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REVIEW ARTICLE

Applications of Artificial Intelligence in Kidney Transplantation: A Scoping Review across the *Continuum* of Care

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ABSTRACT

Objectives: To map the scientific literature on the application of artificial intelligence (AI) in the kidney transplantation process, identifying its main uses, the stages of care in which these applications are concentrated, and the outcomes and processes they aim to influence. **Methods:** A scoping review was conducted and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews guidelines. The search was performed in the Scopus database using terms related to AI and kidney transplantation, covering publications from 2019 to 2023. Peer-reviewed empirical studies applying AI at any stage of the kidney transplantation process were included. Study selection followed a screening and eligibility process, and the included studies were analyzed using inductive content analysis with iterative categorization of applications, stages of care, and investigated outcomes. **Results:** A total of 181 studies were included. AI applications were organized into seven categories: prediction of patient behavior; radiological and pathological assessment; prediction of pre-transplant kidney disease progression; prediction of donor-recipient compatibility; optimization of immunosuppressive drug administration; diagnosis of post-transplant complications; and prediction of graft survival. Applications were predominantly concentrated in the post-transplant phase (65.7%), followed by studies spanning both pre- and post-transplant phases (24.3%), while the pre-transplant phase accounted for 9.9% of publications. Overall, the studies aimed to influence outcomes related to early detection of complications, risk stratification, therapeutic optimization, and graft survival. **Conclusion:** The literature shows growing and heterogeneous applications of AI in kidney transplantation, with a strong focus on diagnostic and predictive tasks in the post-transplant period and important gaps in the pre-transplant phase and in behavioral dimensions of care. This mapping provides an integrated overview of the field and may support researchers, clinicians, and healthcare managers in identifying opportunities for the development and implementation of AI-based solutions across the kidney transplantation care *continuum*.

Descriptors: Kidney Transplantation; Artificial Intelligence; Machine Learning; Scoping Review.

Aplicações da Inteligência Artificial no Transplante Renal: Uma Revisão de Escopo ao Longo do Continuum do Cuidado

RESUMO

Objetivos: Mapear a literatura científica sobre aplicações de inteligência artificial (IA) no processo de transplante renal, identificando os principais usos, as etapas do cuidado em que se concentram e os desfechos e processos que buscam influenciar. **Métodos:** Foi realizada uma revisão de escopo, reportada conforme o Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews. A busca foi realizada na base Scopus, com termos relacionados à IA e ao transplante renal, contemplando publicações no período de 2019 a 2023. Foram incluídos estudos empíricos revisados por pares que aplicassem IA em qualquer fase do transplante renal. A seleção foi realizada por triagem e elegibilidade, e os estudos incluídos foram analisados por meio de análise de conteúdo indutiva, com categorização iterativa das aplicações, fases do cuidado e desfechos investigados. **Resultados:** Foram incluídos 181 estudos. As aplicações de IA foram organizadas em sete categorias: previsão de comportamentos do paciente; avaliação radiológica e patológica; previsão de progressão da doença renal pré-transplante; previsão de compatibilidade doador-receptor; otimização da administração de medicamentos imunossupressores; diagnóstico de complicações pós-transplante; e previsão de sobrevivência do enxerto. Observou-se a predominância de aplicações no pós-transplante (65,7%), seguida por estudos que abrangem pré- e pós-transplante (24,3%); a fase pré-transplante concentrou 9,9% das publicações. De modo geral, os estudos buscaram influenciar desfechos relacionados à detecção precoce de complicações, estratificação de risco, otimização terapêutica e sobrevida do enxerto. **Conclusão:** A literatura evidencia crescimento e heterogeneidade nas aplicações de IA no transplante renal, com forte concentração em tarefas diagnósticas e preditivas no período pós-transplante e lacunas relevantes na fase pré-transplante e em dimensões comportamentais do cuidado. O mapeamento oferece uma visão integrada do campo e pode apoiar pesquisadores, clínicos e gestores na identificação de oportunidades para o desenvolvimento e a incorporação de soluções de IA ao longo do *continuum* do transplante renal.

Descritores: Transplante Renal; Inteligência Artificial; Aprendizado de Máquina; Revisão de Escopo.

