Artificial intelligence with kidney disease
A scoping review with bibliometric analysis, PRISMA-ScR
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Abstract
Background: Artificial intelligence (AI) has had a significant impact on our lives and plays many roles in various fields. By analyzing the past 30 years of AI trends in the field of nephrology, using a bibliography, we wanted to know the areas of interest and future direction of AI in research related to the kidney.

Methods: Using the Institute for Scientific Information Web of Knowledge database, we searched for articles published from 1990 to 2019 in January 2020 using the keywords AI; deep learning; machine learning; and kidney (or renal). The selected articles were reviewed manually at the points of citation analysis.

Results: From 218 related articles, we selected the top fifty with 1188 citations in total. The most-cited article was cited 84 times and the least-cited one was cited 12 times. These articles were published in 40 journals. Expert Systems with Applications (three articles) and Kidney International (three articles) were the most cited journals. Forty articles were published in the 2010s, and seven articles were published in the 2000s. The top-fifty most cited articles originated from 17 countries; the USA contributed 16 articles, followed by Turkey with four articles. The main topics in the top fifty consisted of tumors (11), acute kidney injury (10), dialysis-related (5), kidney-transplant related (4), nephrotoxicity (4), glomerular disease (4), chronic kidney disease (3), polycystic kidney disease (2), kidney stone (2), kidney image (2), renal pathology (2), and glomerular filtration rate measure (1).

Conclusions: After 2010, the interest in AI and its achievements increased enormously. To date, AIs have been investigated using data that are relatively easy to access, for example, radiologic images and laboratory results in the fields of tumor and acute kidney injury. In the near future, a deeper and wider range of information, such as genetic and personalized database, will help enrich nephrology fields with AI technology.

Abbreviations: AI = artificial intelligence, AKI = acute kidney injury, ANN = artificial neural network, CAD = computer-aided diagnosis, CKD = chronic kidney disease, GFR = glomerular filtration rate, REVOLVER = repeated evolution in cancer.

Keywords: artificial intelligence, bibliography, kidney, nephrology

1. Introduction
Artificial intelligence (AI) refers to computer algorithms designed to mimic and augment human thought patterns and actions. AIs have been highlighted in the last several years across multiple technical industry fields. Technical terms, such as artificial neural networks (ANNs), convolutional neural networks, deep learning, machine learning, and big data, are now everyday words.

AIs are used in many medical fields owing to the widespread adoption of electronic healthcare records (EHR) and the improvement of big-data storage devices in hospitals. AIs have various applications in healthcare, including drug development, health monitoring, medical-data management, disease diagnosis, and personalized treatment.[1] DXplain, Germwatcher, Babylon, and International Business Machines Corporation’s Watson Health are examples of AIs in medical fields.[1] These AI technologies enable medical practitioners to perform their jobs more conveniently and efficiently. Indeed, the possibilities for AI in medical fields are endless. In nephrology, there have been many attempts to predict the prognosis of various types of renal disease with machine learning. Studies on anemia control and arteriovenous fistula survival of hemodialysis patients, cardiovascular events, technical failure of peritoneal dialysis patients, and predicting acute kidney injuries (AKIs) were conducted.[2] After the 1990s, the ANN was used for predicting transplanted kidney survival.[3] Clinical research and guidelines are major components of the current medical area with an evidence-based medical paradigm. However, high economic burden is an obstacle to all clinical research. Data-driven medicine is one way to overcome this hurdle.

The status and growth of dominant areas in a particular field can be determined by noting frequently cited articles. Identifying important and reliable AI journals in medical fields will provide
guidelines for cultivating new areas and investigating current positions in depth. The purpose of this bibliometric-analysis study is to find the current position and future direction of AI in the field of nephrology, using the top fifty most-cited articles in terms of data-driven medicine.

2. Methods

Citations regarding AI trends in the fields of nephrology and kidney medicine were analyzed. We examined the frequency and patterns of citations using the bibliometric method, under the banner of the Web of Science (https://www.webofknowledge.com) by Clarivate Analytics. In January 2020, we collected articles published since 1990 with the following words in the title: AI; deep learning; machine learning; and kidney or renal. Next, we selected publications containing renal-specific human data and then selected the top-fifty most-cited articles according to the citation number in sequence. Review articles, editorials, and abstract-only types were excluded. Finally, we manually examined the contents of all the articles.

