



Development trends and knowledge framework in the application of magnetic resonance imaging in prostate cancer: a bibliometric analysis from 1984 to 2022

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Background: Prostate cancer (PCa) is the most common tumor of the male genitourinary system. With the development of imaging technology, the role of magnetic resonance imaging (MRI) in the management of PCa is increasing. The present study summarizes research on the application of MRI in the field of PCa using bibliometric analysis and predicts future research hotspots.

Methods: Articles regarding the application of MRI in PCa between January 1, 1984 and June 30, 2022 were selected from the Web of Science Core Collection (WoSCC) on November 6, 2022. Microsoft Excel 2016 and the Bibliometrix Biblioshiny R-package software were used for data analysis and bibliometric indicator extraction. CiteSpace (version 6.1.R3) was used to visualize literature feature clustering, including co-occurrence analysis of countries, institutions, authors, references, and burst keywords analysis.

Results: A total of 10,230 articles were included in the study. Turkbey was the most prolific author. The USA was the most productive country and had strong partnerships with other countries. The most productive institution was Memorial Sloan Kettering Cancer Center. *Journal of Magnetic Resonance Imaging* and *Radiology* were the most productive and highest impact factor (IF) journals in the field, respectively. Timeline views showed that “#1 multiparametric magnetic resonance imaging”, “#4 pi-rads”, and “#8 psma” were currently the latest research hotspots. Keywords burst analysis showed that “machine learning”, “psa density”, “multi parametric mri”, “deep learning”, and “artificial intelligence” were the most frequently used keywords in the past 3 years.

Conclusions: MRI has a wide range of applications in PCa. The USA is the leading country in this field, with a concentration of highly productive and high-level institutions. Meanwhile, it can be projected that “deep learning”, “radiomics”, and “artificial intelligence” will be research hotspots in the future.

Keywords: Prostate cancer (PCa); magnetic resonance imaging (MRI); bibliometric; CiteSpace

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Introduction

According to the International Agency for Research on Cancer (IARC) Global Cancer Statistics 2020, prostate cancer (PCa) is the most common tumor of the male genitourinary system. It is the 2nd most frequently diagnosed cancer and the 5th most common cause of cancer death among men worldwide (1). PCa is characterized by insidious onset and asymptomatic or minor symptoms in the early stage, causing delayed diagnosis and loss of optimal treatment window (2). Thus, it is extremely important to accurately identify PCa and benign prostatic hyperplasia with early diagnosis. Furthermore, accurate staging of PCa to guide the choice of treatment modality and prevent undertreatment and overtreatment is of great significance in improving the quality of life of patients and extending their survival time (3).

Imaging is considered indispensable in the clinical management of PCa, and the improved soft tissue contrast of magnetic resonance imaging (MRI) compared with ultrasonography and computed tomography shows unique advantages (4). At present, MRI has played an increasingly important role in the diagnosis and management of PCa (5). MRI is highly sensitive in detecting PCa and can accurately localize lesions (6). The introduction of the Prostate Imaging-Reporting and Data System (PI-RADS) guidelines has improved PCa detection and the accuracy of its imaging staging (7). Meanwhile, the therapeutic ratio could be significantly improved by incorporating MRI into prostate brachytherapy due to its ability to differentiate benign and malignant PCa (8). Machine learning (ML) methods based on MRI scans are used for the diagnosis and discrimination of benign and malignant lesions, and most studies have achieved good results (9,10). Furthermore, it has been reported that MRI can be used to predict the recovery situation and biochemical recurrence (11,12).

Bibliometric analysis is an approach that is used to evaluate published scientific articles in a research field. It uses bibliometric tools to quantitatively analyze and visualize the literature data and measure characteristics, to understand the characteristics, trends, and information utilization of scientific articles (13,14). Meanwhile, by using this method, we can also compare the research status of various countries, institutions, authors, or journals to better understand the different areas of research (15). Therefore, the present study sought to summarize the application and development of MRI in PCa by analyzing relevant studies from 1984 to 2022, through a bibliometric approach. We hope to construct a knowledge framework to present

current research hotspots and emerging trends in the field, which can help new researchers to better choose their future research directions.

Methods

Data collection

The Science Citation Index Expanded (SCIE) of the Web of Science Core Collection (WoSCC) database was chosen as the data source. It is the most frequently used and acceptable database for researchers in a variety of fields (16).

All the literature about MRI in PCa published in WoSCC between January 1, 1984, and June 30, 2022 was retrieved on November 6, 2022. The following keywords were used in the search: “prostate cancer” and “magnetic resonance imaging”. Detailed search terms are provided in [Appendix 1](#). The language was limited to English, and the document types were limited to original articles and reviews. Irrelevant documents were excluded. Raw data were downloaded from WoSCC in full-record, plaintext format. The literature feature clustering included titles, keywords, abstracts, authors, and institutions (17). In this study, the exclusion of the articles was based on the WoSCC. The process of inclusion and exclusion is shown in [Figure 1](#). The detailed record of the exclusion process is provided in [Appendix 2](#). Finally, 10,230 articles were included in the present study.

Data analysis and visualization

Microsoft Excel 2016 (Microsoft, Redmond, WA, USA) and the Bibliometrix Biblioshiny R-package software (<https://bibliometrix.org/biblioshiny/biblioshiny1.html>) were used to export statistical charts and tables of top-cited or productive authors, countries, journals, and institutions, and display the trend of the number of articles published by year (18). CiteSpace (version 6.1.R3; Chaomei Chen, Drexel University, Philadelphia, PA, USA) was used to perform a co-occurrence analysis and visualize the collaboration networks of the authors, institutions, countries, references, and keywords, as well as author co-citation analysis (ACA) and reference co-citation analysis (RCA).

ACA was used to establish the closeness of scholarly relationships among core authors to identify and analyze the scientific community within the disciplinary presentation area. RCA was performed to provide an informative snapshot of the network of articles and the professional domain that numerous co-cited articles converge in (19).

