Artificial intelligence and machine learning trends in kidney care

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ABSTRACT

Background: The integration of artificial intelligence (AI) and machine learning (ML) in kidney care has seen a significant rise in recent years. This study specifically analyzed AI and ML research publications related to kidney care to identify leading authors, institutions, and countries in this area. It aimed to examine publication trends and patterns, and to explore the impact of collaborative efforts on citation metrics.

Methods: The study used the Science Citation Index Expanded (SCI-EXPANDED) of Clarivate Analytics Web of Science Core Collection to search for AI and machine learning publications related to nephrology from 1992 to 2021. The authors used quotation marks and Boolean operator "or" to search for keywords in the title, abstract, author keywords, and *Keywords Plus*. In addition, the 'front page' filter was applied. A total of 5425 documents were identified and analyzed.

Results: The results showed that articles represent 75% of the analyzed documents, with an average author to publications ratio of 7.4 and an average number of citations per publication in 2021 of 18. English articles had a higher citation rate than non-English articles. The USA dominated in all publication indicators, followed by China. Notably, the research also showed that collaborative efforts tend to result in higher citation rates. A significant portion of the publications were found in urology journals, emphasizing the broader scope of kidney care beyond traditional nephrology.

Conclusions: The findings underscore the importance of AI and ML in enhancing kidney care, offering a roadmap for future research and implementation in this expanding field.

Keywords: Bibliometric; SCI-EXPANDED; Artificial intelligence; Machine learning; Nephrology; Kidney care; Publication trends; Citation analysis. **[Am J Med Sci 2024;367(5):281–295.]**

INTRODUCTION

Kidney care encompasses the study and management of kidney health, including the diagnosis, treatment, and management of kidney diseases and related conditions.[1] This field, which includes nephrology as a key component, has increasingly incorporated artificial intelligence (AI) and machine learning (ML) to enhance patient care.[2-5] The application of AI and ML in kidney care, particularly in areas such as nephrology,[6-11] has shown significant promise in improving diagnosis, prognosis, and overall management of various kidney condition.

Chronic kidney disease (CKD) is a significant health problem worldwide, affecting approximately 10% of the global population, according to the World Health Organization (WHO). CKD can progress to end-stage kidney disease (ESKD), a condition in which the kidneys fail to function adequately, leading to the need for dialysis or kidney transplantation.[12-17] The incidence and prevalence of CKD and ESKD are expected to rise significantly in the coming years due to aging populations, increased rates of diabetes, hypertension, and obesity.[13,17-21] The integration of AI and ML in nephrology has the potential to aid in the early detection and prevention of kidney diseases.[7] It can predict the risk of developing CKD and identify patients at risk of ESKD, leading to timely intervention and management.[7,22-25] AI and ML can also help personalize treatments for individual patients by identifying optimal therapeutic interventions based on their characteristics. For example, AI algorithms can analyze patient data such as medical history, laboratory tests, and imaging studies to predict the response to a particular treatment or medication, reducing the risk of adverse events and improving patient outcomes.[7,22-25] Additionally, AI and ML can help optimize resource allocation and reduce healthcare costs by reducing the number of unnecessary tests, procedures, and hospitalizations.[7,22-25]

Given the dispersed nature of knowledge regarding the use of AI and ML in kidney care, this study was undertaken to provide a comprehensive analysis of AI and ML research publications in this broad field. Our aim was to identify key contributors (authors, institutions, countries) in this area, explore publication trends and patterns, and examine the impact of collaborative efforts on citation metrics. Additionally, the study investigates the citation histories of the top 10 most frequently cited articles in kidney care, offering insights into influential research and its impact on the field.

METHODS

The data used in this study were retrieved from the Clarivate Analytics Web of Science Core Collection, specifically the online version of the Science Citation Index Expanded (SCI-EXPANDED), with data updated on 11 April 2023. To conduct a comprehensive search for relevant articles in the field of nephrology and AI/machine learning, Chiu and Ho (2021)[26] suggested searching for documents published in 2022 from SCI-EXPANDED after IF_{2022} was presented by the Journal Citation Reports (JCR). The search was conducted using quotation marks (" ") and Boolean operator "or" to ensure the appearance of at least one search keyword in the terms of TOPIC (title, abstract, author keywords, and *Keywords Plus*) from 1992 to 2021. The search keywords used including nephrology search terms: "kidney", "nephrology", "renal", "nephropathy", "kidneys", "nephropathies", "nephropathia", and "nephrotic" as well as search terms in AI/Machine learning: "artificial intelligence", "artificial intelligences", "machine learning", "machine learnings", "deep learning", "deep learnings", "neural networks", "neural network", "natural language processing", "natural language processings", "computer vision", "computer visions", "robotics", "robotic", "expert systems", "expert system", "decision trees", "decision tree", "reinforcement learning", "reinforcement learnings", "unsupervised learning", "unsupervised learnings", "supervised learning", "supervised learnings", "data mining", "data minings", "big data", "big datas", "predictive analytics", "predictive analytic", "pattern recognition", "pattern recognitions", "cognitive computing", "intelligent agents", "intelligent agent", "autonomous systems", "autonomous system", "fuzzy logic", "fuzzy logics", "genetic algorithms", "genetic algorithm", "swarm intelligence", "swarm intelligences", "knowledge representation and reasoning", "knowledge representation and reasonings", "Bayesian networks", "Bayesian network", "support vector machines", "support vector machine", "random forests", "random forest", "ensemble learning", and "ensemble learnings". A total of 6266 documents were identified from the SCI-EXPANDED search. To address potential concerns regarding the duplication of research contributions, our study strictly included only the document type of 'articles' in our analysis. This approach was adopted to prevent any duplication from the inclusion of both an abstract and its subsequent full publication. Rigorous filters were employed in our data collection process to exclude abstracts, conference papers, and other non-article document types, ensuring our analysis was based solely on peer-reviewed, fully published research articles. The *Keywords Plus* feature of the ISI (now Clarivate Analytics) database provides additional search terms by extracting them from the titles of articles cited in bibliographies and footnotes, significantly enhancing title-word and author-keyword indexing.[27] However, it has been noted that documents retrieved solely by *Keywords Plus* may not be relevant to the search topic.[28] To avoid introducing irrelevant publications in bibliometric analyses, Ho and colleagues proposed using the 'front page' filter, which includes the article title, abstract, and author keywords.[29,30] This filter has been shown to produce significant differences in bibliometric research topics published in medical-related journals in SCI-EXPANDED, such as *BioMed Research International,*[31] *Cleft Palate-Craniofacial Journal*,[32] *Indian Journal of Surgery*,[33] *Journal of Foot and Ankle Surgery*, [34] and *World Neurosurgery*.[35]

The full record in SCI-EXPANDED and the number of citations in each year for each document were checked and downloaded into Excel Microsoft 365, and additional coding was manually performed.[36,37] The functions in the Excel Microsoft 365, for example, Counta, Concatenate, Filter, Match, Vlookup, Proper, Rank, Replace, Freeze Panes, Sort, Sum, and Len were applied.[36] A total of 474 documents did not contain the search keywords about nephrology search terms in their 'front page', for example, the highly cited review entitled "Cirrhosis-associated immune dysfunction: Distinctive features and clinical relevance"[38] and 417 documents did not contain the search keywords search terms about AI/Machine learning in their 'front page', for example, the highly cited review entitled "Positive surgical margins after nephron-sparing surgery".[39] Out of 6266 analyzed documents, 5425 (87%) included search keywords on their 'front page.' However, 50 documents, including the highly-cited review article 'Beta-glucan: An ideal immunostimulant in aquaculture,' lacked these keywords on their 'front page.' As a result, these types of articles were excluded from our study.[40] Finally, a total of 5425 documents (87% of 6266 documents) included search keywords in their 'front page'. It has been pointed out that the SCI-EXPANDED is designed for researchers to find published literatures but not intended for bibliometric studies.[31] Therefore, an appropriate bibliometric treatment is always needed when using the SCI-EXPANDED for bibliometric studies.[31] Four of the 5554 articles published in 2023 and 8 early access had not published yet were not include in this study. Finally, 5425 documents published from 1992 to 2021 were defined as AI/machine learning in kidney care research publications. The journal's impact factors (IF_{2021}) were taken from the Journal Citation Reports (JCR) published in 2021.