The characteristics of the analyzed articles were as follows: number of citations, rank, authors, title, year of publication, source titles, and topic categories. As the next step, we divided the listed articles into tertile periods using their publication order (first tertile: 1990–1999, second tertile: 2000–2009, and third tertile: 2010–2019) and reviewed the articles in the same manner. The department, institution, and country of origin were defined by the affiliation of the first author, if there was more than one affiliation.

This study did not need to obtain the approval of an ethics committee or institutional review board due to the study’s properties.

3. Results

We found 435 publications with a total of 4194 instances where the keywords were cited. Out of these, 217 were omitted because they did not have human data or kidney- or renal-oriented content (Fig. 1). When the eligible articles were analyzed in publication order by tertile period, eight articles were published before 2000. Fourteen articles were published from 2000 to 2009, and 196 articles were published from 2010 to 2019.

The trends of the topics differed in each tertile. Before 2000, the article topics were as follows: cancer (2), glomerular disease (2), AKIs (2), kidney-transplant related (1), and chronic kidney disease (CKD) (1). In the second tertile (2000–2009), the subjects of the articles were as follows: dialysis-related (5), tumors (2), AKIs (2), the glomerular filtration rate (GFR) measure (1), kidney images (1), kidney stones (1), glomerular disease (1), and transplant-related (1). During the last 10 years (2010–2019), the article topics were as follows: tumors (41), AKIs (30), kidney-transplant-related (30), dialysis-related (20), glomerular disease (17), kidney images (12), CKD (12), kidney stones (10), renal pathology (6), polycystic kidney disease (PKD) (5), drug toxicity (5), the GFR measure (4), and miscellaneous (4) (Fig. 2).

From the 218 publications, we selected the top-fifty most-cited articles and ranked them according to their citation frequency (Table 1). The top-fifty publications had 1,188 citations among them. The article with the most citations had 84 citations and the one with the fewest had 12 citations. The articles were published in 40 journals. The most-frequently cited source titles were from Expert Systems with Applications and Kidney International (three articles each). Forty articles were published in the 2010s, and seven were published in the 2000s. The top-fifty most-cited articles originated from 17 countries—the USA contributed 16 articles, followed by Turkey, which contributed 4 articles. The
articles came from five continents: North America (17), Europe (15), Asia (15), Africa (2), and Australia/Oceania (1).

Regarding institutions, the Istanbul Training and Research Hospital in Turkey contributed the most, with three articles (two articles ranked 40th, one article ranked 45th), and the Bioinformatics Institute in Singapore was next, with 2 articles (ranked 16th and 31st). Three authors were co-nominated as the top authors in the top fifty: Burak Kocak from the Istanbul Training and Research Hospital in Turkey (ranked 40th and 45th), Ran Su from the Bioinformatics Institute in Singapore (ranked 16th and 31st), and Rainer Schmidt from the University of Rostock in Germany (ranked 14th and 31st). The main topics of the top fifty articles consisted of tumors (11), AKI (10), dialysis-related (5), kidney-transplant related (4), nephrotoxicity (4), glomerular disease (4), CKD (3), PKD (2), kidney stone (2), kidney image (2), renal pathology (2), and GFR measure (1).

4. Discussion

Feasible practical uses of AI in healthcare settings include medical-image analysis, disease diagnosis, and risk and prognosis prediction, with the purpose of clarifying physicians’ decisions, not replacing the physicians themselves. The EHR enables more advanced big data. Using these with AI enables physicians to obtain information more efficiently and make more accurate diagnosis and treatment decisions. However, multi-dimensional advanced medical data are related to high computational complexity and low AI-model interoperability. The easiest method of resolving these overfitting problems is to decrease the amount of data, using feature selection and extraction approaches. This dimensionality reduction can make machine learning models simpler and more robust. Most of the articles listed here used this dimensionality reduction to make more precise models.

In the top fifty articles, AI technologies or algorithms were used to forecast kidney-damage risk, predict future disease status, and identify disease characteristics using image analysis as in Figure 3.