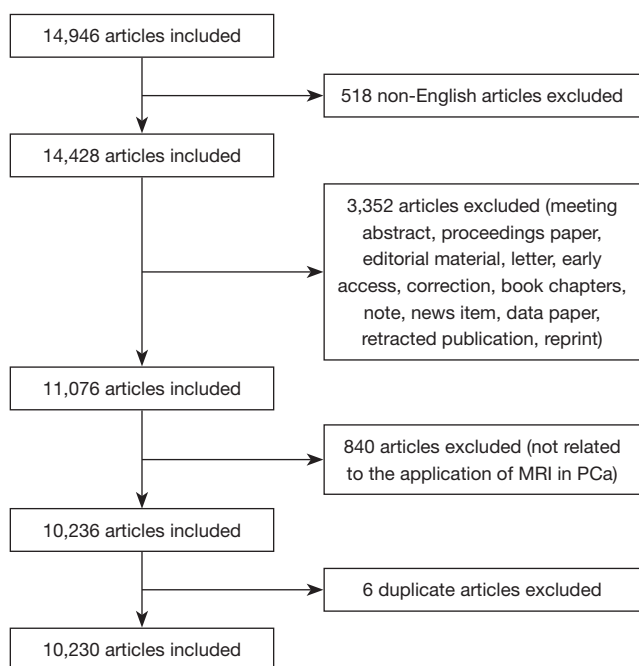


Figure 1 Flowchart of study selection based on the inclusion and exclusion criteria. MRI, magnetic resonance imaging; PCa, prostate cancer.

The modularity value (Q value) and the mean silhouette value (S value) were also used to evaluate the results of clustering and the rationality of clustering, respectively. The Q value is the clustering module value, and $Q > 0.3$ means that the clustering result is significant. The S value is the average contour value of clustering, and $S > 0.5$ means that the clustering is reasonable (20).

The duplication time and annual growth rate can be used as indicators of scientific literature productivity. Duplication time refers to the amount of time it takes for the output of a subject to double. The annual growth rate refers to the percentage increase compared to the previous year. The equation to calculate the doubling time (D) is expressed by the following equation:

$$D = \frac{\ln(2)}{b} \tag{1}$$

where b is the constant that relates the growth rate with the already acquired size of the discipline. The annual growth rate can be calculated using the following equation:

$$R = 100(e^b - 1) \tag{2}$$

Lotka’s law, also known as the inverse square law of

scientific productivity, can be used to express the frequency distribution of scientific productivity in terms of the number of published articles and is widely used to assess the productivity of authors (21). It suggests that there are more authors who publish fewer papers than those who publish many papers. In mathematics, it is expressed mathematically using the following equation:

$$A(n) = \frac{A(1)}{n^2} \tag{3}$$

According to Lotka’s index, authors are classified into three levels of productivity: small producers (those who publish 1 article); medium-sized producers (those who publish 2–9 articles); and large-scale producers (those who publish 10 or more articles).

Results

Trend of global publications

A total of 10,230 articles were included in subsequent analyses. The number of articles published each year and the cumulative number of articles published are shown in *Figure 2*, which shows a consistent overall upward trend in the number of annual publications from 1984 to 2022; the fastest annual growth was in 2017, with an increase of 123 articles. To calculate D, the statistical graph is adjusted to fit an exponential curve, which follows the following equation: with a correlation coefficient of 0.9315. This production corresponds to 38 years and a D of 3.13 years.

Analysis of authors and co-cited authors

A total of 34,233 authors were included in this study, of which 3,256 authors had no less than 5 articles. *Table 1* displays the stratification of authors based on their productivity index grouping. The largest group is composed of authors who have published 1 paper, with a high index of transience (occasional authors) of 69.51. Meanwhile, large producers who have published more than 10 papers make up the smallest part of the group, comprising only 3.45%. *Table 2* summarizes the 20 most productive authors and the top 20 co-cited authors with the highest citations. Most of these authors were from the USA. Among them, Turkbey, Emberton, and Choyke were the top 3 productive authors, with 239, 182, and 181 articles, respectively. *Figure 3A* shows the co-authorship among these representative authors. Co-authorship analysis is an important form to reflect the degree of communication among authors in a

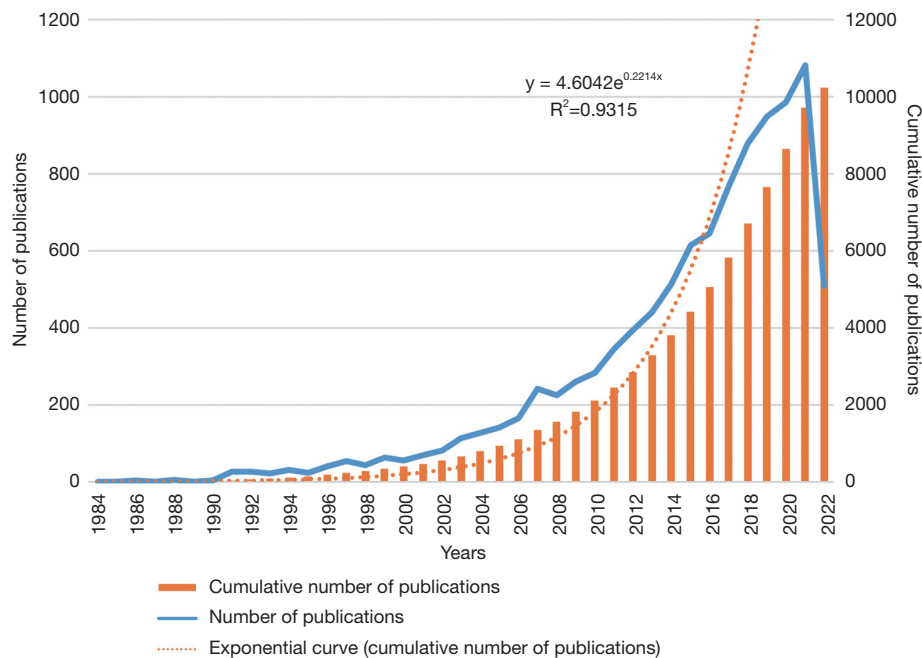


Figure 2 Number of articles published annually from 1984 to 2022. (A total of 509 articles were collected in 2022, up to June 30, 2022).

Table 1 Author dispersion according to productivity level

	No. of authors	%
PI \geq 1 (10 or more articles)	1,183	3.45
0 < PI <1 (2–9 articles)	10,488	30.64
PI =0 (1 article)	22,562	65.91
Total	34,233	100

PI, participation index.

given field (22).

