak, A. Mehrtash, T. Allison, O. Arnaout, C. Abbosh, I.F. Dunn, R.H. Mak, R.M. Tamimi, C.M. Tempany, C. Swanton, U. Hoffmann, L.H. Schwartz, R.J. Gillies, R.Y. Huang, H.J.W.L. Aerts, Artificial intelligence in cancer imaging: clinical challenges and applications, CA Cancer J Clin 69 (2019) 127–157, https://doi.org/10.3322/caac.21552.
[11] J. Shin, N. Seo, S.E. Baek, N.H. Son, J.S. Lim, N.K. Kim, W.S. Koom, S. Kim, MRI radiomics model predicts pathologic complete response of rectal cancer following chemoradiotherapy, Radiology 303 (2022) 351–358, https://doi.org/10.1148/radiol.211986.
[12] C. Wong, Y. Fu, M. Li, S. Mu, X. Chu, J. Fu, C. Lin, H. Zhang, MRI-based artificial intelligence in rectal cancer, J Magn Reson Imaging 57 (2023) 45–56, https://doi.org/10.1002/jmri.28381.
[13] A.K. Shaikh, S.M. Alhashmi, N. Khalique, A.M. Khedr, K. Raahemifar, S. Bukhari, Bibliometric analysis on the adoption of artificial intelligence applications in the e-health sector, Digit Health 9 (2023) 20552076221149296, https://doi.org/10.1177/20552076221149296.
[14] T.N. Poly, M.M. Islam, B.A. Walther, M.C. Lin, Y.C. Jack Li, Artificial intelligence in diabetic retinopathy: bibliometric analysis, Comput Methods Programs Biomed 231 (2023) 107358, https://doi.org/10.1016/j.cmpb.2023.107358.
[15] T. Saheb, T. Saheb, D.O. Carpenter, Mapping research strands of ethics of artificial intelligence in healthcare: a bibliometric and content analysis, Comput. Biol. Med. 135 (2021) 104660, https://doi.org/10.1016/j.compbiomed.2021.104660.
[16] S. Park, B.S. Park, Y.J. Lee, I.H. Kim, J.H. Park, J. Ko, et al., Artificial intelligence with kidney disease: a scoping review with bibliometric analysis, PRISMA-ScR. Med (Baltimore). 100 (14) (2021) e25422, https://doi.org/10.1097/MD.0000000000025422.
[17] P. Huang, Z. Feng, X. Shu, A. Wu, Z. Wang, T. Hu, Y. Cao, Y. Tu, Z. Li, A bibliometric and visual analysis of publications on artificial intelligence in colorectal cancer (2002–2022), Front. Oncol. 13 (2023) 1077539, https://doi.org/10.3389/fonc.2023.1077539.
[18] S. Chen, D. Sun, N. Wang, X. Fang, Z. Xi, C. Wang, H. Chen, L. Xie, Current status and trends in quantitative MRI study of intervertebral disc degeneration: a bibliometric and clinical study analysis, Quant Imaging Med Surg 13 (2023) 2953–2974, https://doi.org/10.21037/qims-22-1219.

[19] M.B. Synnestvedt, C. Chen, J.H. Holmes, CiteSpace II: visualization and knowledge discovery in bibliographic databases, AMIA Annu Symp Proc 2005 (2005) 724–728.

[20] N.J. van Eck, L. Waltman, Software survey: VOSviewer, a computer program for bibliometric mapping, Scientometrics 84 (2010) 523–538, https://doi.org/10.1007/s11192-009-0146-3.

[21] H. Derviş, Bibliometric analysis using Bibliometrix an R package, J Scientometric Res 8 (2019) 156–160, https://doi.org/10.5530/jscires.8.3.32.

[22] Z. Liu, S. Wang, D. Dong, J. Wei, C. Fang, X. Zhou, K. Sun, L. Li, B. Li, M. Wang, J. Tian, The applications of radiomics in precision diagnosis and treatment of oncology: opportunities and challenges, Theranostics 9 (2019) 1303–1322, https://doi.org/10.7150/thno.30309.

[23] Z. Liu, X.Y. Zhang, Y.J. Shi, L. Wang, H.T. Zhu, Z. Tang, S. Wang, X.T. Li, J. Tian, Y.S. Sun, Radiomics analysis for evaluation of pathological complete response to neoadjuvant chemoradiotherapy in locally advanced rectal cancer, Clin. Cancer Res. 23 (2017) 7253–7262, https://doi.org/10.1158/1078-0432.CCR-17-1038.