Ten articles were about AKI. AKI is clinically important, with extensive strong evidence for assessing mortality risk. AKI predictions through machine learning models, for example, neural networks and decision trees, are superior to those using conventional regression models. The numerous features and complex relationships of AKI could not be captured with conventional regression. Contrarily, AIs can easily handle large and complex data automatically. In these 10 articles, the supervised learning AI algorithms, such as support vector machine, decision tree, logistic regression, case-based learning, recurrent neural network, gradient-boosting machine, random forest, and naive Bayes, were used for AKI. In supervised learning, the algorithm makes a functional map from the variables to the outcomes. One study about biomarker finding used an unsupervised ANN for clustering. The reported prediction accuracies differed among the studies, owing to the study subjects, predictors, validation types, and algorithms. AKI is clinically diagnosed with serum creatinine and urine output, considering the clinical situation. This complexity might cause difficulties in finding the best-matched model. Therefore, AKI has gained significant research interest, owing to the researchers’ need to make the best-matched model.

The next topic is CKD. CKD is a major disease in nephrology with a global presence. It is related to anemia, bone disease, heart disease, body-water imbalance, and electrolyte abnormalities. CKD refers to lasting damage to the kidneys that can worsen over time. Thus, early detection and management of CKD are closely related to the patient’s quality of life and socioeconomic burden. Three of the top fifty articles were based on CKD. The topics were nutrition, diagnosis, and progression of CKD. The algorithms used were as follows: multitask temporal as transfer learning, expert systems as supervised learning, and support vector machine as supervised learning with feature selection. When AKI is severe or CKD has progressed to the end stage, renal replacement therapy is required. In an aging society, it is necessary to consider CKD and its complications. Although the subject comprised only 13 articles out of 218 overall, CKD would be a good topic for AI research.

Five articles in the top fifty dealt with dialysis. To determine the dialysis adequacy, algorithms with multilayer perceptrons and iterative dichotomiser 3 as reinforcement learning and ANN as supervised learning were used. For anemia correction and dose-adjusting erythropoietin, a Markov decision process, fitted Q iteration, Q learning, k-means, dose selection, and ANN were used as reinforcement. For kidney transplantation, three articles dealt with graft function and rejection using Bayesian belief networks, support vector machines, linear discriminant analysis, logistic regression, decision trees, and random forest as supervised learning. One article about cardiovascular risk in transplant patients used expert systems and neural networks. Renal replacement therapy, such as dialysis and transplantation, is also a promising topic in terms of anemia correction, dialysis adequacy, phosphate control, graft survival, and many related complications.