INTRODUCTION

Chronic kidney disease constitutes a significant global public health problem, imposing a high clinical and economic burden on healthcare systems. For patients with end-stage renal disease, kidney transplantation represents the therapy of choice, providing greater survival and better quality of life compared to dialysis, as well as greater long-term cost-effectiveness[1-3]. However, despite these benefits, the kidney donation and transplantation process is marked by high clinical, logistical, and organizational complexity[2,4].

Among the main challenges are the scarcity of available organs, the need for immunological compatibility between donor and recipient, the time constraint between organ procurement and implantation, as well as the risk of postoperative complications and graft rejection[4]. Even after a successful transplant, graft failure remains a significant problem, with substantial rates of organ loss occurring in the first few years following the procedure[5]. These factors demonstrate that kidney transplantation is not limited to the surgical procedure itself, but involves a continuum of complex clinical and operational decisions, from pre-transplant assessment to long-term follow-up.

In this scenario, artificial intelligence (AI) has emerged as a technology with the potential to support decision-making at different stages of care for transplant patients. Models based on machine learning and other AI techniques have been used to improve the prediction of donor-recipient compatibility, estimate perioperative risks, anticipate adverse events in the post-transplant period, and predict graft survival[6-8]. These applications indicate that AI can improve the accuracy, speed, and personalization of clinical decisions in kidney transplantation.

Literature reviews have explored the use of AI in nephrology and solid organ transplantation, demonstrating promising results[9-12]. However, most of these studies have focused on specific aspects, such as particular computational methods, isolated clinical outcomes, or specific phases of the transplantation process[13-20]. This fragmented approach hinders an integrated understanding of how different AI tools are being applied throughout the entire kidney transplant journey and which clinical decisions they effectively support.

Considering that kidney transplantation involves multiple interdependent stages – pre-transplant, surgical procedure, and post-transplant follow-up[5,21-28] – a comprehensive synthesis that organizes the applications of AI throughout this process becomes relevant. An integrated view can help researchers, clinicians, and managers identify usage patterns, evidence gaps, and opportunities to develop solutions better aligned with the real needs of transplant care.

Thus, this study aims to answer the following research question: What are the main applications of AI in the kidney transplant process, which phases of care they focus on, and what outcomes and processes they seek to influence?

To answer this question, a scoping review was conducted, an appropriate approach for comprehensively mapping how a given field has been investigated, identifying application patterns, and highlighting gaps in the literature. This synthesis seeks to offer an integrated view of AI applications across the kidney transplant continuum, contributing to guiding future research and supporting clinical decision-making.

METHOD

This study consists of a scoping review, conducted in accordance with the methodological recommendations of the Joanna Briggs Institute for scoping reviews and reported according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) checklist[29]. This type of review is indicated for comprehensively mapping how a research field has been investigated, identifying application patterns, evidence gaps, and future directions, especially when the literature is heterogeneous and still consolidating[30,31]. The choice to conduct a scoping review was motivated by the exploratory nature of the research question, which seeks to understand how AI is being applied throughout the different stages of kidney transplantation and what clinical outcomes these applications aim to influence, rather than evaluating the effectiveness of specific interventions.

The search strategy and eligibility criteria were guided by the PICo (Population, Interest, Context) framework: P (Population) – Patients, donors, or candidates involved in the kidney transplant process; I (Interest) – AI applications, including machine learning, deep learning, neural networks, and predictive models; Co (Context) – Kidney transplant process throughout the continuum of care (pre-transplant, perioperative, and post-transplant).

The search was conducted in the Scopus database, selected for its broad multidisciplinary coverage and indexing of peer-reviewed literature. The strategy included terms related to AI and kidney transplantation, searched in the title, abstract, and keyword fields. The following search expression was used: TITLE-ABS-KEY ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network" OR "large language model") AND TITLE-ABS-KEY ("kidney transplant" OR "kidney transplantation" OR "kidney donation" OR "kidney exchange" OR "renal transplant" OR "renal transplantation" OR "renal donation"). The initial search resulted in 714 records.

Eligibility criteria

Eligible for inclusion were peer-reviewed empirical studies that investigated the application of AI techniques in kidney transplantation. A time frame was established starting in 2019, the year in which the first large language model (LLM) was made publicly available. LLMs are AI models trained on extensive textual datasets to understand and generate natural language in advanced ways. The time frame extends to 2023, as defining a closed time window is recommended in scoping reviews to ensure sample consistency and reproducibility of the synthesis process[32].