[24] K. Nie, L. Shi, Q. Chen, X. Hu, S.K. Jabbour, N. Yue, T. Niu, X. Sun, Rectal Cancer: assessment of neoadjuvant chemoradiation outcome based on radiomics of multiparametric MRI, Clin. Cancer Res. 22 (2016) 5256–5264, https://doi.org/10.1158/1078-0432.CCR-15-2997.

[25] S. Trebeschi, J.J.M. van Griethuysen, D.M.J. Lambregts, M.J. Lahaye, C. Parmar, F.C.H. Bakers, N.H.G.M. Peters, R.G.H. Beets-Tan, H.J.W.L. Aerts, Deep learning for fully-automated localization and segmentation of rectal cancer on multiparametric MR, Sci. Rep. 7 (2017) 5301, https://doi.org/10.1038/s41598-017-05728-9.

[26] D. Cusumano, N. Dinapoli, L. Boldrini, G. Chiloiro, R. Gatta, C. Masciocchi, J. Lenkowicz, C. Casà, A. Damiani, L. Azario, J. Van Soest, A. Dekker, P. Lambin, M. De Spirito, V. Valentini, Fractal-based radiomic approach to predict complete pathological response after chemo-radiotherapy in rectal cancer, Radiol. Med. 123 (4) (2018) 286–295, https://doi.org/10.1007/s11547-017-0838-3.

[27] L. Shi, Y. Zhang, K. Nie, X. Sun, T. Niu, N. Yue, T. Kwong, P. Chang, D. Chow, J.H. Chen, M.Y. Su, Machine learning for prediction of chemoradiation therapy response in rectal cancer using pre-treatment and mid-radiation multi-parametric MRI, Magn. Reson. Imaging 61 (2019) 33–40, https://doi.org/10.1016/j.mri.2019.05.003.

[28] D. Cusumano, G. Meijer, J. Lenkowicz, G. Chiloiro, L. Boldrini, C. Masciocchi, N. Dinapoli, R. Gatta, C. Casà, A. Damiani, B. Barbaro, M.A. Gambacorta, L. Azario, M. De Spirito, M. Intven, V. Valentini, A field strength independent MR radiomics model to predict pathological complete response in locally advanced rectal cancer, Radiol. Med. 126 (3) (2021) 421–429, https://doi.org/10.1007/s11547-020-01266-z.

[29] J. Wang, J. Lu, G. Qin, L. Shen, Y. Sun, H. Ying, Z. Zhang, W. Hu, Technical Note: a deep learning-based autosegmentation of rectal tumors in MR images, Med. Phys. 45 (2018) 2560–2564, https://doi.org/10.1002/mp.12918.

[30] X. Zhou, Y. Yi, Z. Liu, W. Cao, B. Lai, K. Sun, L. Li, Z. Zhou, Y. Feng, J. Tian, Radiomics-based pretherapeutic prediction of non-response to neoadjuvant therapy in locally advanced rectal cancer, Ann. Surg Oncol. 26 (2019) 1676–1684, https://doi.org/10.1245/s10434-019-07300-3.

[31] L. Feng, Z. Liu, C. Li, Z. Li, X. Lou, L. Shao, et al., Development and validation of a radiopathomics model to predict pathological complete response to neoadjuvant chemoradiotherapy in locally advanced rectal cancer: a multicentre observational study, Lancet Digit Health 4 (2022) e8–e17, https://doi.org/10.1016/S2589-7500(21)00215-6.

[32] N. Horvat, H. Veeraraghavan, M. Khan, I. Blazic, J. Zheng, M. Capanu, E. Sala, J. Garcia-Aguilar, M.J. Gollub, I. Petkovska, MR imaging of rectal cancer: radiomics analysis to assess treatment response after neoadjuvant therapy, Radiology 287 (2018) 833–843, https://doi.org/10.1148/radiol.2018172300.

[33] R.J. Gillies, P.E. Kinahan, H.H. Hricak, Radiomics: images are more than pictures, they are data, Radiology 278 (2016) 563–577, https://doi.org/10.1148/radiol.2015151169.

