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Artificial intelligence–driven kidney organ allocation: systematic review of clinical outcome prediction, ethical frameworks, and decision-making algorithms

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Abstract

Kidney transplantation remains the optimal treatment for end-stage renal disease, yet persistent organ shortages and inequitable allocation necessitate innovative solutions. Artificial intelligence (AI) and machine learning (ML) have emerged as promising tools for improving clinical outcomes and optimizing donor-recipient matching. However, their integration into clinical practice remains limited, and significant challenges regarding validation and ethical implementation persist. This systematic review synthesizes current research on AI-driven kidney allocation, focusing on predictive modeling, operational algorithms, and ethical considerations. We conducted a comprehensive literature search with no restrictions on publication year or country across biomedical databases (PubMed/MEDLINE, Embase), AI repositories (arXiv, IEEE Xplore), and clinical trial registries. Sixteen studies met inclusion criteria, encompassing retrospective cohort analyses, simulation studies, and algorithmic frameworks. Data were extracted on model performance, clinical outcomes, and fairness metrics, with quality assessed via modified QUADAS-2 and PROBAST tools. Findings revealed that AI/ML models—particularly deep learning and ensemble methods—outperform traditional risk scores (e.g., KDRI, EPTS) in predicting graft survival (C-index: 0.65–0.72) and waitlist outcomes. However, only a minority of studies integrated these predictions into actionable allocation policies, with most limited to simulation environments. Ethical frameworks were inconsistently applied; while fairness and transparency were frequently cited, few studies embedded them algorithmically. Key gaps included real-world validation, prospective bias audits, and standardized reporting of subgroup impacts. AI holds immense potential to enhance kidney allocation but requires rigorous clinical translation and ethical governance. Future research must prioritize multidisciplinary collaboration to bridge the divide between predictive accuracy and equitable implementation.

Clinical trial number

Not applicable.

Keywords Artificial intelligence, Kidney transplantation, Organ allocation, Machine learning, Ethics

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Introduction

Kidney transplantation remains the treatment of choice for patients with end-stage renal disease, but continues to be constrained by a global imbalance between organ demand and available supply [1, 2]. Allocation systems have traditionally utilized a combination of statistical risk scores—such as the Kidney Donor Risk Index (KDRI) and Estimated Post-Transplant Survival (EPTS)—and rule-based criteria to prioritize recipients according to predicted survival, waiting time, and other factors [3, 4]. In recent years, artificial intelligence (AI) and machine learning (ML) have emerged as promising approaches in this domain, demonstrating improved predictive performance for both graft and patient survival when compared to conventional models [5, 6]. Methods such as deep neural networks, ensemble models, and advanced survival analysis have leveraged large registry datasets, and some studies have reported higher discrimination and better calibration across multiple validation cohorts [7, 8]. However, it is debated whether these improvements are attributable to the algorithmic complexity itself or to the incorporation of a broader set of predictor variables, with some evidence suggesting that well-tuned traditional models can achieve comparable performance [9].

Epidemiological evidence underscores the urgent need to optimize kidney allocation [10, 11]. Large numbers of patients remain on waiting lists, with many experiencing prolonged dialysis and high rates of mortality or dropout before transplantation [12, 13]. Key challenges persist in reducing waitlist mortality, improving long-term transplant outcomes, and ensuring equitable access across increasingly diverse patient populations [14, 15]. At the same time, the field faces growing complexities in donor risk assessment—such as rising use of marginal kidneys—and heightened attention to equity and the ethical implications of algorithm-driven decisions [8, 12, 14, 16].

Despite these advances in predictive accuracy, most AI/ML studies still focus on outcome forecasting, stopping short of integrating these models into actionable allocation or matching algorithms [11, 17–20]. Only a small number of studies move beyond prediction to leverage ML in actual allocation frameworks: examples include representation learning for individualized donor–recipient matching, interpretable counterfactual modeling for queueing policies, and individualized treatment effect estimation for optimal donor offers [19, 21, 22]. These approaches attempt to directly shape allocation decisions using real-time predictions of clinical benefit.

The explicit consideration of ethical and fairness frameworks within these AI-driven systems remains limited [23, 24]. While equity and transparency are commonly cited as important, most research restricts ethical analysis to validating subgroup performance or offering interpretability features, rather than embedding fairness constraints within the allocation objective [23–25]. Notable exceptions are found in the context of dynamic paired kidney exchange, where simulation and algorithmic penalties for inequity have been shown to yield improvements in both fairness and overall transplant rates [26, 27]. Multi-objective optimization frameworks have also begun to examine the trade-offs between maximizing utility (graft years saved) and ensuring equitable access across demographic or clinical subgroups [17, 19, 28, 29].

Some research has aimed to bridge the gap between predictive modeling and practical system-level application by deploying web-based platforms, decision-support tools, and data-driven ranking mechanisms for hard-to-place kidneys [30–32]. However, the majority of these tools are early in their implementation, with ongoing challenges related to regulatory compliance, stakeholder engagement, and recalibration as populations and policies evolve [31, 32].