In the SCI-EXPANDED database, the corresponding author is labelled as reprint author, but in this study, we used the term corresponding author.[41] Single authors in articles with unspecified authorship were both the first as well as corresponding authors.[42] The single institution in articles with unspecified corresponding institutions was both the first as well as corresponding-author institutions.[42] Similarly, in a single-country article, the country is classified as the first as well as the corresponding-author country.[42] In multi-corresponding author articles, all the corresponding authors, institutions, and countries were considered.[43] Articles with corresponding authors in SCI-EXPANDED, that had only address but not affiliation names were checked out and the addresses were changed to be affiliation names.[43] Affiliations in England, Scotland, North Ireland (Northern Ireland), and Wales were reclassified as being from the United Kingdom (UK).[44]

To assess publication performance, this study utilized various citation indicators. C_{year} represents the number of citations from the Web of Science Core Collection in a given year, such as C_{2021} for the citation count in 2021.[41] TC_{year} is the total number of citations from the Web of Science Core Collection received since publication year until the end of the most recent year (TC_{2021} for this study).[45] CPP_{year} is the average number of citations per publication, calculated by dividing TC_{2021} by the total number of publications (*TP*) ($CPP_{2021} = TC_{2021} / TP$).[46]

To evaluate publication performance of countries and institutions, six publication indicators were utilized:[47] *TP* for total number of articles, *IP* for number of single-country (IP_C) or single-institution articles (IP_I), *CP* for number of internationally collaborative articles (CP_C) or inter-institutionally collaborative articles (CP_I), *FP* for number of first-author articles, *RP* for number of corresponding-author articles, and *SP* for number of single-author articles. In addition, six citation indicators related to the six publication indicators were used to evaluate publication impact,[48] all based on CPP_{2021}.

The *Y*-index was used to evaluate publication performance of individual authors, and is calculated using the formula:[41,49]

Y-*index* (j, h)

Where *j* is a constant related to the publication potential, the sum of the first-author articles and the corresponding-author articles; and *h* is a constant related to the publication characteristics, polar angle about the proportion of *RP* to *FP*. The greater the value of *j*, the more the first- and corresponding-author contributes to the articles.

The value of *h* is determined by the ratio of *RP* to *FP*. An *h* value of $\pi/2$ indicates an author who has only published corresponding-author articles, with *j* equal to the number of corresponding-author articles. An *h* value between $\pi/2$ and $\pi/4$ indicates an author with more corresponding-author articles than first-author articles ($FP > 0$). An *h* value of $\pi/4$ indicates an author with the same number of first- and corresponding-author articles ($FP > 0$ and $RP > 0$). An *h* value between $\pi/4$ and 0 indicates an author with more first-author articles than corresponding-author articles ($RP > 0$). An *h* value of 0 indicates an author who has only published first-author articles, with *j* equal to the number of first-author articles.

RESULTS AND DISCUSSION

Characteristics of document types

Ho and colleagues[50] recently developed a method to identify the characteristics of document types in a research topic using two basic pieces of information: the average number of citations per publication per year ($CPP_{year} = TC_{year}/TP$) and the average number of authors per publication ($APP = AU/TP$). To ensure repeatability, they used TC_{2021} and CPP_{2021} instead of the number of citations from the Web of Science Core Collection directly.[51] After analyzing 5425 documents published in SCI-EXPANDED from 1992 to 2021, we found 12 document types, as shown in Table 1. Of these, 75% were articles with an *APP* of 7.4. Reviews had the greatest CPP_{2021} value of 26, which was 1.5 times higher than that of articles. This value was lower than some medical topics, such as temporomandibular disorders (1.7 times)[43] and Q fever (2.7 times),[52] but higher than topics such as breast reconstruction (0.86 times),[53] fracture nonunion (1.3 times),[54] and insomnia (1.4 times).[55] The most frequently cited document was a review titled "Cellular and molecular mechanisms of fibrosis",[56] which had a TC_{2021} of 2631. This review was the only classic document with a TC_{2021} of 1000 or more[57] in the study of AI/machine learning in kidney care. The abstract mentioned "kidney" and "pattern recognition." A total of 653 meeting abstracts were published in 65 different journals, with the majority (36%) appearing in the *Journal of Urology* (IF_{2021} = 7.641), followed by the *American Journal of Transplantation* (13%) with an IF_{2021} of 9.369, and the *Journal of Endourology* (11%) with an IF_{2021} of 2.619. The *Journal of Urology*, in particular, has published over 2000 meeting abstracts since 2008 for the Annual Meeting of the American-Urological-Association. It is important to note that some documents, such as proceedings papers, book chapters, and data papers, were also categorized as articles in the Web of Science Core Collection. Therefore, the cumulative percentages in Table 1 may exceed 100%.[58] The contribution of various document types differs significantly. Therefore, we selected articles, which typically include introduction, methods, results, discussion, and conclusion, for further analysis.[48] Out of the total 4063 articles, the majority (98%) were in English, followed distantly by French (34 articles), German (22 articles), Spanish (22 articles), Chinese (8 articles), and one each in Italian, Portuguese, Russian, and Turkish. Notably, non-English articles had lower citation rates with a CPP_{2021} of 2.4 and *APP* of 5.6, whereas English articles had higher CPP_{2021} of 18 and *APP* of 7.4.

Table 1. Citations and authors according to the document type.

Document type	TP	%	TP*	AU	APP	TC_{2021}	CPP_{2021}
Article	4,063	75	4060	30,036	7.4	71,177	18
Meeting abstract	653	12	651	4623	7.1	101	0.15
Review	500	9.2	500	2680	5.4	12,790	26
Editorial material	153	2.8	152	548	3.6	548	3.6
Proceedings paper	101	1.9	101	564	5.6	2023	20
Letter	40	0.74	40	158	4.0	79	2.0
Book chapter	13	0.24	13	38	2.9	169	13
Correction	12	0.22	12	69	5.8	6	0.50
News item	3	0.055	3	3	1.0	0	0
Data paper	2	0.037	2	10	5.0	7	3.5
Retracted publication	1	0.018	1	3	3.0	2	2.0
Retraction	1	0.018	1	1	1.0	0	0

TP: number of publications; *TP**: number of publications with author information in the SCI-EXPANDED; *AU*: number of authors; *APP*: average number of authors per publication; TC_{2021}: the total number of citations from Web of Science Core Collection since publication year to the end of 2021; CPP_{2021}: average number of citations per publication (TC_{2021}/TP).

Characteristics of publication outputs

In examining the evolution and impact of AI/machine learning in kidney care, we employed a citation analysis approach, as proposed by Ho (2013).[46] This method correlates the annual number of articles (TP) with their average number of citations (CPP_{year}) to discern trends in research topics. Applied in various medical fields, including dengue,[59] breast reconstruction,[53] fracture nonunion,[54] keloid,[60] Q fever,[52] and temporomandibular disorders.[43] Fig. 1 demonstrates the distribution of the annual number of articles and their CPP_{2021} by year. The annual number of AI/machine learning in kidney care articles slightly increased from six articles in 1992 to 36 articles in 2003. Following that, an increase appeared, especially in the last five years to reach 850 articles in 2021.

The growth in AI/machine learning research within kidney care highlights its potential in enhancing the diagnosis and treatment of kidney disorders. The ability of AI/machine learning to analyze large datasets efficiently is invaluable in kidney care, a field characterized by complex patient data. While the increasing volume of publications indicates growing interest and potential impact, it is crucial to note that citation counts alone do not reflect the intrinsic quality of research. Therefore, alongside citation analysis, additional evaluative methods are necessary to ensure a comprehensive assessment of research quality in this evolving field.

Our analysis found that the average number of citations per publication (TC_{2021}) for AI/machine learning kidney care articles was 18, demonstrating the field's growing impact. Notably, the year 1992 saw the highest CPP_{2021} for the six published articles, while a marked increase in both volume and citation impact was observed by 2001.[61] This trend underscores the expanding role of AI/machine learning in kidney care research, yet it also highlights the need for a balanced approach in evaluating both the quantity and quality of scientific contributions in this domain.