A total of 23,086 citations were recorded in this study. Barentsz, Choyke, and Turkbey were the top 3 most cited authors, with 10,318, 8,626, and 8,522 citations, respectively. ACA uses authors as the units of analysis and the co-citations of pairs of authors as the variable that indicates their “distances” from each other (23). The co-citation relationship of the authors in this study is shown in *Figure 3B*.

Analysis of countries and institutions

A total of 64 countries published related articles in this field. *Table 3* shows the top 20 countries and the number of published articles under the classification of

corresponding authors. The USA ranked first with 3,362 articles, accounting for 32.84% of the total number of articles published, followed by China (830, 8.11%), Germany (754, 7.37%), and the UK (737, 7.20%). Multiple country publication (MCP) indicates the number of co-authored papers with authors from other countries, and single country publication (SCP) indicates the number of co-authored papers by authors of the same nationality. Both of MCP and SCP were used to evaluate the degree of international cooperation (24). In addition, 6,144 institutions published articles in this field; *Table 4* and *Figure 4* summarize the top 20 institutions and their partnerships. Memorial Sloan Kettering Cancer Center published the most with 791 articles, accounting for 2.03%, followed by the University of California San Francisco (599, 1.53%), University of Toronto (498, 1.28%), and University of California Los Angeles (451, 1.16%).

Analysis of journals

A total of 795 journals published related articles in this field, of which 264 journals had no less than 5 articles. The top 20 most prolific journals are listed in *Table 5*. Of the top 10 journals, 5 were from the United States (USA), 2 from the UK, 2 from the Netherlands, and 1 from Germany. *Journal of Magnetic Resonance Imaging* [impact factor (IF)

Table 2 Top 20 most published authors and co-cited authors

Rank	Author			Co-cited author		
	Name	Count	Country	Name	Count	Country
1	Turkbey	239	USA	Barentsz	10,318	Netherlands
2	Emberton	182	UK	Choyke	8,626	USA
3	Choyke	181	USA	Turkbey	8,522	USA
4	Pinto	167	USA	Hricak	7,514	USA
5	Hricak	153	USA	Emberton	6,697	UK
6	Kurhanewicz	148	USA	Futterer	6,300	Netherlands
7	Ahmed	142	UK	Pinto	6,121	USA
8	Barentsz	137	Netherlands	Kurhanewicz	5,630	USA
9	Wood	128	USA	Wood	4,994	USA
10	Rosenkrantz	123	USA	Taneja	4,806	USA
11	Futterer	102	Netherlands	Rosenkrantz	4,532	USA
12	Taneja	100	USA	Ahmed	4,463	UK
13	Moore	99	UK	Merino	4,264	USA
14	Freeman	92	UK	Villers	4,223	France
15	Merino	89	USA	Haider	4,188	USA
16	Punwani	88	USA	Rouviere	4,135	France
17	Haider	87	USA	Verma	3,907	Canada
18	Oto	87	USA	Freeman	3,553	UK
19	Schlemmer	86	Germany	Witjes	3,491	Netherlands
20	Vigneron	81	USA	Vigneron	3,394	USA

2021: 5.119] published the most (333 publications, 3.26%), followed by the *Journal of Urology* (IF 2021: 7.641, 308 publications, 3.01%), *Radiology* (IF 2021: 29.146, 260 publications, 2.54%), and *American Journal of Roentgenology* (IF 2021: 6.582, 256 publications, 2.51%). H-index is a mixed index that is used as a significant indicator of appraising both the number and level of academic output of a scientific researcher, country, journal, or institution (25). The journal with the highest IF was *Radiology*.

Analysis of reference citations and co-citations

Table 6 lists the top 10 articles with the highest citation. Barentsz (26) had the highest total citation frequency with 1,283 citations, followed closely by Weinreb (27) with 1,277 citations.

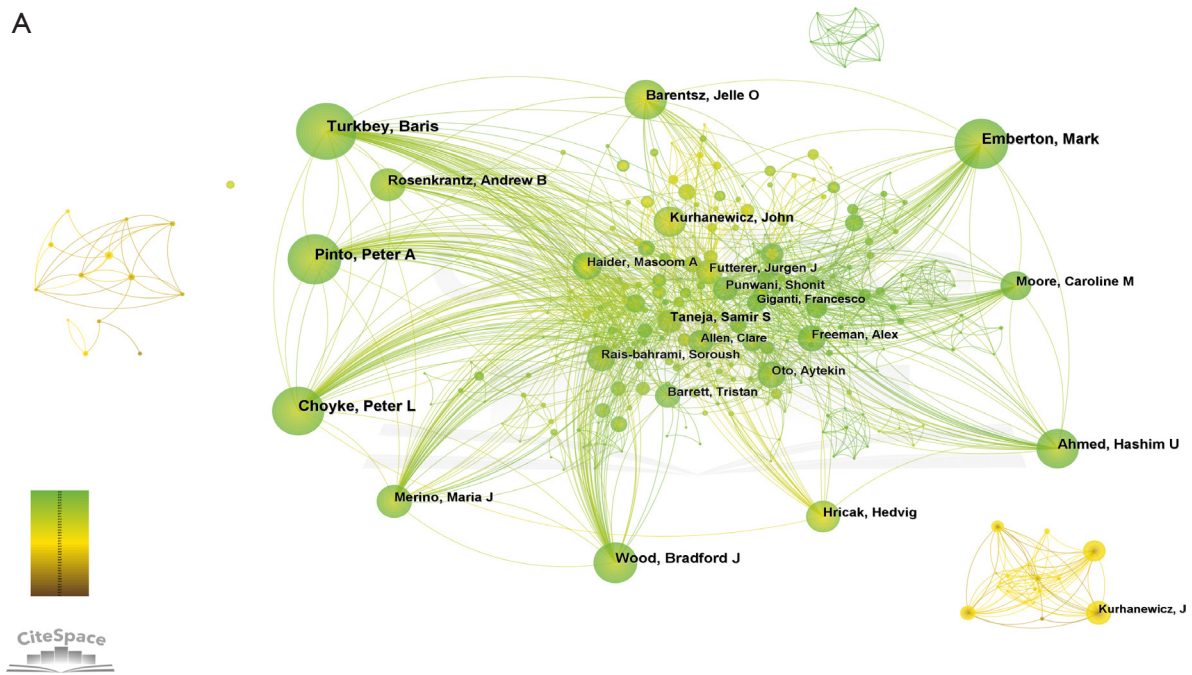
RCA uses reference as the element of analysis to reflect