While foundational research from operations science and computer science has laid the groundwork for algorithmic organ allocation [33, 34], a critical gap remains in the comprehensive integration of clinical outcome prediction, ethical and fairness frameworks, and operational decision-making algorithms within AI-driven kidney organ allocation [14, 15, 24, 29, 35]. The lack of end-to-end, validated, and fairness-aware allocation systems is particularly pronounced in deceased donor transplantation, where existing models rarely progress beyond retrospective prediction or limited simulation [6, 19, 27, 30].

This systematic review aims to synthesize research on AI-based kidney allocation, with a specific focus on studies that bridge the gap between predictive modeling and actionable allocation systems. We critically examine how clinical outcome predictions are integrated into decision-making algorithms and the extent to which ethical frameworks, such as fairness and transparency, are explicitly incorporated into these operational systems.

Methodology

This systematic review employed a structured methodology (PRISMA 2020) [36] to comprehensively synthesize existing research on AI-driven kidney organ allocation. The approach was designed to ensure rigor, transparency, and reproducibility while addressing the study's objectives.

Systematic review methods

The research question was defined using the PICOS (Population, Intervention, Comparator, Outcomes, Study Design) framework to guide the scope and focus of the review. This framework ensured a systematic approach to identifying relevant studies.

- ***Population***: Adult and pediatric patients eligible for kidney transplantation, including deceased or living donor programs.
- ***Intervention***: Use of artificial intelligence (AI) or machine learning (ML)–based predictive models and allocation algorithms for kidney organ matching (covering both paired kidney exchange and deceased donor allocation).
- ***Comparator***: Traditional statistical methods (e.g., KDRI, EPTS, Cox models), non-AI-based allocation policies, or established expert-driven allocation rules.
- ***Outcomes***: Primary outcomes include graft survival/longevity, recipient survival, and waitlist mortality; secondary outcomes include fairness and equity metrics, model explainability, and policy simulation results.
- ***Study Design***: Original research studies involving retrospective/prospective cohort analysis, simulation modeling, or evaluation of allocation systems incorporating AI/ML; excludes purely descriptive reviews or technical papers without evaluation of clinical or ethical implications.

Research question

How are AI and machine learning models being applied to kidney organ allocation and matching, with respect to improving clinical outcomes (graft survival, recipient survival, waitlist mortality) and addressing ethical challenges (fairness, transparency, equity) in real or simulated allocation settings?

Inclusion and exclusion criteria

Studies were selected based on predefined criteria to ensure relevance and quality. The inclusion and exclusion criteria are summarized in Table 1, which outlines the requirements for population, intervention, outcomes, study design, and other key factors.

Database selection and search strategy

A comprehensive search was conducted across multiple databases to identify relevant studies. The search was not limited by publication date or country of origin. Biomedical databases such as PubMed/MEDLINE, Embase, Web of Science, and Scopus were included, alongside AI/computer science repositories like IEEE Xplore, ACM Digital Library, and arXiv. Clinical trial registries such as ClinicalTrials.gov and the WHO International Clinical Trials Registry Platform were also searched.

The search strategy combined keywords related to kidney transplantation (e.g., "*kidney allocation*," "*renal transplant*") with terms for AI/ML methods (e.g., "*machine learning*," "*deep learning*") and outcomes (e.g., "*graft*

Table 1 Inclusion and exclusion criteria for study selection

Criterion	Inclusion	Exclusion
Population	Studies involving human kidney organ allocation, matching, or kidney exchange (including both deceased and living donor transplantation).	Studies focused on other organ transplants (e.g., liver, heart) or unrelated to kidney organ matching/allocation.
Intervention	For this review, we use the term 'AI' inclusively to encompass machine learning (ML) methods, including both classical ML (e.g., Random Survival Forests, SVM) and deep learning. The key inclusion criterion was not the specific algorithm but its application to an allocation-related task as defined below: - Organ allocation - Donor–recipient matching - Waitlist management decisions - Policy simulation relevant to allocation.	Studies using only traditional statistics (e.g., Cox regression, KDRI/EPTS) without an AI/ML component. AI/ML for tasks unrelated to allocation (e.g., imaging, pathology only).
Outcomes	Studies reporting on at least one clinical outcome measure relevant to allocation: • Graft survival/longevity • Recipient/patient survival • Waitlist mortality or related endpoints Studies that discuss ethical implications (fairness, equity, transparency) in the context of allocation/matching.	Studies reporting only surrogate/process outcomes (e.g., discard rate, cold ischemia time) not linked to clinical endpoints; or only technical model metrics disconnected from allocation or clinical impact. Ethics or fairness discussions limited to general AI/ML principles, not applied to allocation/matching.
Study Design	Retrospective/prospective cohort studies, clinical registries, simulation/modeling studies, and policy evaluation using real or synthetic data relevant to allocation/matching.	Case reports, studies unrelated to allocation/matching; reviews/commentaries without original data or algorithmic development.
Integration with Allocation	Studies where AI/ML predictions are explicitly integrated into or informing allocation or matching decisions, algorithms, or policies (including simulation of allocation rules or optimization).	Studies using AI/ML only to predict outcomes post-transplant, without relevance to allocation/matching decisions or simulation.
Ethics/Fairness	Studies that explicitly measure, model, or discuss fairness, equity, transparency, or ethical outcomes at the allocation or matching decision level.	Studies addressing interpretability, bias, or transparency only at the predictive model level, not allocation decisions (e.g., subgroup performance in validation only).
Language	English language	Non-English language (unless translation available)
Publication Type	Peer-reviewed journal articles, major conference proceedings, preprints, and technical reports from transplantation registries/organizations.	Unpublished data, letters to the editor, opinion pieces, dissertations/theses, or white papers lacking sufficient methodological detail.