To be eligible, studies should directly address the use of AI tools, such as machine learning, deep learning, neural networks, or data-driven predictive models, aimed at any stage of the kidney transplant continuum, encompassing the pre-transplant period (e.g., compatibility assessment or recipient prioritization), the perioperative period, and post-transplant follow-up, including the prediction of complications, graft rejection, patient or organ survival.

Studies that did not present original empirical data, such as literature reviews and non-academic articles like editorials, letters to the editor, commentaries, technical notes, and conference abstracts, were excluded. Articles whose primary focus was not related to kidney transplantation or that addressed AI only tangentially, without direct application to clinical decisions, outcome prediction, or data management in the context of transplantation, were also excluded. Studies without an abstract available for initial analysis were also excluded, as they do not meet the criteria of an academic article.

Study selection process

The selection process occurred in sequential stages. Initially, 55 review articles were excluded because the study's objective was to map primary evidence. Non-empirical materials and publications not classified as scientific articles were also removed, resulting in 285 articles. Further screening by article title excluded 22 studies that did not fit the research scope, leaving 263 articles for the next selection phase: analysis of the abstracts.

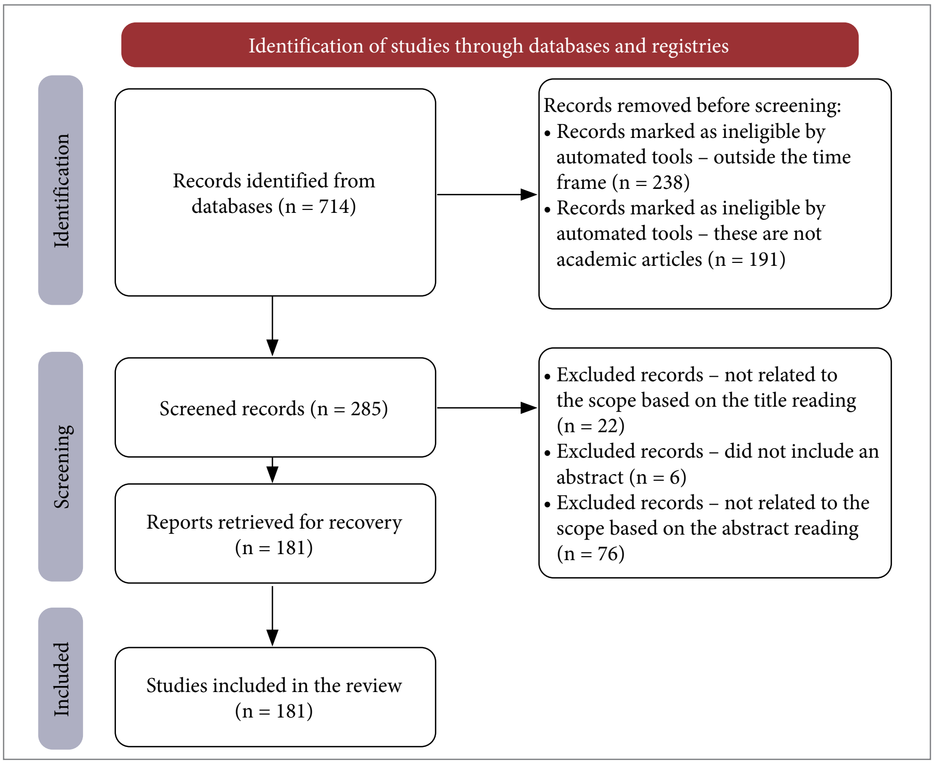
Of the 263 articles, six were excluded for not having an abstract. Of the remaining 257 articles, 76 were excluded for failing to meet the eligibility criteria. At the end of the process, 181 articles comprised the final sample for the review. In the next step, these 181 articles were read in full, and information on AI applications, the transplant phases addressed, and the clinical outcomes evaluated was extracted.

The screening and eligibility process was conducted independently by two authors, both in reading titles and abstracts and in evaluating full texts. Any disagreements were resolved by consensus among the three authors, with discussion among the reviewers until an agreement was reached. This procedure aimed to reduce selection bias and increase the reliability of the final sample included in the review.

For the data extraction and organization phase, a standardized form was developed that captured information on study characteristics, the type of AI application, the transplant stage addressed, and the clinical outcomes investigated. The form was previously tested on a pilot set of articles to ensure clarity and consistency in data collection. The extraction was performed systematically and reviewed by the authors, ensuring the reliability of the data used in the analysis.