Web of Science Category and Journal

In 2021, the Journal Citation Reports (JCR) indexed 9649 journals across 178 Web of Science categories in SCI-EXPANDED. A study by Giannoudis et al. (2021)[54] and Ho and Mukul (2021)[48] presented basic information on the characteristics of Web of Science categories based on their average number of citations per publication (CPP_{year}) and the average number of authors per publication (*APP*) in a given research topic. A total of 1110 journals published articles related to AI/machine learning in kidney care, which were distributed across 131 Web of Science categories in SCI-EXPANDED. The top ten productive categories were identified, with the majority falling under the category of urology and nephrology (which contained 90 journals) and accounting for 1256 articles (31% of the 4063 articles published in journals with category information in SCI-EXPANDED). Of these categories, articles published in the category of immunology had the highest CPP_{2021} value of 22, while articles published in the category of oncology had the highest average number of authors per publication (*APP*) at 9.4. Recently, Ho (2021)[62] proposed a method to identify the characteristics of journals in a research topic based on their average number of citations per publication (CPP_{year}) and the average number of authors per publication (*APP*). Table 3 presents the top 10 most productive journals in AI/machine learning in kidney care research, along with their impact factors, CPP_{2021}, and *APP*. The top four productive journals were all listed under the Web of Science category of urology and nephrology. The *Journal of Endourology* (IF_{2021} = 2.619) published the highest number of articles (155) representing 3.8% of 4063 articles, followed by *Urology* (IF_{2021} = 2.633) with 137 articles. When compared to the top 10 productive journals, *European Urology*

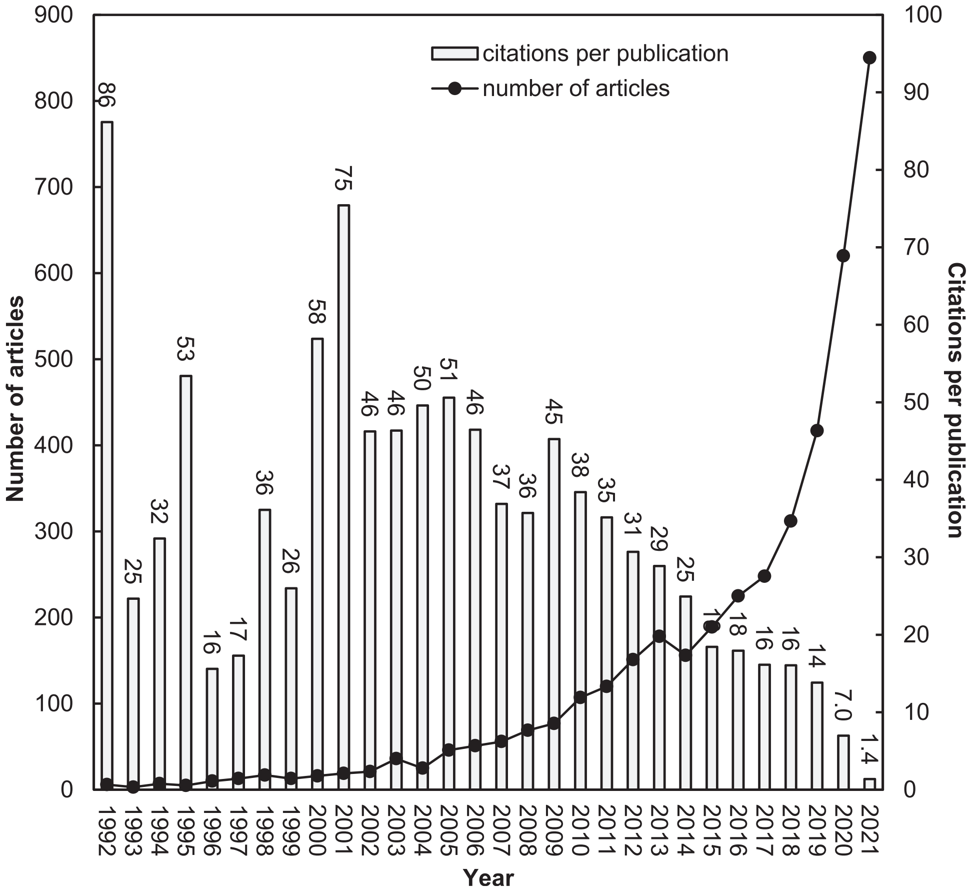

FIG. 1. Number of AI/machine learning in kidney care articles and average number of citations per publication by year.

(IF_{2021} = 24.267) had the highest CPP_{2021} of 63, while the *Journal of Pediatric Urology* (IF_{2021} = 1.921) had a CPP_{2021} of only 7.6. The *APP* ranged from 11 in the *European Urology* to 5.6 in the Journal of Pediatric Urology. Additionally, *JAMA-Journal of the American Medical Association, Lancet Respiratory Medicine, BMJ-British Medical Journal*, and *Nature Medicine* were the journals with the highest impact factors (IF_{2021}) of 157.335, 102.642, 93.333, and 87.241, respectively, with each publishing one article in the field of AI/machine learning in kidney care research.

Publication performances: countries and institutions

There were five articles (0.12% of 4063 articles) without affiliations in SCI-EXPANDED. A total of 4058 articles were published by authors affiliated from 96 countries including 3108 single-country articles (77% of 4058 articles) published by authors from 58 countries with a CPP_{2021} of 17 and 950 internationally collaborative articles (23%) published by authors from 91 countries with a CPP_{2021} of 19. The results demonstrated that internationally collaborative raised citations in the study of AI/machine learning in kidney care. It is widely recognized that two authors: first and the corresponding authors are considered as the most contributed authors in a research article.[63] At the institutional level, the determined institution of the corresponding author might be a home base of the study or origin of the paper.[41] Six publication indicators and the six related citation indicators (CPP_{2021})[48] were applied to compare the top 20 productive countries (Table 4). The USA dominated in all the six publication indicators with a *TP* of 1655 articles (41% of 4058 articles), an IP_C of 1157 articles (37% of 3108 single-country articles), a CP_C of 498 articles (52% of 950 internationally collaborative articles), an *FP* of 1391 articles (34% of 4058 first-author articles), an *RP* of 1435 articles (35% of 4057 corresponding-author articles), and an *SP* of 21 articles (37% of 57 single-author articles). Compared to the top 20 productive countries in Table 4, the UK with a *TP* of 262 articles, an IP_C of 91 articles, an *FP* of 134 articles, and an *RP* of 139 articles had the greatest of $TP\text{-}CPP_{2021}$ of 27, $IP_C\text{-}CPP_{2021}$ of 30, $FP\text{-}CPP_{2021}$ of 34, and $RP\text{-}CPP_{2021}$ of 33 respectively. Japan with a CP_C