[34] Y. Cui, X. Yang, Z. Shi, Z. Yang, X. Du, Z. Zhao, X. Cheng, Radiomics analysis of multiparametric MRI for prediction of pathological complete response to neoadjuvant chemoradiotherapy in locally advanced rectal cancer, Eur. Radiol. 29 (2019) 1211–1220, https://doi.org/10.1007/s00330-018-5683-9.

[35] M. Maas, P.J. Nelemans, V. Valentini, P. Das, C. Rödel, L.J. Kuo, F.A. Calvo, J. García-Aguilar, R. Glynne-Jones, K. Haustermans, M. Mohiuddin, S. Pucciarelli, W. Small, J. Suárez, G. Theodoropoulos, S. Biondo, R.G. Beets-Tan, G.L. Beets, Long-term outcome in patients with a pathological complete response after chemoradiation for rectal cancer: a pooled analysis of individual patient data, Lancet Oncol. 11 (2010) 835–844, https://doi.org/10.1016/S1470-2045(10)70172-8.

[36] P. Lambin, R.T.H. Leijenaar, T.M. Deist, J. Peerlings, E.E.C. de Jong, J. van Timmeren, S. Sanduleanu, R.T.H.M. Larue, A.J.G. Even, A. Jochems, Y. van Wijk, H. Woodruff, J. van Soest, T. Lustberg, E. Roelofs, W. van Elmpt, A. Dekker, F.M. Mottaghy, J.E. Wildberger, S. Walsh, Radiomics: the bridge between medical imaging and personalized medicine, Nat. Rev. Clin. Oncol. 14 (12) (2017) 749–762, https://doi.org/10.1038/nrclinonc.2017.141.

[37] J.J.M. van Griethuysen, A. Fedorov, C. Parmar, A. Hosny, N. Aucoin, V. Narayan, R.G.H. Beets-Tan, J.C. Fillion-Robin, S. Pieper, H.J.W.L. Aerts, Computational radiomics system to decode the radiographic phenotype, Cancer Res. 77 (2017) e104–e107, https://doi.org/10.1158/0008-5472.CAN-17-0339.

[38] Y.Q. Huang, C.H. Liang, L. He, J. Tian, C.S. Liang, X. Chen, Z.L. Ma, Z.Y. Liu, Development and validation of a radiomics nomogram for preoperative Prediction of lymph node Metastasis in Colorectal Cancer, J. Clin. Oncol. 34 (2016) 2157–2164, https://doi.org/10.1200/JCO.2015.65.9128.

[39] R.G.H. Beets-Tan, D.M.J. Lambregts, M. Maas, S. Bipat, B. Barbaro, L. Curvo-Semedo, H.M. Fenlon, M.J. Gollub, S. Gourtsoyianni, S. Halligan, C. Hoeffel, S. H. Kim, A. Laghi, A. Maier, S.R. Rafaelsen, J. Stoker, S.A. Taylor, M.R. Torkzad, L. Blomqvist, Magnetic resonance imaging for clinical management of rectal cancer: updated recommendations from the 2016 European Society of Gastrointestinal and Abdominal Radiology (ESGAR) consensus meeting, Eur. Radiol. 28 (2018) 1465–1475, https://doi.org/10.1007/s00330-017-5026-2.

[40] P. Lambin, E. Rios-Velazquez, R. Leijenaar, S. Carvalho, H.J.W.L. Aerts, Radiomics: extracting more information from medical images using advanced feature analysis, Eur. J. Cancer 43 (4) (2012) 441–446, https://doi.org/10.1016/j.ejca.2011.11.036.

[41] T. Ishida, N. Kadoya, S. Tanabe, H. Ohashi, H. Nemoto, S. Dobashi, K. Takeda, K. Jingu, Evaluation of performance of pelvic CT-MR deformable image registration using two software programs, J. Radiat. Res. 62 (6) (2021) 1076–1082, https://doi.org/10.1093/jrr/rrab078.

[42] J. Cheng, Z.X. Cui, W. Huang, Z. Ke, L. Ying, H. Wang, Y. Zhu, D. Liang, Learning data consistency and its application to dynamic MR imaging, IEEE Trans Med Imaging 40 (11) (2021) 3140–3153, https://doi.org/10.1109/TMI.2021.3096232.