The workflow for identifying, screening, determining eligibility, and including studies is presented in Fig. 1, according to the PRISMA-ScR model.

The 181 included studies were analyzed using inductive qualitative content analysis, in which the analysis dimensions emerge progressively from the examined material. This approach is suitable when the objective is to organize a heterogeneous, still consolidating field of research, allowing the identification of patterns, application categories, and research foci without imposing a prior theoretical framework[34]. The analytical process involved repeatedly reading the articles, coding relevant information related to AI applications, the transplant steps addressed, and the desired outcomes. The categories were iteratively refined as new patterns were identified, ensuring that the constructed dimensions comprehensively reflected the content of the included literature. This type of analysis is particularly suitable for scoping reviews, where concepts and approaches are still dispersed, and the synthesis aims to map the field rather than test specific hypotheses[35]. To support data organization and the coding process, Microsoft Excel was used, enabling the systematization of extracted information and the grouping of studies into emerging categories.



Source: Adapted from Page et al.[33].

Figure 1. Selection and evaluation diagram.

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RESULTS

Characteristics of the studies

Scientific production on AI applications in kidney transplantation showed consistent growth throughout the analyzed period. From 2019 to 2021, the number of publications gradually increased – 16, 21, and 25 articles, respectively – followed by a more pronounced expansion from 2022 onwards, when the annual volume of studies more than doubled compared to previous years: 61 articles in 2022 and 58 in 2023.

The 181 studies were published across 108 journals, indicating the field's multidisciplinary nature. The journals with the highest number of publications are presented in Table 1. The dispersion of publications suggests that the topic is not concentrated in a single disciplinary core but is distributed across nephrology, transplantation, bioinformatics, and translational medicine.

Table 1. Main journals where the articles were published.

Journal	Number of selected articles
Frontiers in Immunology	10
Scientific Reports	8
American Journal of Transplantation	8
Frontiers in Medicine	7
Journal of the American Society of Nephrology	5
Transplantation	5
Others	Fewer than 5 articles each

Source: Elaborated by the authors

Application categories of AI

The 181 articles were classified into seven categories based on the focus of AI application in the context of kidney transplantation, namely: (1) prediction of patient behavior; (2) radiological and pathological assessment; (3) prediction of pre-transplant kidney disease progression; (4) predicting of kidney donor-recipient compatibility; (5) optimizing the administration of immunosuppressive drugs; (6) diagnosis of post-transplant complications; and (7) graft survival prediction. Each category is explained below.

I - Predicting patient behavior: two articles.

Articles that investigated the use of AI in understanding and predicting patient behaviors, such as treatment preferences, treatment adherence, and other relevant behaviors in the context of kidney transplantation – For example, Aljurbua et al.[36] investigated the use of AI to predict patients' attitudes towards kidney transplantation, based on social networks in the context of a hemodialysis clinic and sociodemographic data. Zhu et al.[37], in turn, investigated the use of AI to predict patient adherence to immunosuppressant medications after kidney transplantation

II - Radiological and pathological assessment: 42 articles

Articles that investigated the use of AI in the evaluation of radiological images and pathological samples in the context of kidney transplantation – for example, Jaugey et al.[38] focused on neural networks to automate the classification of biopsies from patients with nephropathy. Fang et al.[39], in turn, investigated the use of label-free quantitative mass spectrometry and machine learning algorithms to improve molecular diagnosis in kidney transplant biopsies, addressing limitations of traditional histological evaluation.

III - Prediction of pre-transplant kidney disease progression: 8 articles

Articles that investigated the use of AI in the assessment and prediction of pre-transplant renal disease progression – For example, Lianget al.[40] investigated the prediction of chronic kidney disease progression to end-stage renal disease using machine learning and deep learning models. Mark et al.[41], in turn, investigated the prediction of patients' functional status while on the transplant waiting list.

IV - Predicting kidney donor-recipient compatibility: 10 articles

Articles that investigated the use of AI in the assessment and prediction of kidney donor-recipient compatibility – For example, Nemati et al.[1] proposed new representations of biological characteristics to incorporate information on human leukocyte antigens (HLAs) into machine learning-based survival analysis algorithms. Dasariraju et al.[6], in turn, investigated the use of an algorithm to discover combinations of amino acid mismatches in HLA that can stratify donor-recipient pairs into low- or high-risk groups for transplant organ failure, improving the prediction of compatibility between kidney donors and recipients.