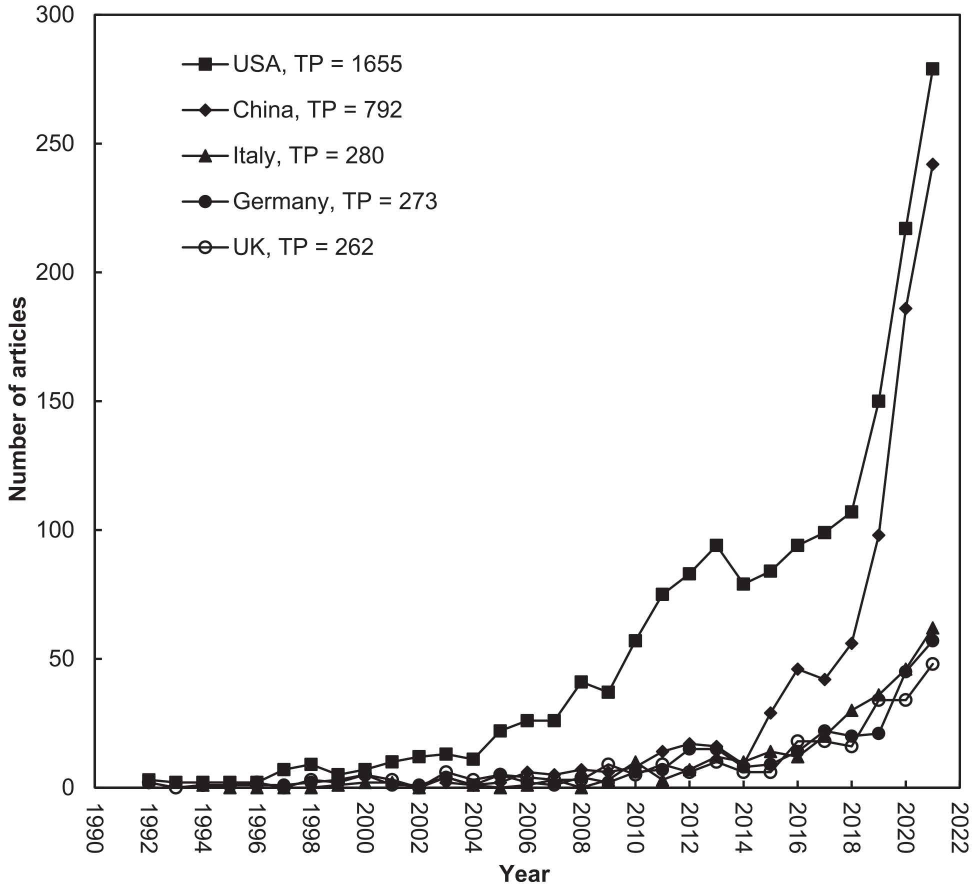

FIG. 2. Development trends of the top five productive countries.

of 50 articles had the greatest of CP_C-CPP_{2021} of 29. Canada with an *SP* of one article had the greatest of *SP*-CPP_{2021} of 133.

Overall, these findings indicate the value of collaborations and international partnerships to foster impactful research in AI/machine learning in kidney care. While the USA has been the most productive country in this field, other countries such as the UK, Japan, and Canada have published research with higher citation impact, as well. It is important to note that citation analysis provides valuable insights into the impact of publications but does not necessarily indicate the quality of the research. Therefore, other methods should be employed to evaluate the quality of the research being published in the field of kidney care.

The development trends in the publication of the top five productive countries are illustrated in Fig. 2. The USA has consistently ranked first from 1992 to 2021, with a sharp increase since 2018, reaching 279 articles in 2021. China has also experienced a sharp increase since 2018, publishing 242 articles in 2021. However, China had lower citation impact, with a *TP*-CPP_{2021} of 11, an IP_C-CPP_{2021} of 11, a CP_C-CPP_{2021} of 12, an *FP*-CPP_{2021} of 11, an *RP*-CPP_{2021} of 11, and an *SP*-CPP_{2021} of 3.0. Similarly, India, with 153 articles (ranked 8th), published 36 articles in 2021 (ranked 8th), but also had lower CPP_{2021} for the six types of publications. The publication output and citation trends of the top five productive countries in AI/machine learning in kidney care provide important information for researchers, clinicians, and policymakers. Fig. 2 shows that the USA has been the most productive country in this field over the last three decades, with a notable increase in publications since 2018. This surge in publications may suggest a growing interest in AI/machine learning in kidney care research and increased funding and resources for research in this area. China has also shown a remarkable increase in publications since 2018, indicating a rising interest in AI/machine learning in kidney care research. However, the lower CPP_{2021} for the six types of publications suggests that the quality of research may be currently lower compared to other productive countries, such as the USA and the UK. This could be due to disparities in research funding, resources, infrastructure and publication priorities. India, despite ranking 8th in total publications, has also demonstrated a surge in publications since 2018. However, the lower CPP_{2021} for the six types of publications from India suggests that the quality of research may also be lower compared to other productive countries. This could be due to various factors, including differences in research funding, resources (including for funding to provide for open access publication fees), and infrastructure, as well as possible obstacles to collaboration and knowledge sharing. Overall, the trends in publication output and citations of the top five productive countries in AI/machine learning in kidney care offer valuable insights into the global research landscape in this area. Researchers and clinicians can use this information to identify opportunities for collaboration and knowledge sharing, and to explore potential research gaps. Policymakers can also utilize this data to make informed funding decisions and allocate resources to support research in this critical and rapidly evolving field.

Regarding institutional affiliations, of the 4058 articles analyzed, 33% (1323) were from single institutions with a CPP_{2021} of 17, while 67% (2735) were inter-institutional collaborations with a CPP_{2021} of 18. Of the inter-institutional collaborative articles, 65% (1785) were national collaborations with a CPP_{2021} of 17, and 35% (950) were international collaborations with a CPP_{2021} of 19. The results show that international collaborations had higher citation impact than national collaborations.

The top 10 productive institutions are presented in Table 5. To be noted, none of the 10 institutions had any single-author articles. Eight of the institutions were in the USA, and one each was in China and South Korea. The Cleveland Clinic in the USA had the highest publication counts in all five indicators, with 140 total articles (3.4% of all articles), 69 articles (5.2% of single-institution articles) as the first institution, 71 articles (2.6% of inter-institutional collaborative articles) as a collaborating institution, 98 articles (2.4% of first-author articles), and 102 articles (2.5% of corresponding-author articles).

Compared to the top 10 productive institutions, the Henry Ford Hospital in the USA had the highest TP-CPP_{2021} of 43 and CP_I-CPP_{2021} of 45, with 58 total articles and 44 articles as a collaborating institution. The Washington University in the USA had the highest FP-CPP_{2021} of 41 and CP_I-CPP_{2021} of 40, with 28 articles as the first institution and 28 articles as a collaborating institution. The Chinese Academy of Sciences in China had the highest IP_I-CPP_{2021} of 47, with 11 articles as the first institution.

The findings of the study suggest that collaborative research efforts between institutions, particularly international collaborations, may lead to higher quality research and more impactful publications. This is due to the exchange of knowledge and resources, along with the diverse perspectives and expertise that international collaborations can offer. Thus, it may be advantageous for researchers and institutions to explore opportunities for international collaborations to improve the quality and impact of their research in the AI/machine learning field of kidney care.

The prevalence of US institutions among the top 10 productive institutions emphasizes the significant investment in research and resources in the US regarding AI/machine learning in kidney care. However, this study also highlights the notable contributions of institutions in other countries, including China and South Korea. Additionally, the higher TP-CPP_{2021} and CP_I-CPP_{2021} of the Henry Ford Hospital and the higher FP-CPP_{2021} and CP_I-CPP_{2021} of the Washington University suggest that these institutions may be producing higher-quality research than other productive institutions. This could be due to various factors, such as differences in research funding, resources, infrastructure, and the expertise and focus of individual researchers and institutions.

Publication performances: authors

For articles related to AI/machine learning in kidney care, the *APP* was 7.4 whereas the maximum number of authors was 106 in one article by Di Castelnuovo et al. (2020).[64] Of the 4060 articles with author information in SCI-EXPANDED, 64% articles were published by groups of three to eight authors, including 512 (13% of 4060 articles), 472 (12%), 466 (11%), 450 (11%), 355 (8.7%), and 325 (8.0%) were written by groups of 6, 7, 4, 5, 8, and 3 authors with a CPP_{2021} of 18, 19, 15, 16, 17, and 17 respectively. Table 6 listed the top 21 productive authors with four publication indicators, their citation indicators, and *Y*-index constants. J.H. Kaouk was the most productive author with 90 articles including nine first-author articles (ranked 2nd) and 58 corresponding-author articles (ranked 1st). R. Abaza with 43 articles including 10 first-author articles (ranked 1st), eight corresponding-author articles (ranked 17th), and one single-author article (ranked 3rd). Compare to the 21 productive authors, I.S. Gill with a *TP* of 34 articles had the greatest TP-CPP_{2021} of 59 (Table 2).