the relationship between the reference by analyzing patterns and trends in co-citation (19). Figure 5A visually represents the 11 main clusters of reference co-citation. From the analysis results, the Q value was 0.7647, and the S value was 0.9253, suggesting that the clustering effect and network homogeneity were reliable. Figure 5B shows the timeline view of the co-citation references, which reflects the evolution of research hotspots through time. “#6 radical retropubic prostatectomy” and “#5 prostate neoplasms” were the earliest research in this field. “#1 multiparametric magnetic resonance imaging”, “#8 psma”, “#10 radiomics”, “#4 pi-rads”, and “#active surveillance” are currently the latest research hotspots.

Analysis of keyword burst

Keyword burst analysis can display the changing trend of

A



B

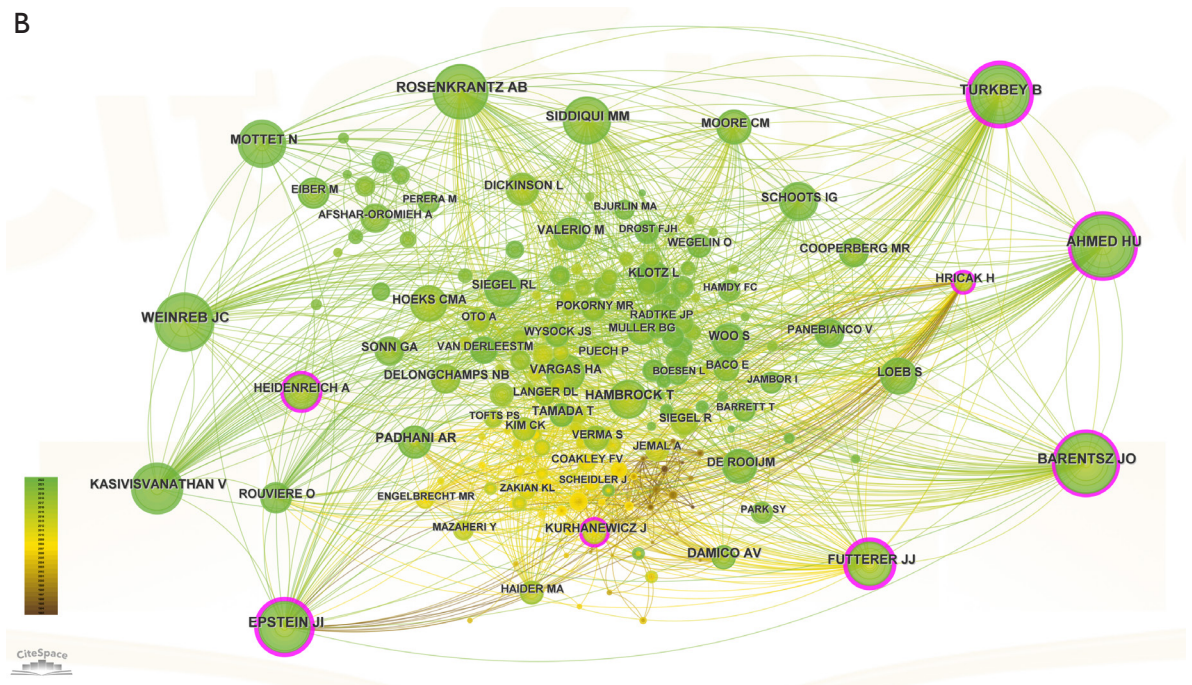


Figure 3 The visualization map of active authors and their co-authorship* (A) and author co-citation networks** (B). *, links between authors represent their co-authorship, and the size of the circles represents the counts of author articles; **, the size of the circles represents the co-citation number of authors. Links between nodes reflect the co-citation of authors, and the thickness of the links represent the intensity of the co-citation. The color of circles and the links between them reflect the occurrence time. The brighter they are, the more recently they occurred.

Table 3 Top 20 productive countries

Rank	Country	Count	Percentage	SCP	MCP
1	USA	3,362	32.84	2,669	693
2	China	830	8.11	701	129
3	Germany	754	7.37	562	192
4	UK	737	7.20	500	237
5	Italy	560	5.47	416	144
6	Netherlands	535	5.23	365	170
7	Canada	486	4.75	349	137
8	Japan	427	4.17	395	32
9	France	371	3.62	277	94
10	Korea	316	3.09	289	27
11	Australia	245	2.39	163	82
12	Switzerland	166	1.62	101	65
13	Belgium	131	1.28	81	50
14	Turkey	113	1.10	106	7
15	Denmark	111	1.08	77	34
16	Spain	108	1.06	76	32
17	Sweden	99	0.97	70	29
18	Austria	94	0.92	39	55
19	Norway	94	0.92	58	36
20	India	89	0.87	75	14

SCP: the number of co-authored papers by authors of the same nationality; MCP: the number of co-authored papers with authors from other countries. SCP, single country publication; MCP, multiple country publication.

research topics over time, which may help scholars grasp the development of research hotspots (28). A total of 338 keywords were detected in the analysis of keywords burst. The top 50 keywords are presented in *Figure 6*, sorted by the initial year of the burst. Among them, “magnetic resonance spectroscopic” had the highest burst intensity, with a burst strength of 114.97. Meanwhile, “machine learning”, “psa density”, “multi parametric mri”, “deep learning”, and “artificial intelligence” appeared frequently in the past 3 years, with burst strengths of 27.01, 14.72, 47.25, 38.14, and 19.49, respectively.