V - Optimizing the administration of immunosuppressive drugs: 16 articles

Articles that investigated the use of AI to optimize immunosuppressant drug doses in post-renal transplant patients – For example, Sridharan and Shah[42] used machine learning algorithms to identify variables that predict therapeutic effects and adverse events after administration of tacrolimus and cyclosporine in renal transplant patients. The main objective was to optimize the doses of these immunosuppressant drugs. Sánchez-Herrero et al.[43], in turn, focused on the use of machine learning models to predict tacrolimus blood concentrations in pediatric renal transplant recipients, a crucial task for adjusting drug doses and ensuring patient safety.

VI - Diagnosis of post-transplant complications: 63 articles

Articles that investigated the use of AI in diagnosing complications that occur soon after a kidney transplant – These studies include the early and accurate identification of health problems that arise in the patient soon after the transplant procedure, such as graft rejection, infections, and surgical complications, among others. For example, Thongprayoon et al.[44] used an unsupervised machine learning approach to identify and characterize clusters of kidney transplant recipients with long pre-transplant dialysis duration, and to compare post-transplant outcomes across these clusters. Minato et al.[7] investigated the use of machine learning techniques to create a predictive model of kidney graft rejection in the first 30 days after transplantation.

VII - Graft survival prediction: 40 articles

Articles that investigated the use of AI to predict kidney graft survival after transplantation – This approach estimates the probability of how long the graft will remain functional in the recipient organism. For example, Truchot et al.[45] developed and compared machine learning-based prediction models for kidney graft survival with a traditional prognostic system. Badrouchi et al.[46], in turn, investigated the use of conventional and AI-based methods to predict long-term kidney graft survival, developing predictive models to assist in therapeutic decision-making.

Distribution throughout the stages of transplantation

The seven identified categories were grouped into three main categories: those related to both pre- and post-transplant (categories I and II), those related primarily to pre-transplant (categories III and IV), and those related mainly to post-transplant (categories V, VI, and VII). It was observed that the majority of studies (119/181; 65.7%) focus on the post-transplant period, while 24.3% (44/181) address applications that span both phases of care. In contrast, only 9.9% (18/181) of the publications predominantly focus on the pre-transplant stage.

DISCUSSION

Previous reviews have highlighted the potential of AI in nephrology and organ transplantation, often focusing on specific machine learning methods or isolated clinical outcomes such as graft failure or acute rejection. While these studies have contributed to demonstrating the technical feasibility of AI applications, they tend to address specific segments of care without offering an integrated view of how these technologies are distributed throughout the entire kidney transplant process[13-20].

This review broadens the perspective by organizing the literature by transplantation stages and the types of clinical decisions supported by AI. By adopting a care-process-oriented approach, it was possible to highlight patterns that are not clearly visible in reviews focused solely on isolated techniques or outcomes. In particular, the intense concentration of studies in the post-transplant period and the scarcity of applications focused on the pre-transplant phase and patient behavior become evident when the literature is analyzed under the logic of the continuum of care.

Although the number of publications has grown substantially in recent years, the findings indicate that the literature focuses predominantly on diagnostic and monitoring applications in the post-transplant period. At the same time, other areas of the process remain relatively unexplored.

The predominance of post-transplant research is consistent with previous literature[47]. It can be explained by the complexity of continuous clinical monitoring and the availability of structured data at this stage, such as laboratory and imaging tests. These factors favor the development of predictive models for early detection of rejection and other complications, contexts in which AI already shows greater maturity in application.

In contrast, the pre-transplant stage remains relatively unexplored, despite the recognized potential of AI to support decisions related to donor selection and donor-recipient compatibility[48]. The identified applications focus primarily on predicting the progression of kidney disease and analyzing immunological compatibility, suggesting opportunities that are not yet fully developed to support critical allocation and prioritization decisions.

Furthermore, only a limited portion of studies address different phases of transplantation in an integrated manner. Most applications remain segmented, and only 24% of the articles identified in this review simultaneously addressed applications in pre- and post-transplant settings. This pattern suggests that current AI development in kidney transplantation remains focused on specific problems rather than integrated care models.