A. Mottrie with an *FP* of one article had the greatest FP-CPP_{2021} of 180. M. Aron with an *RP* of one article had the greatest RP-CPP_{2021} of 131. R. Abaza with an *SP* of one article had the greatest SP-CPP_{2021} of 96. Only 10 of the 21 productive authors including J.H. Kaouk, A.K. Hemal, K.K. Badani, C.G. Rogers, I.S. Gill, R. Abaza, A. Minervini, R. Autorino, K.H. Rha, and M.D. Stifelman were not found to be the top 21 publication potential authors as evaluated by *Y*-index.

In the total of 4039 AI/machine learning in kidney care articles (99% of 4063 articles) had both first and corresponding authors information in SCI-EXPANDED, were extensively investigated based on the *Y*-index. The 4039 articles were contributed by 19,604 authors in which 14,428 authors (70% of 19,604 authors) had no first- and no corresponding-author articles with *Y*-index (0, 0); 1788 (9.1%) authors published only corresponding-author articles with $h = \pi/2$; 179 (0.91%) authors published more corresponding-author articles with $\pi/2 > h > \pi/4$ ($FP > 0$); 1288 (6.6%) authors published the same number of first- and corresponding-author articles with $h = \pi/4$ ($FP > 0$ and $RP > 0$); 108 (0.55%) authors published more first-author articles with $\pi/4 > h > 0$ ($RP > 0$); and 1813 (9.2%) authors published only first-author articles with $h = 0$.

Table 2. The top 10 most productive Web of Science categories.

Web of science category	No. journals	*TP* (%)	APP	CPP_{2021}
Urology and nephrology	90	1,256 (31)	7.7	21
Surgery	212	393 (10)	7.2	15
Radiology, nuclear medicine and medical imaging	136	266 (6.5)	7.5	18
Oncology	246	209 (5.1)	9.4	15
Multidisciplinary sciences	73	192 (4.7)	8.2	15
Medical informatics	31	190 (4.7)	6.6	12
Biomedical engineering	98	186 (4.6)	5.7	15
General and internal medicine	172	177 (4.4)	8.2	12
Immunology	162	174 (4.3)	7.8	22
Interdisciplinary applications computer science	113	161 (4.0)	5.9	16

TP: total number of articles; %: percentage in all articles; *APP*: average number of authors per paper; CPP_{2021} average number of citations per paper (TC_{2021}/TP).

In the polar coordinates (Fig. 3), the distribution of the *Y*-index (*j, h*) of the leading 26 potential authors in AI/ machine learning in kidney care research with $j \geq 10$ was demonstrated. Every point has a coordinate *Y*-index (*j, h*) that could symbolize a single author or multiple authors, for example, L. Wang and A. Antonelli with the same *Y*-index (11, 0.6947). J.H. Kaouk with *Y*-index (67, 1.417) had the much higher publication potential than others.

The study suggests that identifying highly productive authors such as J.H. Kaouk, who has a *Y*-index of (67,

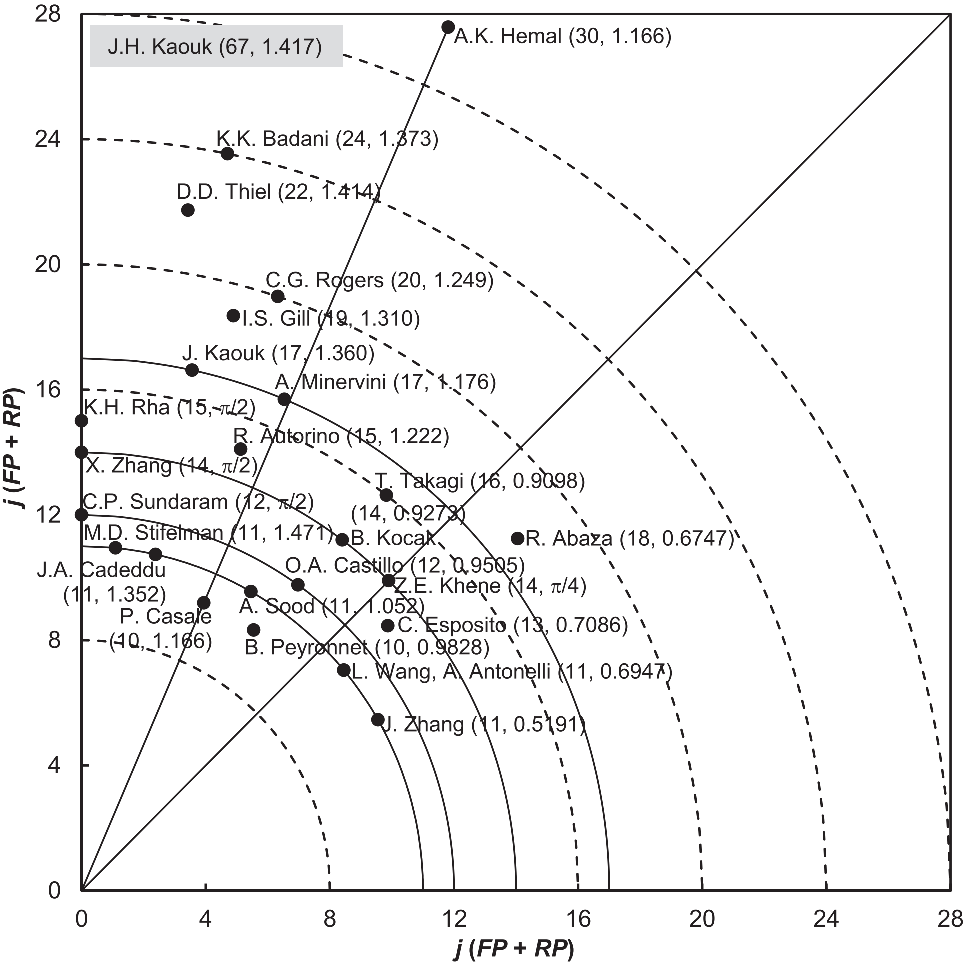

FIG. 3. Top 26 authors with *Y*-index ($j \geq 10$). Footnote: *j*, a constant related to the publication potential and *h* is a constant related to the publication characteristics.

Table 3. The top 10 most productive journals.

Journal	*TP* (%)	IF_{2021}	APP	CPP_{2021}
Journal of Endourology	155 (3.8)	2.619	7.1	13
Urology	137 (3.4)	2.633	6.5	25
Journal of Urology	114 (2.8)	7.600	7.5	50
BJU International	90 (2.2)	5.969	8.4	30
Scientific Reports	79 (1.9)	4.996	8.2	13
European Urology	73 (1.8)	24.267	11	63
PLoS One	70 (1.7)	3.752	7.9	17
World Journal of Urology	68 (1.7)	3.661	10	17
Journal of Pediatric Urology	45 (1.1)	1.921	5.6	7.6
International Journal of Urology	34 (0.84)	2.896	8.1	13

TP: total number of articles; %: percentage of articles; IF_{2021}: journal's impact factor in 2021; *APP*: average number of authors per article; CPP_{2021}: average number of citations per paper (TC_{2021}/TP).

1.417) in AI/machine learning in kidney care research, could have implications for advancing research in this area and improving patient outcomes. Key opinion leaders and potential collaborators in the field could be identified based on their publication potential and authorship patterns, as demonstrated by the *Y*-index analysis. Additionally, understanding authorship patterns and publication potential can inform strategies for career development and mentorship in this field.

The location on the graph along with one of the curves or along a straight line from the origin represents different families of author publication potential or publication characteristics, respectively.[52] M.D. Stifelman (11, 1.471), J.A. Cadeddu (11, 1.352), A. Sood (11, 1.052), L. Wang (11, 0.6947), A. Antonelli (11, 0.6947), and J. Zhang (11, 0.5191), all had the same *j* of 11. All these authors are located on the same curve (j = 11) in Fig. 3, indicating that they had the same publication potential in AI/machine learning in kidney care research with a *j* of 11 but different publication characteristics.[65] Stifelman published more corresponding-author articles than first-author articles with an *h* of 1.471 then Cadeddu with an *h* of 1.352 and Sood with an *h* of 1.052. Zhang published more first-author articles than corresponding-author articles with an *h* of 0.5191, then Antonelli with an *h* of 0.6947 and Wang with an *h* of 0.6947. X. Zhang (14, $\pi/2$), B. Kocak (14, 0.9273), and Z.E. Khene (14, $\pi/4$) also located on the curve (j = 14). They have the same publication potential. However, Zhang published only 14 corresponding-author articles with an *h* of $\pi/2$. Kocak published more corresponding-author articles than first-author articles with an *h* of 0.9273. Khene published the same number of corresponding-author articles and first-author articles with an *h* of $\pi/4$. Similarly, J. Kaouk (17, 1.36) and A. Minervini (17, 1.176); K.H. Rha (15, $\pi/2$) and R. Autorino (15, 1.222); C.P. Sundaram (12, $\pi/2$) and

Table 4. Top 20 productive countries.