Discussion

The current study analyzed the use of MRI in PCa through bibliometrics and found an overall increasing trend in the number of articles published before June 2022, with

a period of pronounced rapid growth after 2003. This rapid growth may be attributed to the emergence and development of multiple MRI-based technologies [such as intravoxel incoherent motion, diffusion kurtosis imaging, dynamic contrast-enhanced (DCE) MRI, etc.] over the past 2 decades. With the advent of the internet age, the increasing number of publications such as journals has led to a corresponding increase in related literature. It can be expected that the number of publications in this field will continue to increase yearly and remain at a high level over the next few years. Future research should also focus on the application of new technologies such as artificial intelligence (AI) and deep learning (DL) combined with MRI in PCa.

From 1984 to 2022, all the top 10 authors in terms of the number of publications published more than 100 articles, of which 8 appear in the list of the top 10 most cited authors. This indicates that articles published by high-producing

Table 4 Top 20 productive institutions

Rank	Institution	Countries/regions	Articles	Percentage
1	Memorial Sloan Kettering Cancer Center	USA	791	2.03
2	University of California San Francisco	USA	599	1.53
3	University of Toronto	Canada	498	1.28
4	University of California, Los Angeles	USA	451	1.16
5	Radboud University Nijmegen	Netherlands	420	1.08
6	The University of Texas MD Anderson Cancer Center	USA	331	0.85
7	The Johns Hopkins University	USA	317	0.81
8	German Cancer Research Center	Germany	302	0.77
9	Harvard University	USA	275	0.70
10	University of Michigan	USA	267	0.68
11	Stanford University	USA	262	0.67
12	The Institute of Cancer Research	UK	243	0.62
13	The University of Chicago	USA	235	0.60
14	University College London Hospitals NHS Foundation Trust	UK	226	0.58
15	Case Western Reserve University	USA	219	0.56
16	Duke University	USA	211	0.54
17	Seoul National University	Korea	210	0.54
18	University of Cambridge	UK	208	0.53
19	Universitair Medisch Centrum Utrecht	Netherlands	200	0.51
20	Division of Surgery & Interventional Science	UK	198	0.51

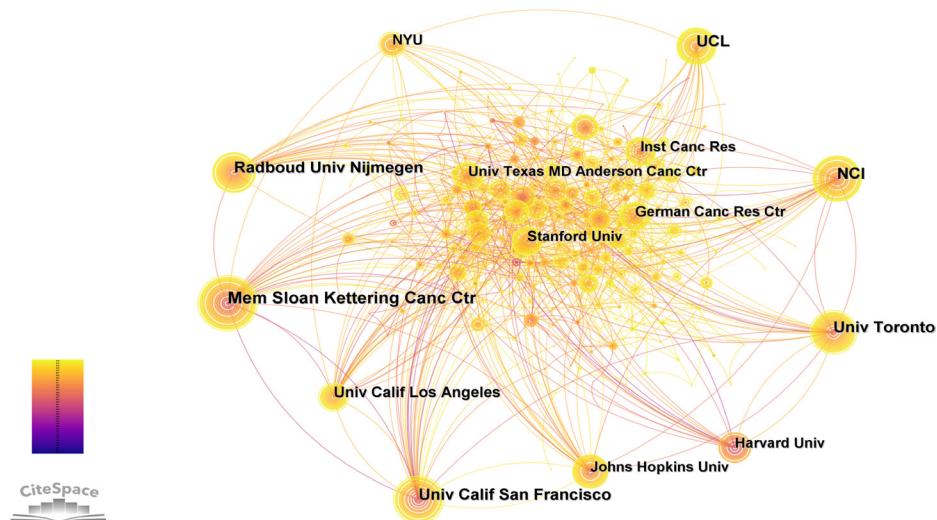


Figure 4 Visualization map of institutional cooperation. The size of the node represents the publication counts of an institution, and the lines between nodes represent the strength of collaborations. The color of circles and the links between them reflect the occurrence time. The brighter they are, the more recently they occurred.

Table 5 Top 20 journals according to the number of articles published

Journal	Country	Number	Percentage	IF 2021	H-index
<i>Journal of Magnetic Resonance Imaging</i>	USA	333	3.26	5.119	60
<i>Journal of Urology</i>	Netherlands	308	3.01	7.641	74
<i>Radiology</i>	USA	260	2.54	29.146	100
<i>American Journal of Roentgenology</i>	USA	256	2.51	6.582	55
<i>European Radiology</i>	Germany	253	2.48	7.034	56
<i>International Journal of Radiation Oncology Biology Physics</i>	Netherlands	252	2.47	8.013	63
<i>BJU International</i>	UK	248	2.43	5.969	55
<i>Medical Physics</i>	UK	199	1.95	4.506	40
<i>Urology</i>	USA	199	1.95	2.633	36
<i>Magnetic Resonance in Medicine</i>	USA	189	1.85	3.737	44
<i>World Journal of Urology</i>	USA	183	1.79	3.661	28
<i>European Urology</i>	Netherlands	182	1.78	24.344	92
<i>European Journal of Radiology</i>	Netherlands	171	1.67	4.531	39
<i>Abdominal Radiology</i>	USA	168	1.64	2.886	17
<i>Urologic Oncology-Seminars and Original Investigations</i>	Netherlands	166	1.62	2.954	23
<i>Radiotherapy and Oncology</i>	Netherlands	142	1.39	6.901	43
<i>British Journal of Radiology</i>	UK	141	1.38	3.629	26
<i>NMR in Biomedicine</i>	USA	138	1.35	4.478	33
<i>Physics in Medicine and Biology</i>	UK	137	1.34	4.174	36
<i>Frontiers in Oncology</i>	Switzerland	130	1.27	5.738	15

IF: an internationally recognized journal evaluation index to evaluate the journals quality; H-index: a composite index can be used as an indicator to evaluate the academic output quantity and level of a journal. IF, impact factor.

authors receive more attention from researchers, which suggests that they may be of higher academic value. A total of 8 of the top 12 authors in terms of the number of publications and citations are from the USA, underscoring the significant influence of the USA in this field. Barentsz's article published in *European Radiology* received the highest number of citations. It argued cogently that multiparametric MRI (mpMRI) should be an integral part of PCa diagnosis and treatment (26).