Drug toxicity in the kidneys is related to many complications, including AKI and CKD. Four articles in the top fifty dealt with nephrotoxicity. A library for support vector machines, random forest, feature elimination, C5.0 trees, extreme gradient boosting, and k-NN classifiers as supervised learning, was used for model development. In the field of nephrotoxicity, genetic data may be helpful for concise prediction models if possible. Two articles dealt with kidney stones. One was about kidney-stone diagnosis using a fuzzy expert system on various clinical values. The other was about the possibility of a spontaneous kidney-stone passage with an ANN and support vector machine.
| Rank | Title                                                                 | 1st author           | Institute/ Nationality                | Source titles                           | Publication year | No. of citations |
|------|-----------------------------------------------------------------------|----------------------|--------------------------------------|-----------------------------------------|-----------------|-----------------|
| 1    | Pattern analysis of serum proteome distinguishes renal cell carcinoma from other urologic diseases and healthy persons | Yonggwan Won         | Chonnam National University Medical School/ South Korea | Proteomics                              | 2003            | 84              |
| 2    | Defining cell-type specificity at the transcriptional level in human disease | Wenjun Ju            | University of Michigan/ USA           | Genome research                         | 2013            | 83              |
| 3    | Fast neural network learning algorithms for medical applications      | Ahmed Taher Azar     | Mar University for Science and Technology/ Egypt | Neural computing and applications       | 2013            | 61              |
| 4    | Application of irregular and unbalanced data to predict diabetic nephropathy using visualization and feature selection methods | Baek Heon Cho        | Hangyoun University/ South Korea      | Artificial intelligence in medicine     | 2008            | 55              |
| 5    | Prediction of drug-induced nephropathy and injury mechanisms with human induced pluripotent stem cell-derived cells and machine learning methods | Karthikeyan Kandasamy | Institute of Bioengineering and NanoTechnology/ Singapore | Scientific reports                      | 2015            | 40              |
| 6    | Texture analysis as a radiomic marker for differentiating renal tumors | HeShiun Yu           | Boston Medical Center/ USA            | Abdominal radiology                     | 2007            | 34              |
| 7    | Application of Machine Learning Techniques to High-Dimensional Clinical Data to Forecast Postoperative Complications | Paul Thottanvar        | University of Rorida/ USA            | Nephrolgy                               | 2016            | 32              |
| 8    | Incorporating temporal EHR data in predictive models for risk stratification of renal function deterioration | Anima Singh          | Massachusetts Institute of Technology/ USA | Journal of Biomedical Informatics       | 2015            | 31              |
| 10   | Machine learning-based quantitative tissue analysis of CT images of small renal masses: Differentiation of angiosarcoma without visible fat from renal cell carcinoma | Zhizhao Feng         | Central South University/ China       | European radiology                      | 2018            | 28              |
| 11   | The Development of a Machine Learning Inpatient Acute Kidney Injury Prediction Model | Kayner Jay L.        | University of Chicago/ USA           | Critical care medicine                  | 2018            | 26              |
| 12   | Prediction and detection models for acute kidney injury in hospitalized older adults | Rohit J. Kate        | University of Wisconsin-Milwaukee/ USA | BMC medical informatics and decision making | 2016            | 26              |
| 13   | Constructing a nutrition diagnosis expert system | Yuchuan Chen         | Taipei Medical University/ Taiwan     | Expert Systems With Applications        | 2012            | 25              |
| 14   | The Pattern of Longitudinal Change in Serum Creatinine and 90-Day Mortality After Major Surgery | Dimitry Kolesnikov    | University of Rorida/ USA            | Annuals Of Surgery                      | 2016            | 24              |
| 15   | Medical multiparameter time course processes applied to kidney function assessments | Rainer Schmidt       | University of Rorida/ Germany         | International Journal Of Medical Informatics | 1999 | 24 |
| 16   | High-throughput imaging-based nephropathy prediction with diverse chemical structures | Rain Su              | Bioinformatics Institute/ Singapore   | Archives of Toxicology                   | 2016            | 23              |
| 16   | Incidence, risk factors and prediction of post-operative acute kidney injury following cardiac surgery for active infective endocarditis: an observational study | Matthew Legrand       | Uniñverstite Paris Descartes/ France  | Critical Care                           | 2013            | 23              |
| 16   | Evolving convension system versus algebraic formulas for prediction of renal function from serum creatinine | Mark Roger Marshall   | Auckland University of Technology/ New Zealand | Kidney International                    | 2005            | 23              |
| 17   | Assessing rejection-related disease in kidney transplant biopsies based on archetypal analysis of molecular phenotypes | Jeff Reeve           | University of Alberta/ Canada         | JCI insight                             | 2017            | 22              |
| 18   | Deep Semantic Analysis of Kidney and Space-Occupying Lesion Area Based on SSN and PerNet Models Combined with SIFT-Flow Algorithm | Kai-jun Xia          | China University of Mining and Technology/ China | Journal Of Medical Systems            | 2019            | 21              |
| 19   | An end stage kidney disease predictor based on an artificial neural networks ensemble | Tommaso Di Nata      | PediaSichina University of Basel/ Italy | Expert Systems with applications        | 2013            | 21              |
| 20   | Detecting repeated cancer evolution from multigenre tumor sequencing data | Giulio Garagnagna    | Institute of Cancer Research/ UK      | Nature Methods                          | 2018            | 20              |
| 21   | Performance of an Artificial Multi-observer Deep Neural Network for Fully Automated Segmentation of Polycystic Kidney | Timothy L. Kline     | Mayo Clinic College of Medicine/ USA  | Journal of Digital Imaging              | 2017            | 20              |
| 22   | Automatic Segmentation of Kidneys using Deep Learning for Total Kidney Volume Quantification in Autosomal Dominant Polycystic Kidney Disease | Kanika Sharma        | IRCCS-Instituto di Ricerche Farmacologiche Mario Negri/ Italy | Scientific Reports                     | 2017            | 20              |