Country	TP	TP		IP_C		CP_C		FP		RP		SP	
		R (%)	CPP_{2021}	*R* (%)	CPP_{2021}	*R* (%)	CPP_{2021}	*R* (%)	CPP_{2021}	*R* (%)	CPP_{2021}	*R* (%)	CPP_{2021}
USA	1,655	1 (41)	24	1 (37)	24	1 (52)	22	1 (34)	24	1 (35)	24	1 (37)	17
China	792	2 (20)	11	2 (20)	11	2 (19)	12	2 (18)	11	2 (18)	11	7 (3.5)	3.0
Italy	280	3 (6.9)	18	5 (3.9)	13	5 (17)	21	3 (4.6)	15	3 (4.6)	15	2 (11)	13
Germany	273	4 (6.7)	23	6 (3.5)	16	4 (17)	28	4 (4.0)	19	4 (4.1)	19	9 (1.8)	1.0
UK	262	5 (6.5)	27	8 (2.9)	30	3 (18)	26	7 (3.3)	34	7 (3.4)	33	N/A	N/A
France	224	6 (5.5)	16	3 (4.1)	11	6 (10)	22	4 (4.0)	12	4 (4.1)	12	4 (5.3)	4.3
South Korea	179	7 (4.4)	12	4 (3.9)	11	13 (6.0)	14	6 (3.6)	12	6 (3.9)	12	9 (1.8)	15
India	153	8 (3.8)	11	9 (2.9)	8.1	12 (6.7)	16	9 (2.9)	7.5	9 (2.7)	8.1	4 (5.3)	4.7
Japan	149	9 (3.7)	17	7 (3.2)	10	14 (5.3)	29	8 (2.9)	12	8 (3.0)	12	4 (5.3)	10
Canada	140	10 (3.4)	22	11 (1.7)	22	8 (9.3)	21	11 (2.1)	25	11 (2.1)	24	9 (1.8)	133
Spain	126	11 (3.1)	14	13 (1.4)	8.6	9 (8.6)	16	12 (1.8)	11	12 (2.0)	11	9 (1.8)	2.0
Taiwan	111	12 (2.7)	8.8	10 (2.6)	9.2	20 (3.2)	7.5	10 (2.3)	8.7	10 (2.3)	8.6	9 (1.8)	12
Belgium	105	13 (2.6)	19	20 (0.51)	21	7 (9.4)	19	18 (0.91)	15	18 (0.91)	15	9 (1.8)	23
Netherlands	97	14 (2.4)	31	17 (0.80)	19	10 (7.6)	35	14 (1.3)	28	14 (1.4)	25	N/A	N/A
Turkey	97	14 (2.4)	16	12 (1.6)	18	15 (4.8)	14	13 (1.5)	18	13 (1.5)	17	9 (1.8)	8.0
Australia	96	16 (2.4)	15	15 (0.90)	15	11 (7.2)	15	17 (1.0)	17	16 (1.1)	15	9 (1.8)	1.0
Switzerland	69	17 (1.7)	24	19 (0.74)	16	15 (4.8)	28	16 (1.0)	19	15 (1.1)	18	N/A	N/A
Brazil	60	18 (1.5)	8.2	14 (1.0)	9.2	21 (3.1)	7.1	15 (1.1)	7.5	17 (1.1)	7.6	N/A	N/A
Singapore	46	19 (1.1)	18	24 (0.35)	20	18 (3.7)	17	21 (0.67)	24	21 (0.67)	24	N/A	N/A
Austria	45	20 (1.1)	30	31 (0.19)	48	17 (4.1)	28	31 (0.25)	29	32 (0.25)	29	N/A	N/A

TP: number of total articles; *TP R* (%): total number of articles and the percentage of total articles; IP_C *R* (%): rank and percentage of single-country articles in all single-country articles; CP_C *R* (%): rank and percentage of internationally collaborative articles in all internationally collaborative articles; *FP R* (%): rank and the percentage of first-author articles in all first-author articles; *RP R* (%): rank and the percentage of corresponding-author articles in all corresponding-author articles; *SP R* (%): rank and the percentage of first-author articles in all first-author articles; CPP_{2021}: average number of citations per publication ($CPP_{2021} = TC_{2021}/TP$); N/A: not available.

Table 5. Top 10 productive institutions.

Institution	TP	TP		IP_I		CP_I		FP		RP	
		R (%)	CPP_{2021}	*R* (%)	CPP_{2021}	*R* (%)	CPP_{2021}	*R* (%)	CPP_{2021}	*R* (%)	CPP_{2021}
Cleveland Clin, USA	140	1 (3.4)	30	1 (5.2)	36	1 (2.6)	25	1 (2.4)	33	1 (2.5)	32
Mayo Clin, USA	77	2 (1.9)	16	2 (1.7)	7.9	2 (2.0)	20	2 (1.0)	16	2 (1.2)	15
Washington Univ, USA	62	3 (1.5)	38	3 (1.5)	28	7 (1.5)	42	7 (0.69)	41	8 (0.69)	40
Chinese Acad Sci, China	59	4 (1.5)	28	8 (0.83)	47	3 (1.8)	24	3 (0.94)	30	3 (1.0)	28
Henry Ford Hosp, USA	58	5 (1.4)	43	5 (1.1)	39	6 (1.6)	45	5 (0.71)	40	9 (0.67)	35
Yonsei Univ, South Korea	53	6 (1.3)	15	24 (0.53)	9.1	5 (1.7)	15	5 (0.71)	15	4 (0.89)	16
Harvard Med Sch, USA	52	7 (1.3)	12	50 (0.30)	4.8	3 (1.8)	12	46 (0.25)	7.2	23 (0.42)	5.9
Icahn Sch Med Mt Sinai, USA	47	8 (1.2)	9.1	35 (0.45)	4.0	8 (1.5)	10	4 (0.79)	9.0	5 (0.82)	8.5
Univ Michigan, USA	47	8 (1.2)	25	10 (0.76)	16	9 (1.4)	28	10 (0.62)	31	11 (0.59)	27
Stanford Univ, USA	45	10 (1.1)	27	13 (0.68)	13	10 (1.3)	30	13 (0.49)	18	16 (0.52)	17

TP: total number of articles; *TP R* (%): total number of articles and percentage of total articles; IP_I *R* (%): rank and percentage of single-institute articles in all single-institute articles; CP_I *R* (%): rank and percentage of inter-institutionally collaborative articles in all inter-institutionally collaborative articles; *FP R* (%): rank and percentage of first-author articles in all first-author articles; *RP R* (%): rank and percentage of corresponding-author articles in all corresponding-author articles; CPP_{2021}: average number of citations per publication ($CPP_{2021} = TC_{2021}/TP$).

O.A. Castillo (12, 0.9505); and P. Casale (10, 1.166) and B. Peyronnet (10, 0.9828) are also located on the same curve with *j* of 17, 15, 12, and 10 respectively. A.K. Hemal (30, 1.166) and P. Casale (10, 1.166) are located on the straight line (*h* = 1.166) indicating that they had the same publication characteristics but different publication potential. Hemal had the much greater publication potential with a *j* of 30 than Casale with a *j* of 10. Similarly, K.H. Rha (15, π/2), X. Zhang (14, π/2), and C.P. Sundaram (12, π/2) are located on the y-axis (*h* = π/2) indicating that they had the same publication characteristics. Rha had the greatest publication potential with a *j* of 15 followed by Zhang with a *j* of 14, and Sundaram with a *j* of 12. A potential for bias in the analysis of

Table 6. Top 21 productive authors with 27 articles or more.