All the top 10 contributing countries or regions had a high proportion of SCP in the volume of publications, implying that all countries are primarily engaged in domestic co-authorship. Meanwhile, the USA also had the largest MCP, suggesting that it has strong ties with other countries and is their main collaborator in this field. Although China ranked second after the USA, with 830 publications, the MCP was only 129, and even lower than

that of Canada with 486 publications. This indicates that although the number of papers in China is large, there is little collaboration with other countries. Furthermore, 7 of the top 10 institutions were from the USA, which explains why the USA is far more influential than any other country. The disparity between the USA and China may be explained by several factors, including the later start and slow early development in the early stage of MRI in China, few opportunities for communication with the international community, and the language barrier that may impact external collaboration. Therefore, China should actively maintain close cooperative relationships with the international community to increase its influence in this field.

The top 10 journals published 2,497 articles, accounting for 24.43% of the total number of publications. These journals have made a great contribution to the development

Table 6 Top 10 co-cited references

Title	Journals	Authors	Year	Citations
ESUR prostate MR guidelines 2012	<i>European Radiology</i>	Barentsz et al.	2012	1,283
PI-RADS prostate imaging-reporting and data system: 2015, version 2	<i>European Urology</i>	Weinreb et al.	2016	1,277
Diagnostic accuracy of multi-parametric MRI and TRUS biopsy in prostate cancer (PROMIS): a paired validating confirmatory study (PROMIS): a paired validating confirmatory study	<i>Lancet</i>	Ahmed et al.	2017	1,021
MRI-targeted or standard biopsy for prostate-cancer diagnosis	<i>The New England Journal of Medicine</i>	Kasivisvanathan et al.	2018	842
Comparison of MR/ultrasound fusion-guided biopsy with ultrasound-guided biopsy for the diagnosis of prostate cancer	<i>The Journal of the American Medical Association</i>	Siddiqui et al.	2015	712
EAU-ESTRO-SIOG guidelines on prostate cancer. Part 1: screening, diagnosis, and local treatment with curative intent	<i>European Urology</i>	Mottet et al.	2017	519
Prostate Imaging Reporting and Data System version 2.1: 2019 update of Prostate Imaging Reporting and Data System version 2	<i>European Urology</i>	Turkbey et al.	2019	439
The 2014 International Society of Urological Pathology (ISUP) consensus conference on Gleason grading of prostatic carcinoma: definition of grading patterns and proposal for a new grading system	<i>American Journal of Surgical Pathology</i>	Epstein et al.	2016	429
Magnetic resonance imaging for the detection, localization, and characterization of prostate cancer: Recommendations from a European consensus meeting	<i>European Urology</i>	Dickinson et al.	2011	389
Can clinically significant prostate cancer be detected with multiparametric magnetic resonance imaging? A systematic review of the literature	<i>European Urology</i>	Futterer et al.	2015	385

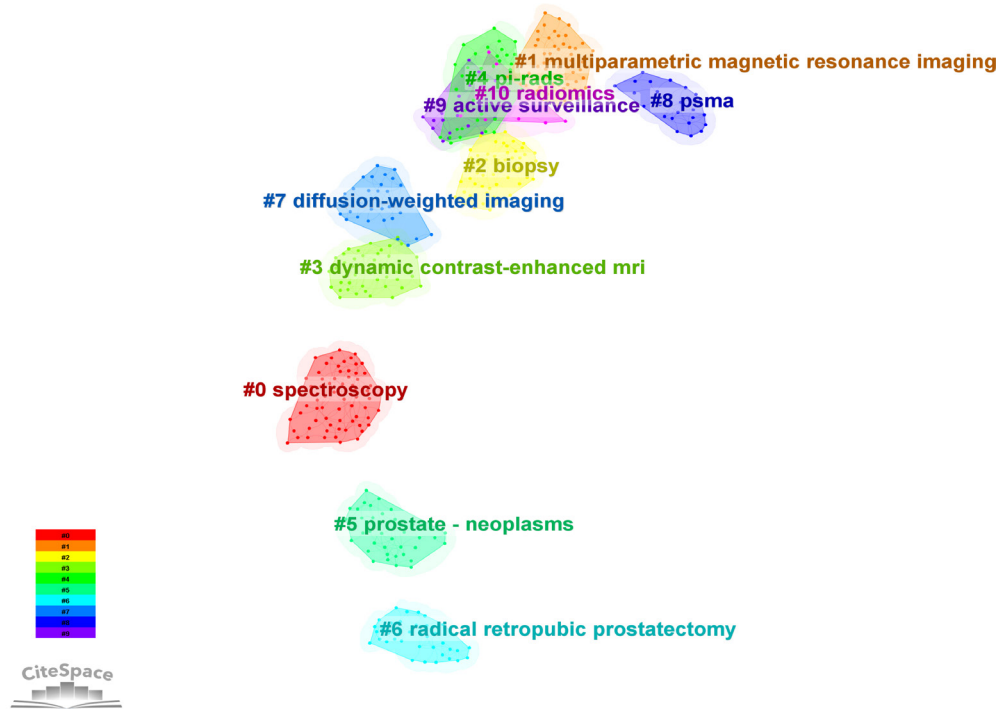
ESUR, European Society of Urogenital Radiology; MR, magnetic resonance.

of the field, indicating that more high-quality articles on the application of MRI in PCa will be published in these journals as a priority in the future. In addition, the *Journal of Magnetic Resonance Imaging*, *Journal of Urology*, and *American Journal of Roentgenology* were extremely prolific journals with great potential to publish high-quality articles to increase the IF in the future.

Co-citation clustering analysis revealed the core issue and developmental process of this field through the cluster analysis chart and the timeline view (29). The earliest studies were focused on “#6 radical retropubic prostatectomy” and “#5 prostate neoplasms”, whereas the current hot topics are “#1 multiparametric magnetic resonance imaging”, “#8 psma”, “#10 radiomics”, “#4 pi-rads”, and “#active surveillance”. In earlier studies, MRI was only used to determine the need for radical retropubic prostatectomy, and thus it was insufficient in achieving accurate preoperative staging of PCa owing to technical limitations (30).