| 25   | Bayesian Modeling of Pretransplant Variables Accurately Predicts Kidney Graft Survival | Brown T.S.           | Naval Medical Research Center/ USA    | American Journal of Nephrology          | 2012            | 19              |
| 26   | Classification strategies for the grading of renal cell carcinomas, based on nuclear morphometry and denstometry | Christine François   | Université Libre de Bruxelles/ Belgium | Journal of Pathology                    | 1997            | 18              |
| 27   | ADME/ Evaluation in Drug Discovery. 18. Reliable Prediction of Chemical-Induced Urinary Tract Toxicity by Using Machine Learning-Approaches | Tailong Lei          | Zhejiang University/ China           | Molecular Pharmaeutics                   | 2017            | 18              |
| 28   | A medical decision support system for disease diagnosis under uncertainty | Belal Malik           | Kansas State University/ USA          | Expert Systems With Applications        | 2017            | 17              |
| 28   | Diagnosis of Chronic Kidney Disease Based on Support Vector Machine by Feature Selection Methods | Huseyin Pirat        | Gaz University/ Turkey                | Journal of medical systems              | 2017            | 17              |
| 28   | Artificial intelligence: A new approach for prescription and monitoring of hemodialysis therapy | Ahmed I. A.          | Mansoura University/ Egypt            | American Journal of Kidney Diseases     | 2001            | 17              |
| 31   | A clinically applicable approach to continued prediction of future acute kidney injury | Neda Tomljen           | DeepMind/ UK                         | Nature                                   | 2019            | 16              |
| 31   | Quantitative Ultrasound for Measuring Obstructive Severity in Children with Hydronephrosis | Juan J. Gerolaza    | Children’s National Health System/ USA | Journal of urology                      | 2016            | 16              |
| 31   | Prediction of delayed graft function after kidney transplantation: comparison between logistic regression and machine learning methods | Alexander Decuyensare | Ghent University Hospital/ Belgium   | BMC medical informatics and decision making | 2016 | 16 |
| Rank | Title                                                                 | 1st author         | Institute/ Nationality                       | Source titles                  | Publication year | No. of citations |
|------|-----------------------------------------------------------------------|--------------------|----------------------------------------------|-------------------------------|-----------------|-----------------|
| 31   | Supervised prediction of drug-induced nephrotoxicity based on interleukin-6 and-8 expression levels | Ran Su             | Bioinformatics Institute / Singapore         | BMC bioinformatics            | 2014            | 16              |
| 31   | A prognostic model for temporal courses that combines temporal abstraction and case-based reasoning | Rainer Schmidt     | Universitat Rostock / Germany                | International Journal Of Medical Informatics | 2005            | 16              |
| 31   | Cardiac risk stratification in renal transplantation using a form of artificial intelligence | Thomas F Heston    | Oregon Health Sciences University / USA      | American Journal Of Cardiology | 1997            | 16              |
| 31   | Computer aided detection of exophytic renal lesions on non-contrast CT images | Jianfei Liu        | National Institutes of Health Clinical Center / USA | Medical Image Analysis        | 2015            | 15              |
| 31   | Optimization of anemia treatment in hemodialysis patients via reinforcement learning | Pablo Escandell-Montero | University of Valencia / Spain | Artificial intelligence in medicine | 2014            | 15              |
| 31   | A novel approach for accurate prediction of spontaneous passage of ureteral stones: Support vector machines | F DalMore          | University of Padova / Italy                 | Kidney International          | 2006            | 15              |
| 37   | Decision tree and random forest models for outcome prediction in antibody incompatible kidney transplantation | Torgyn Shaikhina   | University of Warwick / UK                  | Biomedical Signal Processing And Control | 2019            | 14              |
| 37   | Radiogenomics in Clear Cell Renal Cell Carcinoma: Machine Learning-Based High-Dimensional Quantitative CT Texture Analysis in Predicting PBRM1 Mutation Status | Burak Kocak       | Istanbul Training and Research Hospital / Turkey | American Journal Of Roentgenology | 2019            | 14              |
| 37   | Clear Cell Renal Cell Carcinoma: Machine Learning-Based Quantitative Computed Tomography Texture Analysis for Prediction of Fuhrman Nuclear Grade | Ceyda Tunur Bektas | Istanbul Training and Research Hospital / Turkey | European Radiology            | 2019            | 14              |
| 40   | Development of Biomarker Models to Predict Outcomes in Lupus Nephritis | Bethany J. Wolf    | Medical University of South Carolina / USA   | Arthritis & Rheumatology      | 2016            | 14              |
| 40   | Ratsnake: A Versatile Image Annotation Tool with Application to Computer-Aided Diagnosis | D.K. Isakudis      | Technological Educational Institute of Lamia / Greece | Scientific World Journal      | 2014            | 14              |
| 45   | Textural differences between renal cell carcinoma subtypes: Machine learning-based quantitative computed tomography texture analysis with independent external validation | Burak Kocak       | Istanbul Training and Research Hospital / Turkey | European Journal Of Radiology | 2018            | 13              |
| 45   | An international observational study suggests that artificial intelligence for clinical decision support optimizes anemia management in hemodialysis patients | Caro Barberi       | Fresenius Medical Care / Germany             | Kidney International          | 2016            | 13              |
| 45   | Efficient Small Blob Detection Based on Local Convexity, Intensity and Shape Information | Min Zhang          | Mayo Clinic / USA                           | IEEE transactions on medical imaging | 2016            | 13              |
| 48   | Calibration drift in regression and machine learning models for acute kidney injury | Sharon E Davis     | Vanderbilt University School of Medicine / USA | Journal of the American medical informatics association Medical Physics | 2017            | 12              |
| 48   | Differentiation of fat-poor angiomyolipoma from clear cell renal cell carcinoma in contrast-enhanced MDCT images using quantitative feature classification | Han Sang Lee       | Korea Advanced Institute of Science and Technology / South Korea | Medical Physics | 2017            | 12              |
| 48   | Application of rough set classifiers for determining hemodialysis adequacy in ESRD patients | You-Shyang Chen    | Hwa Hwa Institute of Technology / Taiwan    | Knowledge And Information Systems | 2013            | 12              |