Author	TP		FP		RP		SP		h	Rank (*j*)
	Rank (*TP*)	CPP_{2021}	Rank (*FP*)	CPP_{2021}	Rank (*RP*)	CPP_{2021}	Rank (*SP*)	CPP_{2021}		
J.H. Kaouk	1 (90)	37	2 (9)	86	1 (58)	42	N/A	N/A	1.417	1 (67)
R. Autorino	2 (62)	30	21 (4)	27	12 (11)	14	N/A	N/A	1.222	11 (15)
R.J. Stein	3 (48)	36	130 (2)	85	65 (4)	22	N/A	N/A	1.107	64 (6)
G.P. Haber	4 (46)	42	435 (1)	142	28 (6)	34	N/A	N/A	1.406	46 (7)
A.K. Hemal	5 (44)	22	2 (9)	39	2 (21)	26	N/A	N/A	1.166	2 (30)
R. Abaza	6 (43)	18	1 (10)	25	17 (8)	27	3 (1)	96	0.6747	7 (18)
A. Mottrie	7 (40)	22	435 (1)	180	39 (5)	48	N/A	N/A	1.373	64 (6)
M. Menon	8 (37)	39	130 (2)	86	N/A	N/A	N/A	N/A	0	515 (2)
F. Porpiglia	9 (36)	17	44 (3)	14	110 (3)	16	N/A	N/A	π/4	64 (6)
I.S. Gill	10 (34)	59	21 (4)	134	5 (15)	77	N/A	N/A	1.310	6 (19)
C.G. Rogers	11 (32)	58	15 (5)	85	5 (15)	41	N/A	N/A	1.249	5 (20)
Y. Wang	11 (32)	11	130 (2)	1.5	39 (5)	5.4	N/A	N/A	1.190	46 (7)
Y. Zhang	11 (32)	16	130 (2)	4.5	110 (3)	3.0	N/A	N/A	0.9828	98 (5)
K. Bensalah	14 (31)	16	21 (4)	12	65 (4)	12	N/A	N/A	π/4	30 (8)
A. Minervini	14 (31)	17	15 (5)	18	10 (12)	21	N/A	N/A	1.176	8 (17)
K.H. Rha	14 (31)	14	N/A	N/A	5 (15)	14	N/A	N/A	π/2	11 (15)
M. Aron	17 (30)	43	435 (1)	131	584 (1)	131	N/A	N/A	π/4	515 (2)
H. Laydner	17 (30)	32	130 (2)	18	N/A	N/A	N/A	N/A	0	515 (2)
K.K. Badani	19 (29)	10	21 (4)	22	3 (20)	12	N/A	N/A	1.373	3 (24)
A. Mari	20 (27)	15	130 (2)	21	N/A	N/A	N/A	N/A	0	515 (2)
M.D. Stifelman	20 (27)	54	435 (1)	25	13 (10)	47	N/A	N/A	1.471	19 (11)

TP: total number of articles; *FP*: first-author articles; *RP*: corresponding-author articles; *SP*: single-author articles; CPP_{2021}: average number of citations per publication ($CPP_{2021} = TC_{2021}/TP$); *j*: a *Y*-index constant related to the publication potential; *h*: a *Y*-index constant related to the publication characteristics; N/A: not available.

authorship might attributes to different authors having the same name, or the same author using different names over time.[66]

Citation histories of the ten most frequently cited articles

Total citations are updated from time to time on the Web of Science Core Collection. To improve bibliometric study, the total number of citations from the Web of Science Core Collection since publication year to the end of the most recent year of 2021 (TC_{2021}) was applied to improve the bias using data from the database directly.[45] A total of 715 articles (12% of 6043 articles), 3454 articles (85% of 4048 articles with abstract in SCI-EXPANDED), and 987 articles (32% of 3091 articles with author keywords in SCI-EXPANDED) contain search keywords in their title, abstract, and author keywords respectively. None, one, and ten of the top ten most frequently cited articles contain search keywords in their title, abstract, and author keywords respectively. It was recommended that search keywords in article title or author keywords have more focus on a bibliometric study topic.[48] Table 7 shows the top 10 most frequently cited articles with search keywords in their title or author keywords. The USA published eight of the top ten articles and the UK published two. The University of Southern California and the Washington University in the USA published two of the top 10 articles respectively. Other 11 institutions in the USA and four in the UK published only one of the top 10 articles respectively. Four of the top 10 articles published in the *Journal of Urology*, two in the *European Urology*, and one in each of the *Radiology*, the *Toxicological Sciences*, the *Cancer Research*, and the *IEEE Transactions on Medical Imaging*.

Citations of a highly cited article is not always high.[49] It is recommended to understand citation history of a highly cited article. The citation histories of the top ten articles contain search keywords in their title or author keywords are shown in Fig. 4. Green Giants are articles that have sharply increasing citations after publication year for some years compared with others in the same research topic. They also become high-impact publications in recent years with a high C_{year} which is higher than others several times.[67] One example of Green Giant in AI/machine learning in kidney care research was article entitled "Automatic multi-organ segmentation on abdominal CT with dense V-networks"[68] by 10 authors from the University College London (UCL) and the University College Hospital Trust in the UK. The authors mentioned "deep-learning" and "kidney" in the abstract and author keywords respectively.

The article titled "Automatic multi-organ segmentation on abdominal CT with dense V-networks" by Gibson et al.[68] is a highly influential publication in the area of AI/machine learning in kidney care research, specifically focused on the emerging field of AI-assisted interpretation of medical imaging. The article

Table 7. Top 10 most frequently cited articles with search keywords in their title or author keywords.

Rank (TC_{2021})	Rank (C_{2021})	Title	Country	Reference
5 (371)	229 (12)	Robot assisted partial nephrectomy versus laparoscopic partial nephrectomy for renal tumors: A multi-institutional analysis of perioperative outcomes	USA	Benway et al. (2009)[71]
17 (228)	201 (13)	"Zero Ischemia" partial nephrectomy: Novel laparoscopic and robotic technique	USA	Gill et al. (2011)[72]
18 (226)	919 (4)	Robotic partial nephrectomy with sliding-clip renorrhaphy: Technique Robe outcomes	USA	Benway et al. (2009)[73]
19 (218)	60 (24)	"Trifecta" in partial nephrectomy	USA	Hung et al. (2013)[74]
19 (218)	258 (11)	Pediatric robot assisted laparoscopic dismembered pyeloplasty: Comparison with a cohort of open surgery	USA	Lee et al. (2006)[75]
23 (207)	4 (110)	Automatic multi-organ segmentation on abdominal CT with dense V-networks	UK	Gibson et al. (2018)[68]
24 (203)	1185 (3)	Metabonomics: Evaluation of nuclear magnetic resonance (NMR) and pattern recognition technology for rapid *in vivo* screening of liver and kidney toxicants	USA	Robertson et al. (2000)[76]
27 (189)	1552 (2)	Proteomic profiling of urinary proteins in renal cancer by surface enhanced laser desorption ionization and neural-network analysis: Identification of key issues affecting potential clinical utility	UK	Rogers et al. (2003)[77]
29 (187)	2044 (1)	Segmental stenosis of the renal-artery: Pattern-recognition of Tardus and Parvus abnormalities with duplex sonography	USA	Stavros et al. (1992)[78]
32 (181)	179 (14)	Trends in renal surgery: Robotic technology is associated with increased use of partial nephrectomy	USA	Patel et al. (2013)[79]

TC_{2021}: the total number of citations from Web of Science Core Collection since publication year to the end of 2021; C_{2021}: number of citations of an article in 2021 only.

