

EDITORIAL

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How artificial intelligence is transforming nephrology

Miguel Hueso^{1,2*} and Alfredo Vellido^{3,4*}

Abstract

Current research in nephrology is increasingly focused on elucidating the complexity inherent in tightly interwoven molecular systems and their correlation with pathology and related therapeutics, including dialysis and renal transplantation. Rapid advances in the omics sciences, medical device sensorization, and networked digital medical devices have made such research increasingly data centered. Data-centric science requires the support of computationally powerful and sophisticated tools able to handle the overflow of novel biomarkers and therapeutic targets. This is a context in which artificial intelligence (AI) and, more specifically, machine learning (ML) can provide a clear analytical advantage, given the rapid advances in their ability to harness multimodal data, from genomic information to signal, image and even heterogeneous electronic health records (EHR). However, paradoxically, only a small fraction of ML-based medical decision support systems undergo validation and demonstrate clinical usefulness. To effectively translate all this new knowledge into clinical practice, the development of clinically compliant support systems based on interpretable and explainable ML-based methods and clear analytical strategies for personalized medicine are imperative. Intelligent nephrology, that is, the design and development of AI-based strategies for a data-centric approach to nephrology, is just taking its first steps and is by no means yet close to its *coming of age*. These first steps are not even homogeneously taken, as a digital divide in access to technology has become evident between developed and developing countries, also affecting underrepresented minorities. With all this in mind, this editorial aim to provide a selective overview of the current use of AI technologies in nephrology and heralds the “Artificial Intelligence in Nephrology” special issue launched by BMC Nephrology.

Keywords Artificial Intelligence, Machine learning, Data Science, Digital Pathology, Large Language models, Bioengineered organs, Digital Twins, Nephrology, Precision Medicine, Ethics

*Correspondence:

Miguel Hueso
mhueso@idibell.cat
Alfredo Vellido
avellido@cs.upc.edu

¹Department of Nephrology, Hospital Universitari Bellvitge and Bellvitge Research Institute (IDIBELL), L'Hospitalet de Llobregat, C/Feixa lllarga, s/n, Barcelona 08907, Spain

²BigData and Artificial Intelligence Group (BigSEN Working Group) from the Spanish Society of Nephrology (SENEFRO), Santander, Spain

³Intelligent Data Science and Artificial Intelligence (IDEAI) Research Center, Universitat Politècnica de Catalunya (UPC BarcelonaTech), C. Jordi Girona, 1-3, 08034 Barcelona, Spain

⁴Centro de Investigación Biomédica en Red (CIBER), Santander, Spain



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Introduction

Over the last few decades, Data Science (DS) has become central to clinical medicine due to the intense digitalization of clinical space, including at the point of care. Digitally acquired medical data and their use in the structured form of electronic health records (EHR) are part of the medical DS ecosystem, along with integrated medical domain knowledge (protocols, guidelines, etc.) and data analysis methods from multivariate statistics and, increasingly, artificial intelligence (AI), mostly in the form of machine learning (ML). These technologies efficiently sift through enormous volumes of health data, ranging from EHR and clinical studies to genetic information, in diverse formats (including but not limited to signals, images and text) and analyze them faster and more systematically than humans. Cancer research has been at the forefront of the use of AI and ML in medicine and clinical practice, particularly in personalized and precision medicine [1], but this topic is rapidly spreading toward other areas of medical research, including nephrology.

Another area benefiting from DSs is medical expert communication with patients. Poor communication is a handicap in the relationship between patients and medical doctors, especially when contemporary healthcare prioritizes the speed and quantity of patients visited rather than the quality of care. In that context, AI approaches to natural language processing (NLP) are becoming a research focus due to the emergence of deep learning (DL)-based large language models (LLMs), which have the potential to facilitate communication by providing specific information about diagnosis and treatment options and adapting communication with patients according to their cultural level using nontechnical language. Additionally, healthcare organizations are beginning to trust AI to improve the efficiency of various processes, from back-office tasks to patient care.

Despite the continuous and rapid evolution of this field, we present some potential applications of DSs in nephrology where we expect to publish significant contributions in this collection. These include but are not limited to:

1) **Omics analysis** to identify genetic variants associated with kidney diseases and study disease progression and treatment responses. Late diagnoses often result from the multifactorial cause of kidney damage with complex and overlapping phenotypes. While many genes involved in kidney diseases are used in clinical management, the combination of omics with AI in clinical diagnostics and patient care still lacks sufficient evidence [2].