survival," "*fairness*"). Boolean search strings were tailored for each database to maximize sensitivity and specificity. Grey literature, including conference proceedings and preprints, was also reviewed. The full keywords and search strategy for each database are provided in Supplementary File 1.

Data extraction and synthesis of evidence

Data from included studies were systematically extracted and categorized. Key variables included study characteristics (year, country, cohort size), AI/ML methodologies, integration with allocation systems, clinical outcomes, and ethical considerations. The synthesis process involved organizing studies into thematic groups, such as predictive modeling, allocation algorithms, and fairness frameworks. Narrative synthesis was used to compare findings across studies, highlighting trends, gaps, and areas for future research.

Quality assessment

The quality of included studies was assessed using modified QUADAS-2 and PROBAST frameworks, focusing on study design, cohort size, validation methods, and reporting of clinical and fairness outcomes. Key findings from the quality assessment revealed that while many studies utilized large datasets and robust validation, real-world deployment and fairness integration were often lacking. Discrepancies in reporting, such as missing cohort details or limited transparency in algorithmic studies, were noted as common limitations. This methodology ensured a thorough and unbiased review of the literature, enabling a clear synthesis of advancements and challenges in AI-driven kidney organ allocation.

Results

Article selection processing

A comprehensive literature search was conducted across biomedical databases, AI/computer science repositories, and clinical trial registries, yielding 1,880 initial records. After removing 732 duplicates, we screened 1,148 records by title and abstract, excluding 1,056 studies that did not meet our inclusion criteria (e.g., non-kidney transplantation focus, non-allocation AI applications, or review articles without original data).

Of the 92 full-text articles assessed for eligibility, 76 were excluded due to: (1) lack of AI-driven allocation integration (n = 39), (2) absence of relevant clinical outcomes (n = 21), (3) insufficient ethical/fairness analysis (n = 8), or (4) methodological limitations (n = 8). Sixteen studies met al.l criteria and were included in the qualitative synthesis [16, 19–22, 27–32, 35, 37–40].

The selection process is summarized in Fig. 1, which provides a detailed PRISMA-style flowchart of identification, screening, eligibility assessment, and final inclusion. This visual representation highlights the rigorous multi-stage filtering applied to ensure the relevance and quality of selected studies to our systematic review objectives.

Data extraction process

A detailed extraction of methodological and outcome variables for all sixteen included AI-driven kidney-allocation studies is provided in Supplementary File 2. This table summarises study characteristics, modelling approaches, degree of integration into allocation or decision-support pipelines, validation strategies and main quantitative findings, together with any fairness or explainability measures that were explicitly addressed. It highlights the heterogeneity of evidence: only a minority of studies embed predictive models within an operational allocation framework, whereas most focus on retrospective outcome prediction without simulated policy impact or equity analysis. Supplementary File 2 therefore supports the narrative synthesis by making transparent which evidence gaps remain (e.g., external validation, prospective fairness audits) and by allowing readers to trace each conclusion to the specific features and results of the underlying studies.

Quality assessment

A quality assessment of the included studies was performed based on key aspects relevant to multi-disciplinary AI and clinical research: clarity of study design, cohort size and source, model validation approach, reporting of clinical and fairness outcomes, and transparency regarding limitations (Table 2).

AI/ML models for predicting clinical outcomes in kidney transplantation

AI and machine learning models have been widely applied to predict clinical outcomes such as graft survival, recipient survival, and waitlist mortality in the context of kidney transplantation. Commonly employed methods include both classical survival analysis (such as Cox proportional hazards models and decision trees), ensemble techniques (e.g., random survival forests, Cox ensemble), and various deep learning strategies (e.g., DeepSurv, DeepHit, Deep Cox mixture models, neural networks) [29, 32, 39]. These models utilize features from both donors and recipients—such as age, comorbidities, human leukocyte antigen (HLA) mismatch, donor eGFR, cold ischemia time, and transplant center characteristics—to improve risk stratification and guide decision support (Table 3).