With the development of medical imaging technology, the applications of MRI in PCa have evolved into using rich imaging sequences, dynamic enhancement, and even AI to achieve an accurate evaluation of PCa. MpMRI refers to the combination of multiple MRI sequences required to make a diagnosis, it consists of both anatomic [T1-weighted (T1W) and T2-weighted (T2W) MRI] sequences as well as functional sequences, including diffusion-weighted imaging (DWI) MRI, DCE MRI, and magnetic resonance spectroscopy (MRS) (31-33). Meanwhile, the PI-RADS classification as an imaging assessment based on mpMRI can provide more detailed clinical information, leading to the refinement of the clinical evaluation of PCa (34). It has been continuously updated since its initial release by the European Society of Urogenital Radiology (ESUR) in 2012 (26), and the latest version, PI-RADS v2.1, was released in 2019 (27,35). Prostate-specific membrane antigen (PSMA) is a type II transmembrane glycoprotein

A



B

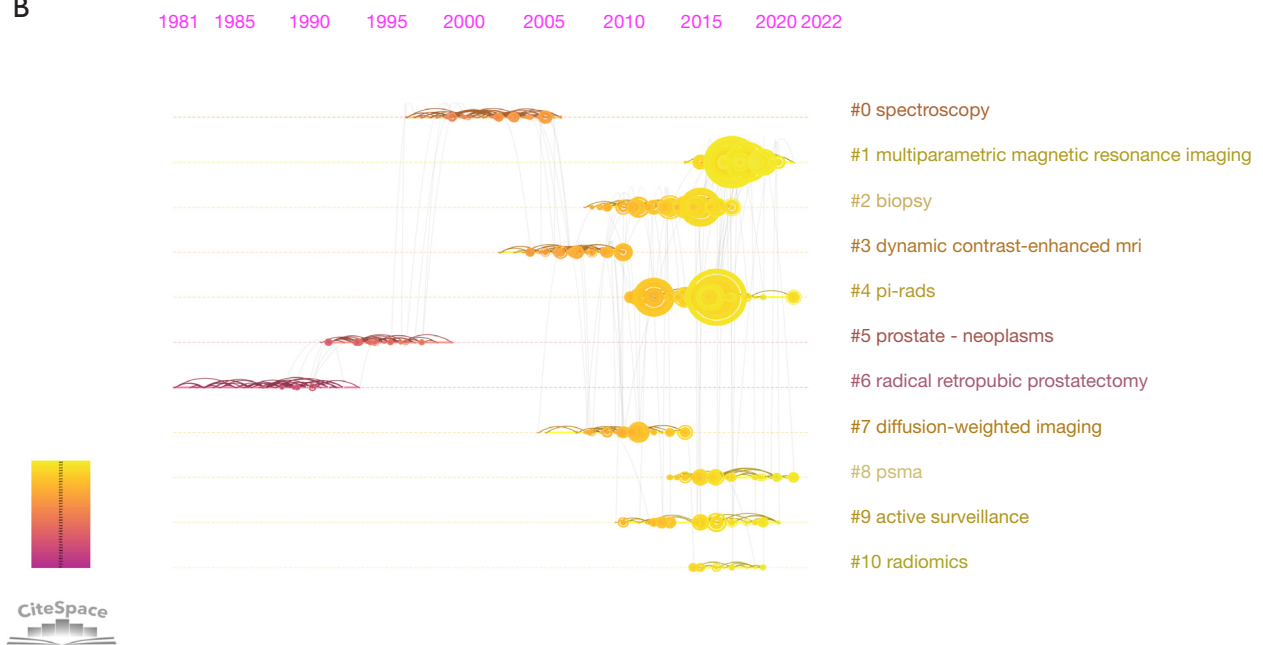


Figure 5 Clustering visualization map of co-cited literature analysis (A) and the timeline graph of co-cited reference clusters (B). The color of circles and the links between them reflect the occurrence time. The brighter they are, the more recently they occurred.