CT = computed tomography, ESRD = End stage renal disease, IEEE = Institute of Electrical and Electronics Engineers, MDCT = Multi Detector Computed Tomography, SCNN = Siamese Convolutional neural network.
The AIs in most of these articles were based on supervised learning. Documented results and those gained from experience supported various types of decision-support systems.

For image analysis, computer-aided diagnosis (CAD) was applied. The key to CAD is the combination of medical and computer image processing to appreciate the image characteristics.[11] Kidney tumors are categorized as cancerous (clear cell, papillary, chromophobe, cystic renal cell carcinoma, Wilms tumor, etc.) and non-cancerous lesions (angiomyolipoma, oncocytoma, etc.). Kidney tumors are sometimes associated with genetic diseases. In addition, it is especially difficult to confirm the diagnosis using an invasive diagnostic method, such as biopsy because of its diagnostic yield rates and complications. Hence, knowing the kidney-tumor subtype is essential for deciding on a treatment plan. There were 11 tumor-related articles within the top fifty. Most of these articles dealt with cancer diagnosis using images. The remainder were about cancer proteomes and genes. Depending on the study characteristics, decision trees, support vector machines, sparse convolutional neural networks, multilayer perceptron, naïve Bayes, k-nearest neighbor, and belief propagation models were used as supervised learning means. Feature selection and extraction were used for dimensionality reduction. One study on cancer genes used a learning means. Feature selection and extraction were used for dimensionality reduction. The remaining were recurrent neural networks and sparsity.

The remaining topics included kidney anatomy, PKD, and renal pathology. Specifically, two articles were about kidney anatomy. A Hessian-based difference of Gaussians, as unsupervised learning, was used for finding glomeruli with magnetic resonance imaging. Quantitative image analysis and a support vector machine were used to detect hydronephrosis by means of supervised learning. Two articles dealt with PKD. The cyst size was measured using convolutional neural networks and semantic mapping as supervised learning, and feature extraction was used for dimensionality reduction.

For renal pathology, one article was about clustering renal transplant-rejection pathology with archetypal analysis and principal component analysis. The other was about CAD using Ratsnake,[13] a publicly available generic image-annotation tool, based on gradient vector-field[14] and boundary vector-field models.[15] In this field, other relevant generic image-annotation tools, for example, LabelMe, Photostuff, Phitocopyain, K-space annotation tool, and graphic annotation tool, were nominated as other methods.

In general, machine learning has been applied to various problems in many studies, for example, classifying subjects, searching for associations between variables, finding objects with similar patterns, and predicting risks and results based on basic characteristics. In diagnostic and therapeutic areas, AIs can help quickly detect risks, precisely predict prognoses, and enhance the accuracy of the final diagnoses to support proper management of diseases in various medical fields. The nephrology field is no exception.