While many studies report improved performance for predicting graft and patient survival over traditional risk-scoring systems (e.g., EPTS, KDRI), with C-indices ranging from approximately 0.65 to 0.72 [29, 32] the evidence is not universal. Critical comparisons suggest that

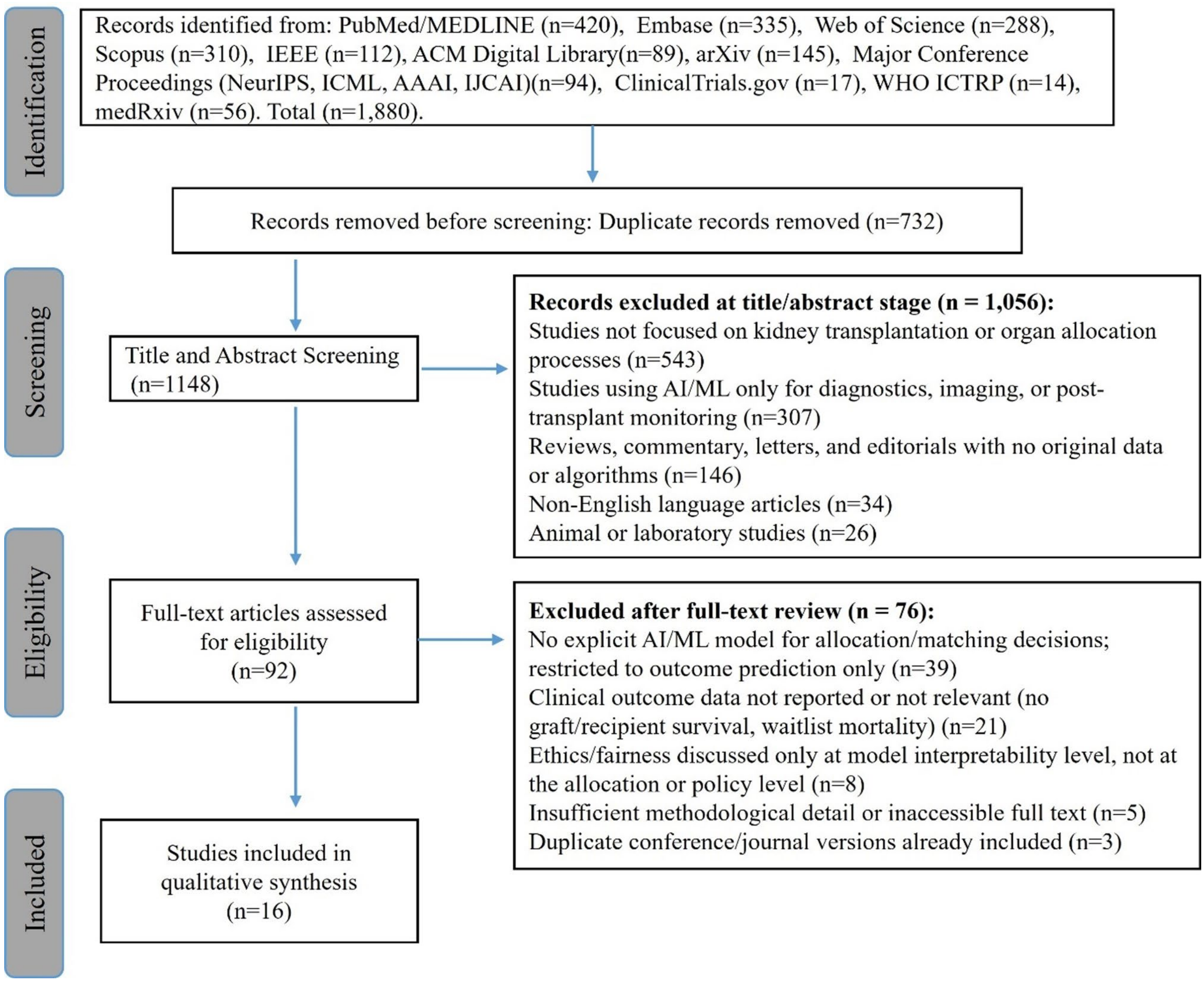

Fig. 1 PRISMA Flow diagram of study identification, screening, and selection process

such gains may often be driven by the number and type of variables used rather than the algorithmic superiority of ML techniques, with well-specified regression models sometimes matching or exceeding ML performance [9].

Several studies have included calibration analysis (e.g., integrated Brier score), internal validation via train/test splits or cross-validation, and, in a few cases, external validation using data from different countries [29]. Neural network–based models and random survival forests often outperform classical approaches, offering improved discrimination and calibration for long-term transplant outcomes. Moreover, feature importance analyses consistently identify donor and recipient age, primary renal disease, HLA mismatch, and donor eGFR as highly predictive variables [32].