Another significant gap concerns AI applications related to patient behavior, including treatment adherence and care engagement. Despite their recognized importance for long-term outcomes, these aspects are poorly represented in the literature, possibly because collecting behavioral data is more complex and integrating subjective information into traditional computational models is difficult.

From a clinical and organizational perspective, the findings indicate that AI adoption in kidney transplantation has primarily served as a tool to support diagnosis and risk stratification in the post-transplant period. For managers and clinical teams, this suggests that the technologies currently available are more mature for monitoring applications than for supporting structural decisions in the transplant process, such as donor selection or patient preparation—areas that remain underexplored despite their potential systemic impact.

In summary, this review demonstrates that AI applications in kidney transplantation primarily focus on diagnostic and predictive tasks in the post-transplant period, particularly for detecting complications, risk stratification, and predicting graft survival. To a lesser extent, AI has been applied in the pre-transplant phase, primarily to predict kidney disease progression and assess donor-recipient compatibility. In general, the identified models aim to influence clinical outcomes by reducing complications, improving graft survival, and optimizing therapeutic management, while behavioral factors and decisions prior to transplantation remain underexplored.

CONCLUSION

This scoping review comprehensively synthesized how AI has been applied throughout the kidney transplant process, highlighting not only the diversity of applications but also their uneven distribution across different stages of care. The results show that AI applications are predominantly concentrated in the post-transplant period, especially in tasks such as complication diagnosis, risk stratification, and graft survival prediction. In contrast, the pre-transplant phase and aspects related to patient behavior remain relatively unexplored, despite their potential to influence critical decisions and long-term outcomes.

By organizing the literature by transplantation phases and the types of clinical decisions supported by AI, this review contributes to a more integrated understanding of the field, overcoming previous approaches that focused on isolated techniques or outcomes. This perspective reinforces the need to broaden the research focus to encompass more prospective and integrated applications across the entire continuum of care.

Although AI has already demonstrated greater maturity in post-transplant monitoring contexts, its full incorporation into clinical practice depends on advances in methodological standardization, large-scale validation, and integration into care flows. Future studies should prioritize multicenter approaches, more heterogeneous databases, and the inclusion of behavioral and social dimensions of care to broaden the clinical reach of these technologies.

This review has limitations, including the restriction of the search to the Scopus database and the absence of an assessment of the methodological quality of the included studies, characteristics inherent to the design of scoping reviews. Even so, the findings offer relevant contributions in three complementary dimensions.

In the academic context, the review proposes an integrative framework for analyzing AI applications in kidney transplantation, shifting the focus from isolated techniques to clinical decisions distributed throughout the care process.

For managers and healthcare professionals involved in kidney transplant programs, the findings of this review offer practical guidance on where AI is already more mature and where development opportunities remain. The predominance of applications in the post-transplant period suggests that AI-based tools are better positioned to support continuous clinical monitoring, especially for risk stratification and early detection of complications, and can serve as a starting point for the gradual adoption of these technologies. At the same time, the lower prevalence of applications in the pre-transplant phase highlights a strategic field for organizational innovation, with the potential to support decisions on patient prioritization, compatibility assessment, and care planning. These advances, however, depend on investments in data infrastructure, interoperability between systems, and staff training, since the effectiveness of AI is directly linked to the quality of available data and the ability of services to integrate algorithmic recommendations into care flows.

Finally, from a social perspective, identifying gaps and opportunities for AI across the entire kidney transplant process points to the potential for more precise, equitable, and efficient care systems, with possible impacts on reducing complications, better use of available organs, and improving outcomes for transplant patients.

CONFLICT OF INTEREST

Nothing to declare.

AUTHOR’S CONTRIBUTION

Substantive scientific and intellectual contributions to the study: Fernandes B, Araujo CAS; **Conception and design:** Fernandes B, Araujo CAS; **Data analysis and interpretation:** Fernandes B, Araujo CAS; **Article writing:** Fernandes B, Moura IB; **Critical revision:** Araujo CAS; **Final approval:** Araujo CAS.

DATA AVAILABILITY STATEMENT

Data will be provided upon request.

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DECLARATION OF USE OF ARTIFICIAL INTELIGENCE TOOLS

ChatGPT version 4.0 artificial intelligence application was used to assist in organizing the analyzed content and reviewing the text, aiming for greater fluency and grammatical accuracy.

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