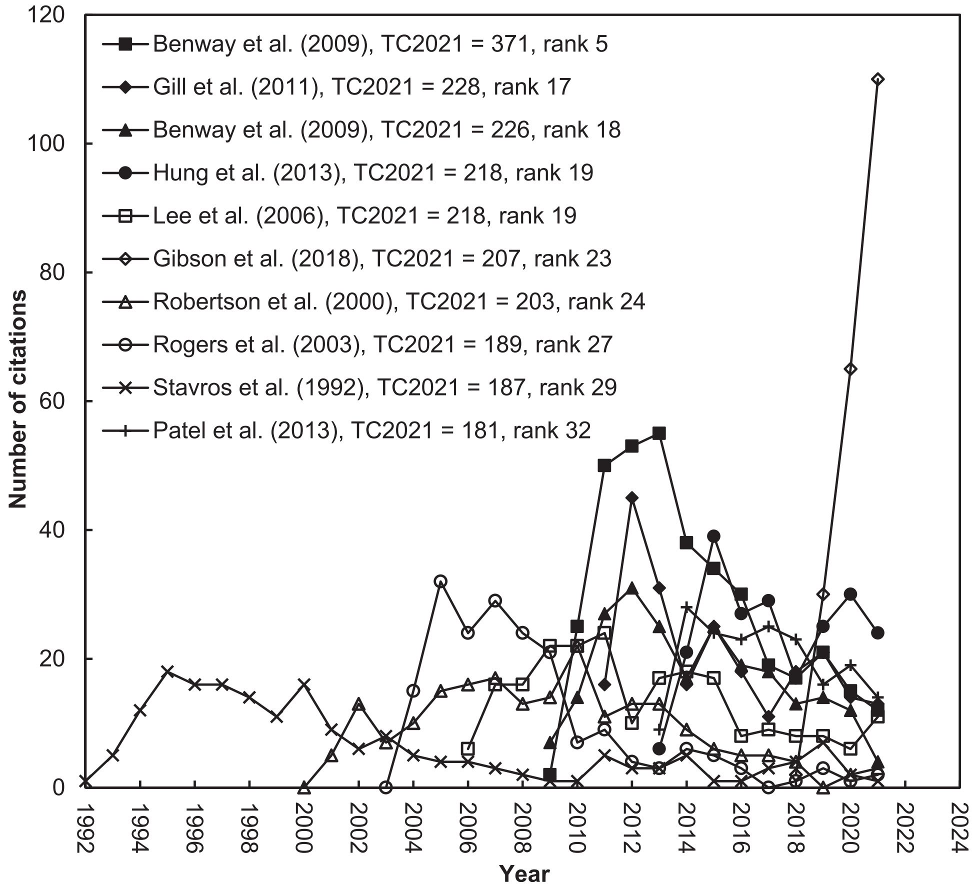

FIG. 4. The citation histories of the top ten highly cited articles with search keywords in their title or author keywords

addresses the issue of identifying and segmenting abdominal organs on CT scans, including the kidneys, which is important for accurate diagnosis and treatment of kidney disease. The authors developed a method that uses deep learning techniques and a dense V-network architecture to automatically segment abdominal organs, achieving high accuracy in identifying and segmenting multiple organs simultaneously. This has important implications for identifying and quantifying changes in kidney structure over time. One reason why this article has gained high citation numbers and influence in recent years is due to the rapid advancements in AI and machine learning in the medical field. The use of deep learning techniques and dense V-network architectures has enabled precise and accurate identification of kidney structure and function, leading to better patient outcomes and treatment strategies.

Research foci

In the last decade, Ho's research group proposed distributions of words in article titles and abstracts, author keywords, and *Keywords Plus* to determine research focuses and their trends.[69,70] The article title, article abstract, author keywords, and *Keywords Plus* were analyzed during the research period to show rough trends.[69] Excepted search keywords, the 21 most frequently used author keywords in AI/machine learning in kidney care research and their distribution in three subperiods (1992−2001, 2002−2011, and 2012−2021) are listed in Table 8. The most frequently used author keywords were "partial nephrectomy", "laparoscopy", and "nephrectomy" which were applied in 275, 204, and 192 articles as author keywords respectively. "Chronic kidney disease", "acute kidney injury", "robotic surgical procedures", "minimally invasive surgery", and "clear cell renal cell carcinoma" were getting popular in the last decade.

This information is significant for researchers and institutions interested in keeping abreast of the latest trends and developments in AI/machine learning in kidney care research. By analyzing the distribution of author keywords over time, researchers can identify emerging topics and areas of interest, as well as the most commonly used terms and concepts in the field. This can help guide future research and the development of novel approaches and techniques to enhance patient outcomes in the diagnosis and treatment of kidney disease.

Table 8. The 21 most frequently used author keywords.

Author keywords	TP	1992-2021 rank (%)	1992-2001 rank (%)	2002-2011 rank (%)	2012-2021 rank (%)
Partial nephrectomy	275	1 (8.9)	N/A	3 (6.5)	1 (10)
Laparoscopy	204	2 (6.6)	1 (7.2)	1 (18)	5 (4.9)
Nephrectomy	192	3 (6.2)	6 (4.3)	2 (6.7)	2 (6.2)
Robotic surgery	178	4 (5.8)	N/A	4 (6.2)	4 (5.8)
Renal cell carcinoma	173	5 (5.6)	2 (5.8)	6 (3.5)	3 (5.9)
Chronic kidney disease	108	6 (3.5)	N/A	225 (0.25)	6 (4.1)
Acute kidney injury	104	7 (3.4)	N/A	42 (1.0)	7 (3.8)
Kidney transplantation	102	8 (3.3)	N/A	7 (3.2)	8 (3.4)
Kidney cancer	86	9 (2.8)	N/A	10 (2.5)	9 (2.9)
Robotic partial nephrectomy	74	10 (2.4)	N/A	16 (1.7)	10 (2.6)
Kidney neoplasms	62	11 (2.0)	N/A	16 (1.7)	12 (2.1)
Robotic surgical procedures	58	12 (1.9)	N/A	N/A	11 (2.2)
Complications	52	13 (1.7)	N/A	42 (1.0)	13 (1.8)
Minimally invasive surgery	50	14 (1.6)	N/A	66 (0.74)	14 (1.8)
Nephron-sparing surgery	46	15 (1.5)	N/A	21 (1.5)	17 (1.5)
Artificial neural network	45	16 (1.5)	13 (2.9)	21 (1.5)	20 (1.4)
Classification	45	16 (1.5)	N/A	42 (1.0)	16 (1.6)
Pyeloplasty	45	16 (1.5)	N/A	5 (4.0)	29 (1.1)
Clear cell renal cell carcinoma	43	19 (1.4)	N/A	N/A	15 (1.6)
Outcomes	43	19 (1.4)	N/A	42 (1.0)	18 (1.5)
Prognosis	43	19 (1.4)	2 (5.8)	42 (1.0)	21 (1.3)

TP: number of articles contain the keywords; %: percentage in each period; N/A: not available.

Further, it demonstrates the large overlap between nephrology and urology publications, when assessing research output derived from key word searches.

Future Implications

This study's findings, which underscore the significance of collaboration in promoting the field, highlight research focuses and commonly used author keywords. The outcomes of this study can assist researchers and practitioners in pinpointing important research areas, identifying productive partnerships, and furthering the use of AI and ML in kidney care research. Future research may explore the potential of AI and ML in predicting and preventing kidney disease, as well as in enhancing patient outcomes and clinical decision-making. In addition, upcoming research may probe the ethical concerns linked with employing AI and ML in kidney care research, such as algorithm development biases and data privacy issues. In conclusion, this study provides valuable insights into the use of AI and ML in kidney care research and emphasizes the value of collaboration in advancing the field.

In summary, this research provides an extensive investigation of the application of AI and ML in kidney care research publications from 1992 to 2021. The study underscores the significance of collaborative research in advancing the field and highlights the research focuses and frequently used author keywords in this area. The findings of this study can aid researchers and practitioners in identifying key research areas, productive partnerships, and promoting the use of AI and ML in kidney care research. This research provides valuable insights into the implementation of AI and ML in kidney care research and highlights the importance of collaboration among researchers and practitioners in the field's advancement. The identification of research focuses and commonly used author keywords in this study can inform future research and uncover further research opportunities. AI and ML have the potential to significantly improve patient outcomes and advance the field of kidney care with continued collaboration and research. However, the ethical concerns of using these technologies must be addressed, and strategies must be developed to ensure their responsible use.

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