Integration of AI predictions into allocation algorithms and policies

A subset of studies explicitly integrates AI/ML-driven predictions into allocation and matching decision systems, aiming to improve clinical outcomes and operational efficiency. Notably, representation learning and counterfactual survival analysis frameworks, such as OrganITE and related work, formulate the donor–recipient matching process as an individualized treatment effect problem, using simulated or retrospective data to recommend matches that maximize expected graft survival [19, 21, 22]. Other studies deploy algorithmic strategies, including dynamic queueing or matching policies [21], center ranking for "hard-to-place" organ allocation [30], and fairness-optimized matching in paired exchange programs [27]. These approaches move beyond static survival prediction, embedding outcome forecasts into decision-making logic for organ offers, recipient prioritization, or system-level policy adjustments (Table 4).

Table 2 Quality assessment findings across included studies

Quality Domain	Subcategory	Findings	References
Study Design and Reporting	Reporting clarity	Majority of studies clearly stated their design.	[16, 19, 29, 37]
	Data source transparency	Several leveraged large national/international registries (e.g., UNOS, SRTR, UK Transplant) for model development and validation.	[21, 22, 29, 38]
	Cohort details in simulation studies	Algorithmic/policy simulation papers often omitted traditional cohort details, reflecting methodological focus.	[37–39]
Cohort Size and Data Source	Large registry datasets	Clinical outcome prediction studies often used very large datasets (e.g., >150,000 transplants).	[19, 21, 22, 28, 29, 37, 39]
	Semi-synthetic or real-world derived data	Simulation/matching algorithm studies used real-world-derived or semi-synthetic datasets.	[21, 22, 28, 29]
	Reporting gaps	Cohort construction details not always explicitly described.	[37, 39]
Validation and Generalizability	Internal validation	Several performed robust internal validation (e.g., train/test split, cross-validation).	[19–22], 27–29, 32], 38–40]
	External validation	Some studies used cross-country datasets (e.g., UK and US) for external validation.	[29, 32, 38]
	Calibration metrics	Calibration indices variably reported; stronger reporting in clinical outcome studies.	[29, 32, 38]
	Real-world testing	Few studies reported real-world deployment or prospective trials.	[19–22], 27–29, 32], 38–40]
Clinical and Fairness Outcome Reporting	Clinical outcomes	Explicit clinical outcome reporting (e.g., graft survival, recipient survival, waitlist mortality) was robust in predictive modeling.	[20, 27, 28, 32, 35, 40]
	Allocation-level linkage	Clinical outcomes inconsistently linked to allocation outputs.	[27, 28, 32]
	Fairness/equity integration	Minority of studies operationalized fairness/equity as explicit constraints or measured allocation-level impacts.	[27, 40]
	Model interpretability	Explainability tools (e.g., SHAP) were reported in select studies for model interpretation.	[32, 35]
Limitations and Transparency	Acknowledged study limitations	Many studies acknowledged limitations such as retrospective design and lack of real-world deployment.	[16], 19–22], 27–32, 35], 37–40]
	Reporting gaps	Details on data missingness, bias assessment, and generalizability sometimes limited, especially in simulation studies.	[19–22], 27–32, 35], 37–40]

Table 3 Analytical aspects of AI/ML prediction models in kidney transplantation

Ref	Model Types Used	C-index	Brier Score	AUROC	Other Metrics	Validation Approach	Key Predictive Features
[29]	Deep Cox mixture model; compared with EPTS/KDRI	Yes (0.66–0.68)	Yes (IBS = 0.12)	Yes (AUC at 6, 9, 12 years)	CTD = 0.66	Internal (train/test split); External (UK data)	Not specified
[39]	DeepSurv, DeepHit, RNN, Cox, Random Survival Forest	Yes (0.650–0.661)	Yes (Integrated Brier Score)	No	Integrated Calibration Index	Internal (train/validation split)	Not specified
[32]	Neural networks, Cox PH, classification models	Yes (0.71 for graft failure, 0.81 for patient death at 10 years)	No	Yes	Not detailed	Internal (not specified)	Donor & recipient age, renal disease, donor eGFR, mismatches
[13]	Ensemble (Random Survival Forest + Cox PH) vs. EPTS	Yes (0.724 vs. 0.697)	No	No	None reported	Not detailed	Age-dependent effects
[35]	Explainable AI (SHAP-based)	No	No	No	Mean Squared Error (0.089–0.085)	Not specified	Genetic compatibility, comorbidities
[31]	Multiple classifiers (logistic regression, decision tree, random forest, SVM, boosting, CatBoost, LightGBM, neural nets)	No	No	Yes (up to 0.98 accuracy for gradient boosting)	Accuracy	Not detailed	Not specified
[19, 22, 40]	Representation learning, counterfactual models, matching networks	No (not explicitly reported)	No	No	Outperformed state-of-art (qualitative only)	Semi-synthetic and real-world data	Not specified