[43] M.J.M. van der Valk, D.E. Hilling, E. Bastiaannet, E. Meershoek-Klein Kranenbarg, G.L. Beets, N.L. Figueiredo, A. Habr-Gama, R.O. Perez, A.G. Renehan, C.J. H. van de Velde, I.W.W.D. Consortium, Long-term outcomes of clinical complete responders after neoadjuvant treatment for rectal cancer in the International Watch & Wait Database (IWWD): an international multicentre registry study, Lancet 391 (2018) 2537–2545, https://doi.org/10.1016/S0140-6736(18)31078-X.

[44] X.Y. Zhang, L. Wang, H.T. Zhu, Z.W. Li, M. Ye, X.T. Li, Y.J. Shi, H.C. Zhu, Y.S. Sun, Predicting rectal cancer response to neoadjuvant chemoradiotherapy using deep learning of diffusion kurtosis MRI, Radiology 296 (2020) 56–64, https://doi.org/10.1148/radiol.2020190936.

[45] V.S. Jayaprakasam, V. Paroder, P. Gibbs, R. Bajwa, N. Gangai, R.E. Sosa, I. Petkovska, J.S. Golia Pernicka, J.L. Fuqua, D.D.B. Bates, M.R. Weiser, A. Cercek, M. J. Gollub, MRI radiomics features of mesorectal fat can predict response to neoadjuvant chemoradiation therapy and tumor recurrence in patients with locally advanced rectal cancer, Eur. Radiol. 32 (2022) 971–980, https://doi.org/10.1007/s00330-021-08144-w.

[46] Q.Y. Wu, S.L. Liu, P. Sun, Y. Li, G.W. Liu, S.S. Liu, J.L. Hu, T.Y. Niu, Y. Lu, Establishment and clinical application value of an automatic diagnosis platform for rectal cancer T-staging based on a deep neural network, Chin Med J (Engl) 134 (2021) 821–828, https://doi.org/10.1097/CM9.0000000000001401.

[47] M. Hou, L. Zhou, J. Sun, Deep-learning-based 3D super-resolution MRI radiomics model: superior predictive performance in preoperative T-staging of rectal cancer, Eur. Radiol. 33 (2023) 1–10, https://doi.org/10.1007/s00330-022-08952-8.

[48] J. Li, Y. Zhou, P. Wang, H. Zhao, X. Wang, N. Tang, K. Luan, Deep transfer learning based on magnetic resonance imaging can improve the diagnosis of lymph node metastasis in patients with rectal cancer, Quant Imaging Med Surg 11 (2021) 2477–2485, https://doi.org/10.21037/qims-20-525.

[49] S. Kasai, A. Shiomi, H. Kagawa, H. Hino, S. Manabe, Y. Yamaoka, K. Chen, K. Nanishi, Y. Kinugasa, The effectiveness of machine learning in predicting lateral lymph node metastasis from lower rectal cancer: a single center development and validation study, Ann Gastroenterol Surg 6 (2022) 92–100, https://doi.org/10.1002/ags3.12504.

[50] H. Tibermacine, P. Rouanet, M. Sbarra, R. Forghani, C. Reinhold, S. Nougaret, GRECCAR Study Group, Radiomics modelling in rectal cancer to predict disease-free survival: evaluation of different approaches, Br. J. Surg. 108 (2021) 1243–1250, https://doi.org/10.1093/bjs/znab191.

[51] Y. Cui, W. Yang, J. Ren, D. Li, X. Du, J. Zhang, X. Yang, Prognostic value of multiparametric MRI-based radiomics model: potential role for chemotherapeutic benefits in locally advanced rectal cancer, Radiother. Oncol. 154 (2021) 161–169, https://doi.org/10.1016/j.radonc.2020.09.039.
[52] X. Liu, D. Zhang, Z. Liu, Z. Li, P. Xie, K. Sun, W. Wei, W. Dai, Z. Tang, Y. Ding, G. Cai, T. Tong, X. Meng, J. Tian, Deep learning radiomics-based prediction of distant metastasis in patients with locally advanced rectal cancer after neoadjuvant chemoradiotherapy: a multicentre study, EBioMedicine 69 (2021) 103442, https://doi.org/10.1016/j.ebiom.2021.103442.
[53] F. Wang, L.P. Casalino, D. Khullar, Deep learning in medicine-promise, progress, and challenges, JAMA Intern. Med. 179 (2019) 293–294, https://doi.org/10.1001/jamainternmed.2018.7117.