Top 50 keywords with the strongest citation bursts

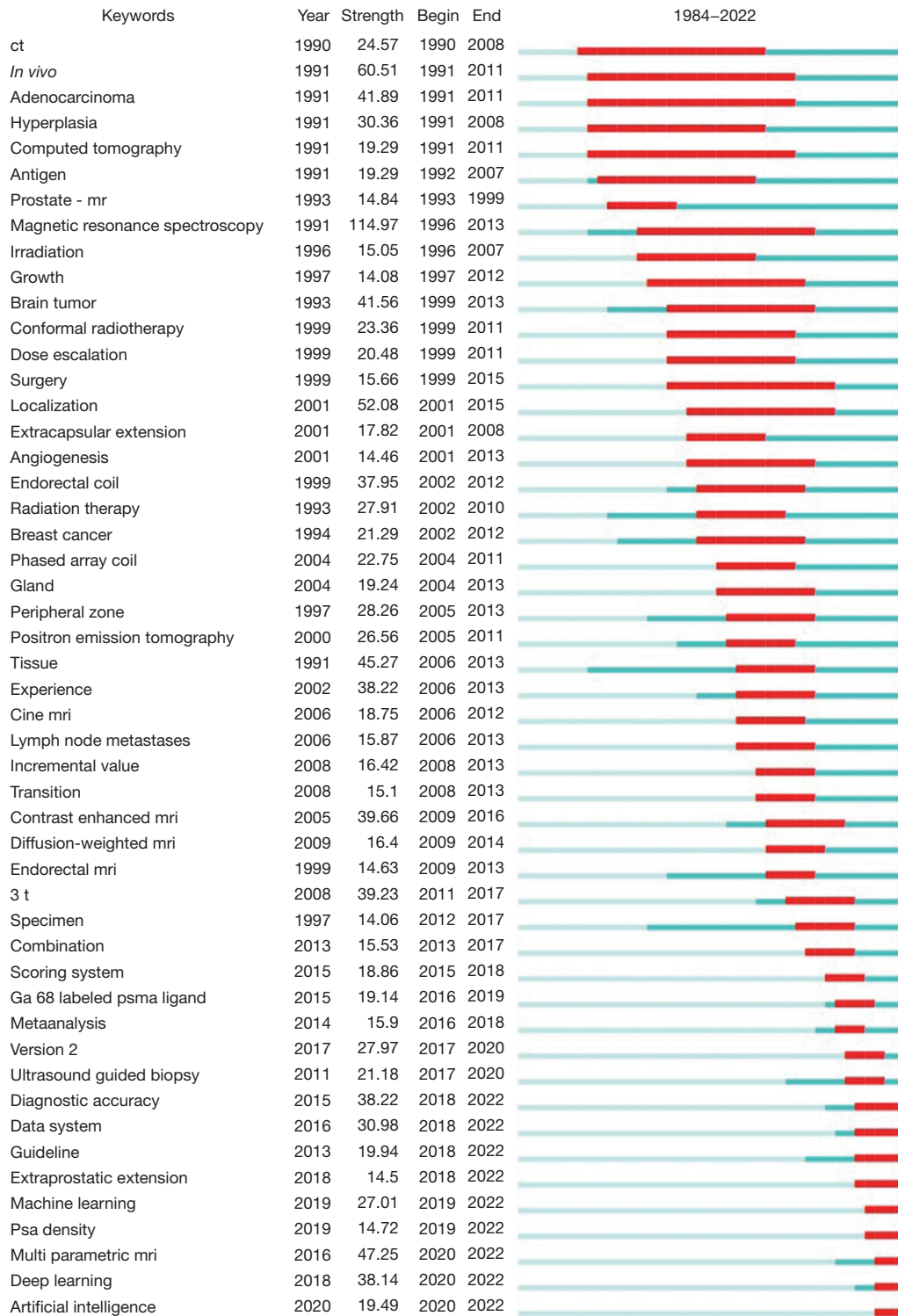


Figure 6 The top 50 keywords with the strongest citation bursts from 1984 to 2022. The blue line represents time period, and the red line represents the time span of the burst.

that is overexpressed on PCa cells, and its expression increases with the tumor grade (36,37). Therefore, PSMA can be used as an excellently targeted probe to combine with MRI molecular contrast agent, advance the capability for early detection of primary and metastatic PCa, and track disease progression and treatment, thereby facilitating image-guided interventional therapy (38,39). A study pointed out that the introduction of imaging agents targeting PSMA has shown high diagnostic accuracy for primary staging and restaging during biochemical recurrence compared with conventional imaging (40). This has received little attention so far. Radiomics is a technique for extracting quantitative features from medical images, providing numerous imaging biomarkers for tumor detection, diagnosis, aggressiveness determination, staging, and prognosis, including for PCa (41,42). Ma *et al.* confirmed that radiomics combined with the ML classifier model has strong classification performance in identifying benign and PCa lesions in the PI-RADS 4/5 score (43). Furthermore, Zhang *et al.* showed that nomograms constructed based on radiomics features combined with total prostate-specific antigen (tPSA) levels improved the diagnostic accuracy of clinically significant PCa and reduced unnecessary biopsies (44). It also plays an important role in the treatment and prediction of prognosis in PCa. Shiradkar *et al.* presented a radiomics-assisted targeted treatment radiotherapy planning method to accurately localize malignant lesions to increase the biological effect of the tumor region while achieving a reduction in dosage to noncancerous tissue (45). Radiomics features predicted the risk of metastatic progression in high-risk PCa (clinical stage \geq T2c, biopsy Gleason score \geq 8, or PSA level $>$ 20 ng/mL), and classified high-risk patients into favorable and unfavorable prognostic groups (46). A recent study also found that the majority of low-risk (clinical stage \leq T2a, biopsy Gleason score \leq 6, and PSA level \leq 10 ng/mL) were not at risk of death for PCa in a 10-year time frame (47). For these patients, active surveillance (AS) may be a better option than surgery (48). The two main roles of mpMRI in AS are to improve the selection of eligible patients at diagnosis and evaluate significant changes over serial scans that would indicate radiologic progression (49).

Keyword burst analysis can reflect the main research hotspots and the trend of research hotspots in a specific period (50). After 2018, the keywords gradually evolved to use new technology combined with MRI, and “machine learning”, “psa density”, “multi parametric mri”, “deep learning”, and “artificial intelligence” were the keywords

with the highest burst strength. AI is a discipline that focuses on using a computer to simulate human intelligent behavior. Applications of medical-image diagnostic systems have expanded the frontiers of AI into the area of medical practice (51). AI has a wide range of applications in the diagnosis, staging, treatment, and prognosis of PCa. The main methods of AI include ML and DL. The ML technique is a representative method for exploring the risk factors or high-risk groups of disease by analyzing medical big data (52). It often combines with radiomics, and plays an important role in the accurate diagnosis and treatment of PCa by building various models (53-55). DL is an important branch of AI that uses networks of simple interconnected units to extract patterns from data to solve complex problems (56). Some researchers use DL methods to achieve highly accelerated MRI processes of the prostate and improved image quality through image reconstruction (57-59). Accurate detection and localization of PCa in men undergoing prostate MRI is the most extensive application of DL (60). DL models based on convolutional neural networks can be used to achieve the semi-automatic classification of PCa on mpMRI (61). Some studies are focused on methods using DL to achieve fully automatic segmentation of prostate lesions and gland through various algorithms (62,63). “PSA density” is a keyword with high emergence intensity. PSA density (relating the serum PSA to the volume of the prostate) is a better indicator than PSA for predicting PCa in patients with a PSA below 10 ng/mL (64,65). A combination of the PI-RADS v2 score and PSA density is considered an important management tool for low-risk PCa (66).

Nonetheless, this study has some limitations. First, all publications included in this study were downloaded from WoSCC; therefore, they may not represent the complete research field of MRI in PCa. Second, our study only included English literature, which may have led to language bias and the consequent omission of high-quality literature from other languages. Finally, it takes time for articles to reach a certain number of citations after publication, which may mean that high-quality articles published in recent years have not yet reached the level of citations commensurate with their quality and may have led to research bias.

Conclusions

In summary, MRI has a wide range of applications in the study of PCa, especially in adjuvant diagnosis and tumor

staging. A large number of scholars have devoted their efforts to research related to the MRI of PCa. The USA remains the leader in this field with a large number of core authors and high-level institutions and will continue to lead in the future. Currently, the main research hotspot in this field is to provide an important reference for accurate diagnosis and treatment of PCa through DL, radiomics, and AI.

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Footnote

Conflicts of Interest: All authors have completed the ICMJE uniform disclosure form (available at <https://qims.amegroups.com/article/view/10.21037/qims-23-446/coif>). The authors have no conflicts of interest to declare.

Ethical Statement: The authors are accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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