Table 4 AI/ML integration into kidney Allocation—Evidence overview

Reference	Explicit AI/ML Integration into Allocation/Matching? (Y/N)	Nature of Allocation Outputs or System-Level Impacts Reported
[21]	Yes	Simulated queueing/allocation policy learning; improved graft survival vs. expert rules in simulation
[22]	Yes	Retrospective and semi-synthetic evaluation; model outperforms conventional allocation in predicted outcomes
[19]	Yes	ITE-based optimal matching; simulated allocation recommendations with improved predicted clinical outcomes
[30]	Yes	Center ranking for expedited hard-to-place kidney allocation; simulation shows 4x–10x reduction in centers contacted before placement
[27]	Yes	Simulation of fairness-optimized matching in paired exchange; increased transplants, shorter waiting times, improved equity
[37]	Yes	Simulation-based evaluation of dynamic matching (FutureMatch framework); learns policies to maximize graft survival overtime
[40]	Yes	Matching networks for individualized allocation; details on system-level impact not provided in abstract
[28]	Yes (proposed framework)	Conceptual/policy simulation proposals for balancing fairness and precision; implementation details not specified

The impact of these integrated allocation systems is evaluated primarily in simulated environments or by off-policy analysis. For instance, Berrevoets et al. demonstrate allocation policies learned with interpretable counterfactual survival yielding improved simulated graft survival compared to expert-designed rules [21]. Representation learning models similarly outperform conventional allocations using retrospective datasets [22]. Simulation studies targeting process optimization, such as Berry et al. [30], report significant reductions in time to placement and improved placement rates of marginal kidneys. Fairness-aware learning frameworks show not only increased transplants but also enhanced equity across patient groups in simulated paired exchange settings [27]. However, there are no reports among these references of real-world clinical deployment or outcomes based on prospective policy implementation.

Impact on clinical endpoints: graft survival, recipient mortality, and waitlist outcomes

Across the reviewed literature, most AI/ML models focus on predicting graft survival (longevity) and recipient survival as primary clinical endpoints, with several models reporting significant improvements in predictive accuracy compared to traditional indices [29, 32, 39]. Some allocation-oriented studies explicitly use predicted outcomes, such as individual graft survival or simulated patient survival, to optimize the organ matching process [19, 21, 22]. While these endpoints are commonly embedded as direct optimization targets in allocation or matching algorithms, waitlist mortality is less frequently included—though certain policy simulation and fairness-oriented studies make efforts to incorporate it alongside transplant-related endpoints [27, 28, 37].

Regarding multi-objective balancing, only a limited subset of studies design allocation algorithms to explicitly trade off competing outcomes such as maximizing total graft-years versus minimizing waitlist mortality or ensuring fairness [27, 28, 37]. For example, dynamic kidney exchange simulations have incorporated measures of both clinical utility (total transplants, transplant rates) and equity (access for highly sensitized patients) [27, 37]. Most evidence supporting the impact of these integrated approaches comes from off-policy analysis or simulation studies; no studies in the current set report prospective, real-world clinical outcomes or policy implementation, although robust internal and external validation for predictive endpoints is present in several works [29, 32, 39] (Table 5).

Ethical considerations: fairness, transparency, and equity in AI-driven allocation

Ethical challenges related to fairness, transparency, and equity are recognized across much of the AI/ML kidney allocation literature, but explicit, systematic integration at the allocation decision level is relatively rare. Dynamic allocation and paired exchange studies such as those by Carvalho et al. [27] and Dickerson & Sandholm [37] go beyond subgroup performance reporting: they explicitly operationalize fairness as constraints, penalties, or outcome metrics in their allocation algorithms, demonstrating that such approaches can lead to both increased fairness and overall system utility in simulation studies. Ding [28] similarly proposes computational frameworks to balance fairness and precision, but does not provide implementation details (Table 6).

On transparency and explainability, several works incorporate post hoc interpretability techniques such as SHAP (SHapley Additive exPlanations) to help clarify model predictions for clinicians [32, 35]. However, these explainability efforts generally address model interpretation rather than allocation auditability or governance,

Table 5 Addressing clinical endpoints in AI/ML allocation methods

Ref	Graft Survival	Recipient Survival	Waitlist Mortality	Other Outcomes	Multi-Outcome Balancing	Evaluation Type
[21]	Yes	No	No	—	No	Simulation
[19, 22, 40]	Yes	Yes	No	—	No	Semi-synthetic / retrospective
[16, 29, 32, 39]	Yes	Yes	No	—	No	Predictive validation (internal/external)
[27]	Yes	Yes	Yes	Transplant rates, waiting times, equity	Yes	Simulation (Canadian paired exchange)
[37]	Yes	No	Yes	Match rates	Yes	Simulation (dynamic matching)
[28]	Not specified	Not specified	Not specified	Fairness/precision trade-off	Yes (proposed)	Conceptual framework
[30]	No	No	No	Acceptance rates for hard-to-place kidneys	No	Simulation (operational outcomes)