2) **Personalized and precision medicine**, where Clinical Decision Support Systems (CDSS) and predictive analytic models integrate molecular data with medical history and lifestyle factors, can identify individuals' risk

of disease and promote tailored treatments. For instance, the **iBox scoring system** predicts kidney transplant outcomes by integrating multiple features to reflect graft function and the immunologic response (<https://www.predict4health.com/ibox>). The iBox, with a concordance statistic (C-Stat) of 0.81, can aid in decision-making on organ allocation or in clinical trial design. Predigraft (<https://www.predict4health.com/solution/doctors>) and the UNOS Organ Transplant Tracking Record (<https://unos.org/solutions/organ-tracking>) were approved by the European Medicines Agency (EMA) in June 2021 [3]. **Personalized dialysis** also takes advantage of increasingly sophisticated monitoring systems to analyze vital signs and detect early signs of fluid overload, electrolyte imbalance, and medication adherence using wearable devices and smartphone apps [4].

3) **Digital pathology (DP) and AI**. The digitalization of pathology slides allows pathologists to examine high-resolution images on computers, enabling advanced analysis. AI-based image analysis enhances diagnostic precision, reduces interobserver variability and improves the consistency of pathology reports. However, challenges include image analysis variety, staining and scanning variations across sites, and biological variance [5].

4) **Use in drug discovery, development and pharmacovigilance** to identify potential drug candidates, predict their efficacy, avoid unnecessary clinical trials and detect adverse drug effects to prevent them.

5) **Healthcare operations and resource optimization**. Analyzing data on patient flow, resource utilization and other factors helps healthcare facilities improve efficiency and reduce costs.

However, several identified barriers hinder the widespread adoption and effective implementation of DS strategies in healthcare. Thus, there is interest in addressing the following topics. (1) **Data privacy and security concerns** about sharing information, along with regulatory and legal barriers. (2) **Data fragmentation and interoperability issues**, as healthcare data are often stored in disparate systems and formats, making it challenging to integrate and exchange information seamlessly. (3) **Data quality and accuracy** are key factors in the reliability and effectiveness of data-driven healthcare initiatives. (4) **Limited access to data and data silos** might hinder analytical approaches. (5) **Resource constraints**, as implementing data-driven healthcare initiatives, require significant investments in technology infrastructure, data analytic tools, workforce training and ongoing support. Finally, (6) **Resistance to change** among healthcare professionals and stakeholders can impede the adoption of data-driven practices and technologies.

In parallel to these barriers, we cannot ignore the existence of a digital divide in access to the data-centric technologies fueling the success of AI applications in the

medical domain that has become increasingly evident between developed and developing countries, also affecting underrepresented minorities [6]. The response to the recent COVID19 pandemic has further exposed these weaknesses and technological gaps in global health. It is important though to realize that many AI-based developments of interest to this medical domain are not proprietary and, instead, build on open-source software initiatives, making them globally accessible [7]. A number of potential solutions to the digital divide in healthcare have been broached by Anita Makri in Lancet [8]. Additionally, building on eHealth and mHealth technologies and services has been proven to be useful to increase the reach of healthcare delivery [9].

Future trends

The following decade is likely to provide advances in several emerging technologies with great potential impacts on nephrology, among which we foresee the emergence of the following:

1) **Digital twins (DTs)**, which are direct digital representations of individual patients created from comprehensive biological data, offer personalized insights into disease onset and progression [10]. Nephrologists can use DTs to simulate highly accurate models of patient renal function and disease processes, enabling targeted interventions and treatment plans. DTs can model complex diseases such as chronic kidney disease, dialysis, or renal transplantation. Integration with generative adversarial networks (GANs) can simulate realistic randomized clinical trials using synthetic data [11]. The benefits of DT include the following: (i) personalized disease models, (ii) disease progression prediction, (iii) optimization of dialysis and transplantation, and (iv) enhanced research and development.

2) **Innovations in Personalized Medicine and Nanotechnology** AlphaFold2 [12], developed by the Google DeepMind AI Lab, has overcome the difficulty of predicting protein 3D structures from amino acid sequences with high accuracy. This breakthrough has implications for nanotechnology, particularly in nanobiotechnology, by enabling synthetic biology to tailor proteins with specific shapes and functions. This capability is crucial for creating nanoscale devices, sensors and targeted drug delivery systems.

3) **Bioengineered organs**. Organoids and organs-on-chips are miniature in vitro model systems that mimic organ structure and function. They have potential applications in disease modeling, drug screening, personalized medicine and tissue engineering. AI-enabled organoids could lead to improved understanding of organ development and disease progression [13].

4) **Generative AI (GAI) tools** offer better predictive performance, simpler model development and

more cost-effective deployment, potentially automating and facilitating the work of clinicians [14]. The GAI can relieve medical experts from unproductive tasks, allowing more time for patient care. However, concerns abound about their reliability and tendency to generate “hallucinations” (and therefore about their lack of robustness) and about the generation of incorrect responses due to insufficient information.

5) **Interactive AI and autonomous software** can execute tasks by orchestrating various software components [15]. Automated AI algorithms, such as those under the AutoML concept, may improve nephrologists’ capabilities through training but could also reduce autonomous skills due to lack of practice or decreased attention. Transparency is essential for fostering trust in automated medical AI systems.