As the kidneys play an important role in homeostasis, kidney diseases might be related to other organ disorders. At times, the opposite might occur, for example, systemic dysfunctions might affect kidney disorders. Most kidney diseases have complicated and overlapping multifactorial clinical phenotypes.[16] This could lead to mistakes and missed diagnoses, leading to late diagnoses and disease progression. In addition, the high prevalence and low awareness of kidney diseases sometimes make early diagnoses with intervention impossible, if the resources show inadequate features.[17] AIs can help physicians reduce these shortcomings and reinforce personalized medicine to help preserve the kidneys.

Our study has some limitations due to the bibliometric study itself. The results of a citation analysis can change depending on the research time. Moreover, it cannot reflect the most recent status, owing to lead-time bias. However, we can check the current status and trends of AI in nephrology and matters for nephrologists’ concern during the last 30 years, through the top fifty most-cited articles. AIs’ flexibility and learning capability can help clinicians’ decision-making processes. Adequately used AI models allow for more plentiful data with reliable prediction of disease outcomes.

Compared to the past, interest in and studies about AI increased considerably during the 2010s. Previously, AI algorithms were investigated using relatively easy-to-access data, for example, radiologic images and laboratory results. A deeper and wider range of statistical and reference data will enable the use of AI in the diverse fields of nephrology. Currently, many nephrologists, bio-informaticists, and computer engineers are trying to develop more precise and concise AI models using novel advanced algorithms. These efforts will help improve kidney health in the near future. With this bibliometric analysis, the former common interest of AI such as AKI and tumor will be the source for concrete and accurate machine learning models that will be developed by many researchers. In addition, less highlighted items (CKD, kidney transplant, etc.) would be relatively good subjects for rising and new researchers.

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References

[1] Amisha PM, Pathania M, Rathaur VK. Overview of artificial intelligence in medicine. J Family Med Prim Care 2019;8:2328–31.
[2] Burlacu A, Iftene A, Jugrin D, et al. Using artificial intelligence resources in dialysis and kidney transplant patients: a literature review. Biomed Res Int 2020;2020:9867872.
[3] Diez-Sanmartin C, Sarasa Cabezuelo A. Application of artificial intelligence techniques to predict survival in kidney transplantation: a review. J Clin Med 2020;9:572.
[4] Shortliffe EH, Sepulveda MJ. Clinical decision support in the era of artificial intelligence. JAMA 2018;320:2199–200.
[5] Obermeyer Z, Lee TH. Lost in thought: the limits of the human mind and the future of medicine. N Engl J Med 2017;377:1209.
[6] Yang C, Kong G, Wang L, et al. Big data in nephrology: are we ready for the change? Nephrology 2019;24:1097–102.
[7] Group Kdigoakiw. KDIGO clinical practice guideline for acute kidney injury. Kidney Int Suppl 2012;2:1–38.
[8] Zhang Z. Machine learning method for the management of acute kidney injury: more than just treating biomarkers individually. In: Future Medicine; 2019;13:1251–3.
[9] Kellum JA, Bihorac A. Artificial intelligence to predict AKI: is it a breakthrough? Nat Rev Nephrol 2019;15:663–4.
[10] Chang C-C, Lin C-J. LIBSVM: a library for support vector machines. ACM transactions on intelligent systems and technology (TIST) 2011;2:1–27.
[11] Yuan Q, Zhang H, Deng T, et al. Role of artificial intelligence in kidney disease. International Journal of Medical Sciences 2020;17:970.
[12] Caravagna G, Giarratano Y, Ramazzotti D, et al. Detecting repeated cancer evolution from multi-region tumor sequencing data. Nat Methods 2018;15:707–14.
[13] Iakovidis DK, Smailes CV. Efficient semantically-aware annotation of images. Paper presented at: 2011 IEEE International Conference on Imaging Systems and Techniques 2011.
[14] Xu C, Prince JL. Snakes, shapes, and gradient vector flow. IEEE Trans Image Process 1998;7:359–69.
[15] Sum K, Chung PY. Boundary vector field for parametric active contours. Pattern Recognition 2007;40:1635–45.
[16] Saez-Rodriguez J, Rinschen MM, Floege J, et al. Big science and big data in nephrology. Kidney international 2019;95:1326–37.
[17] Xie G, Chen T, Li Y, et al. Artificial intelligence in nephrology: how can artificial intelligence augment nephrologists’ intelligence? Kidney Dis 2020;6:1–6.