Table 6 Ethical challenge handling in AI/ML allocation models

Reference	Explicit Fairness Metrics or Constraints in Allocation?	Transparency / Explainability Approaches	Equity Impacts Assessed at Allocation/System Level?
[27]	Yes—fairness constraints/penalties in paired exchange	Not specified	Yes—simulated: measures of group fairness, transplant equity
[37]	Yes—value judgments and fairness integrated in dynamic matching	Not specified	Yes—simulation: fairness and utility trade-offs reported
[28]	Proposed—framework balances precision and fairness	Not specified	Policy/conceptual simulation only (no empirical data)
[32]	No—focuses on interpretability, not allocation fairness	SHAP for model interpretation	No; feature interpretation only
[35]	No—aimed at explainability for clinical use	SHAP for transparency in prediction	No; patient/physician understanding focus
[19, 21, 22]	No explicit fairness constraints in abstract	Not described (focus on outcome optimization)	Not stated; reports improved outcomes but no equity metrics
[16, 29, 31, 39]	No (subgroup performance sometimes reported)	Not described	No; fairness interpreted as model validation only

with no evidence of systematic audit trails or public reporting of allocation impacts by subgroup. Only a handful of studies formally assess equity at the allocation/system level through simulation or operational metrics—most commonly in the context of kidney exchange markets [27, 37]—while the majority confine fairness assessment to reporting subgroup predictive accuracy without linking this to system-level allocation outcomes.

Limitations, research Gaps, and future directions

Many of the included studies emphasize several shared limitations. First, there is a reliance on retrospective registry data, and few studies report real-world clinical deployment or external, prospective validation [29, 32, 39]. Concerns about bias and generalizability are frequently noted, with underrepresentation of certain subgroups and limited discussion of missing data or shifting population profiles. Algorithmic and simulation-focused papers often lack traditional reporting of cohort characteristics and may use semi-synthetic or off-policy datasets, complicating direct transferability to clinical environments [19, 21, 22, 27, 28, 38, 40].

A key gap is the disconnect between high-performing predictive models and actual integration into allocation policy or decision-making. Most predictive modeling studies stop short of operationalizing their findings in matching algorithms or policy simulations [16, 29, 32, 35, 39]. Where allocation frameworks are proposed [19, 21, 22, 27, 30], there is usually only simulation-based evidence, with real-world clinical impact not assessed. Areas flagged for further research include prospective deployment and policy impact analysis, effective incorporation of ethical/fairness constraints into allocation systems (especially in deceased-donor programs), and methodologies for continuous calibration and validation in the face of evolving patient populations (Table 7).

Discussion

This systematic review reveals a rapidly advancing yet fragmented landscape for AI/ML in kidney organ allocation. While predictive modeling for graft and patient survival is well established, its translation into real-world allocation policy—with systematic attention to fairness and transparency—remains nascent.

A trend emerging from the literature is that more complex models, such as neural networks and ensemble methods, often show improved discrimination and calibration over traditional statistical indices in retrospective

Table 7 Common limitations and future research directions

Reference	Reported Limitations: Data, Bias, Generalizability, Implementation	Predictive–Allocation Disconnect?	Areas Identified for Further Research/Development
[16, 29, 32, 39]	Retrospective design; Limited prospective/real-world validation; Generalizability concerns	Yes—focus on prediction, no operational allocation tested	Prospective and external validation, integrating predictions into allocation systems
[19, 21, 22]	Simulation or semi-synthetic datasets; Methodological focus; Lack of detailed clinical cohort info	No (partially)—propose allocation policies, but mostly simulation-based	Real-world deployment, external validation, policy impact studies
[27, 37]	Simulation-based evaluation only; Dynamic modeling complexity; No clinical implementation	No (for paired exchange); Dynamic models, but largely in silico	Real-world policy trials, broader application to deceased-donor systems
[30]	Simulation study; Operational (not clinical outcome) focus; No real-world testing	Yes—optimizes placement, not direct clinical outcome	Linking process optimization to patient-level outcomes, prospective testing
[31, 35]	Not specified or unclear in abstracts; Focused on matching or explainability	Yes—matching/explainability, not allocation or clinical outcomes	Comprehensive evaluation in allocation policy context, transparency governance structures
[28]	Conceptual/proposed framework with no implementation/evidence	N/A—no empirical demonstration	Empirical evaluation of proposed fairness/precision trade-offs

analyses. It is crucial to note, however, that 'traditional methods' in these comparisons are often limited to EPTS/KDRI, and a broader comparison including well-tuned Cox models or Random Survival Forests (which itself is an ML technique) is less common. The marginal gains in performance must also be weighed against the increased complexity and reduced interpretability [16, 29, 32, 39, 41]. This enhancement is driven by the integration of a wide spectrum of donor, recipient, and transplant variables and, in some cases, by the explicit modeling of complex feature interactions. However, an enduring limitation is that the majority of these studies focus almost exclusively on outcome prediction rather than operational allocation. That is, while the models successfully stratify risk or identify important predictors, they do not close the loop by using these predictions to drive actual donor–recipient matching decisions.