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Data availability

No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

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Competing interests

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References

1. Jang Y, Choi T, Kim J, Park J, Seo J, Kim S, Kwon Y, Lee S. An integrated clinical and genomic information system for cancer precision medicine. *BMC Med Genomics*. 2018;11(Suppl 2):34. <https://doi.org/10.1186/s12920-018-0347-9>.
2. Grobe N, Scheiber J, Zhang H, Garbe C, Wang X. Omics and Artificial Intelligence in kidney diseases. *Adv Kidney Dis Health*. 2023;30(1):47–52. <https://doi.org/10.1053/jakdh.2022.11.005>.
3. Klein A, Loupy A, Stegall M, Helanterä I, Kosinski L, Frey E, Aubert O, Divard G, Newell K, Meier-Kriesche HU, Mannon RB, Dumortier RB, Aggarwal T, Podichetty V, O’Doherty JT, Gaber I, Fitzsimmons A. And Transplant Therapeutics Consortium. Qualifying a novel clinical trial endpoint (iBOX) predictive of long-term kidney transplant outcomes. *Am J Transpl*. 2023;23(10):1496–506. <https://doi.org/10.1016/j.ajt.2023.04.018>.
4. Hueso M, Vellido A, Montero N, Barbieri C, Ramos R, Angoso M, Cruzado JM, Jonsson A. Artificial Intelligence for the Artificial kidney: pointers to the future of a personalized hemodialysis therapy. *Kidney Dis (Basel)*. 2018;4(1):1–9. <https://doi.org/10.1159/000486394>.

5. Feng C, Liu F. Artificial intelligence in renal pathology: current status and future. *Biomol Biomed*. 2023;23(2):225–34. <https://doi.org/10.17305/bjbms.2022.8318>.
6. Van Dijk J, Hacker K. The digital divide as a complex and dynamic phenomenon. *Inf Soc*. 2023;19(4):315–26. <https://doi.org/10.1080/01972240309487>.
7. Hueso M, de Haro L, Calabria J, Dal-Ré R, Tebé C, Gibert K, Cruzado JM, Vellido A. *Kidney Dis*. 2020;6(6):385–94. <https://doi.org/10.1159/000507291>. Leveraging Data Science for a Personalized Haemodialysis.
8. Makri A. Bridging the digital divide in health care. *Lancet: Digit Health*. 2019. [https://doi.org/10.1016/S2589-7500\(19\)30111-6](https://doi.org/10.1016/S2589-7500(19)30111-6).
9. Armao M, Araviaki E, Musikanski L. eHealth and mHealth interventions for ethnic minority and historically underserved populations in developed countries: an umbrella review. *Int J Community Well-Being*. 2020;3(2):193–221. <https://doi.org/10.1007/s42413-019-00055-5>.
10. Viceconti M, De Vos M, Mellone S, Geris L. Position paper from the digital twins in healthcare to the virtual human twin: a moon-shot project for digital health research. *IEEE J Biomed Health Inf*. 2023. <https://doi.org/10.1109/JBHI.2023.3323688>.
11. Thangaraj PM, Shankar SV, Huang S, Nadkarni G, Mortazavi B, Oikonomou EK, Khera RA. Novel Digital Twin Strategy to Examine the Implications of Randomized Control Trials for Real-World Populations. *medRxiv* 2024. <https://doi.org/10.1101/2024.03.25.24304868>
12. Tunyasuvunakool K, Adler J, Wu Z, Green T, Zielinski M, Židek A, Bridgland A, Cowie A, Meyer C, Laydon A, Velankar S, Kleywegt GJ, Bateman A, Evans R, Pritzel A, Figurnov M, Ronneberger O, Bates R, Kohl SAA, Potapenko A, Ballard AJ, Romera-Paredes B, Nikolov S, Jain R, Clancy E, Reiman D, Petersen S, Senior AW, Kavukcuoglu K, Birney E, Kohli P, Jumper J, Hassabis D. Highly accurate protein structure prediction for the human proteome. *Nature*. 2021;596(7873):590–6. <https://doi.org/10.1038/s41586-021-03828-1>.
13. Bai L, Wu Y, Li G, Zhang W, Zhang H, Su J. AI-enabled organoids: construction, analysis, and application. *Bioact Mater*. 2024;31:525–48. <https://doi.org/10.1016/j.bioactmat.2023.09.005>.
14. Raza MM, Venkatesh KP, Kvedar JC. Generative AI and large language models in health care: pathways to implementation. *NPJ Digit Med*. 2024;7(1):62. <https://doi.org/10.1038/s41746-023-00988-4>.
15. Bitterman DS, Aerts HJWL, Mak RH. Approaching autonomy in medical artificial intelligence. *Lancet Digit Health*. 2020;2(9):e447–9. [https://doi.org/10.1016/S2589-7500\(20\)30187-4](https://doi.org/10.1016/S2589-7500(20)30187-4).

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