A smaller body of research integrates predictive analytics into dynamic allocation frameworks, using counterfactual and representation learning to simulate outcomes for personalized matching [19, 21, 22, 27, 28, 42]. These methods represent a significant conceptual advance over rule-based systems, demonstrating superior performance in simulated environments for both kidney exchange and deceased donor allocation [19, 21, 22, 37]. However, their validation remains largely theoretical, with no reported real-world clinical deployments, raising unanswered questions about their practical scalability and integration into clinical workflows.

A critical comparative insight relates to the balance between maximizing utility (e.g., total graft-years, number of transplants, patient survival) and upholding equity or fairness in allocation. This challenge has been a long-standing focus of operations research, with pioneering work using optimization and simulation to reverse-engineer allocation policies that explicitly incorporate multi-criteria objectives with built-in equity constraints [43, 44]. The studies in our review that operationalize fairness as a concrete constraint [27, 28, 37, 45]. represent a more recent, data-driven evolution of this concept, often leveraging ML for prediction within such optimized frameworks. They demonstrate that penalizing unfair pairings can enhance both equity and transplant volume [27], a finding that aligns with the goals of these earlier optimization-based approaches. However, a key distinction is that the evidence for most ML-driven methods remains largely simulation-based, whereas the operations research literature has a longer history of engaging with policy design and trade-off analysis at a systems level.

Transparency and explainability, while widely championed in clinical AI, are not yet uniformly addressed at the allocation decision level. Some works employ post hoc interpretation (e.g., SHAP) to aid clinicians in understanding the drivers of predictions [32, 35], yet these techniques are generally not extended to the upstream allocation or matching algorithms themselves. The lack of systematic auditability, version tracking, and real-world governance structures limits the policy relevance and social acceptance of such methods. Most fairness and explainability discussions remain siloed in model validation or visualization, rather than being connected to allocation-level audit or disclosure—highlighting a significant implementation gap.

These thematic divergences are mirrored in the limitations and calls for future research articulated across the literature. The field's strongest studies utilize large, well-documented national registries and rigorous external validation, providing confidence in model performance for retrospective cohorts [16, 29, 32]. However, the generalizability of simulation-based or representation learning allocation frameworks is often constrained by the use of retrospective, semi-synthetic, or non-clinical datasets, with prospective evaluation still lacking [19, 21, 22, 27, 28, 37]. There is a notable absence of real-world trials or regulatory pathways for safety and efficacy in practice. Additionally, standard reporting on bias, subgroup effects, and missing data remains variable.

In summary, despite progress in prediction and early operational prototypes, convergence of outcome optimization, fairness, transparency, and real-world integration remains incomplete. Future research must move toward real-world validation through experimental policy variances, which can generate evidence on efficacy and equity compared to the status quo in a controlled manner. This will require systematic partnership between algorithm developers, clinicians, ethicists, regulators, and patients, as well as ongoing assessment of model calibration and allocation impacts as populations and practices evolve. Bridging the gap from sophisticated prediction to actionable, fair, and transparent allocation policy remains the central challenge and opportunity for digital medicine in kidney transplantation.

Limitations

This systematic review has several limitations that should be acknowledged. First, the reliance on retrospective data in most included studies raises concerns about potential biases, such as unmeasured confounders or incomplete registry records. While AI/ML models demonstrated strong predictive performance in validation cohorts, few studies reported real-world clinical implementation, limiting generalizability. Additionally, the heterogeneity in study designs, datasets, and outcome measures made direct comparisons challenging.

Another key limitation is the scarcity of research integrating ethical frameworks into operational allocation systems. While fairness and equity were frequently discussed, few studies implemented these principles algorithmically, and none reported prospective audits of bias in clinical practice. Furthermore, the lack of standardized reporting on model calibration, subgroup performance, and missing data reduced the ability to assess robustness across diverse populations.

Furthermore, the variety of AI/ML models and traditional benchmarks used across studies made direct, quantitative meta-analysis and universal performance claims impractical. Our review highlights a need for future studies to include a more standardized set of comparator models, including robust baselines like Cox regression and Random Survival Forests, to allow for clearer benchmarking.

Finally, the review was restricted to English-language publications, potentially omitting relevant studies from non-English-speaking regions. Despite these limitations, this work provides a comprehensive synthesis of current advancements and gaps in AI-driven kidney allocation.

Conclusion

The findings of this systematic review underscore the significant advancements and remaining challenges in applying artificial intelligence to kidney organ allocation. AI and machine learning models have demonstrated superior performance in predicting graft survival, recipient outcomes, and waitlist mortality compared to traditional statistical methods, marking a crucial step toward precision medicine in transplantation. However, the transition from predictive modeling to actionable allocation systems remains incomplete, with few studies progressing beyond simulation-based validation to real-world implementation. This gap highlights the need for a structured evidence-generation pathway, such as controlled policy variances, to evaluate these systems against the status quo before full-scale implementation.

Equally important is the ethical dimension of AI-driven allocation. While fairness and equity are frequently acknowledged as critical considerations, most studies fail to operationalize these principles within their algorithms. The lack of standardized frameworks for transparency, bias mitigation, and accountability poses a barrier to widespread adoption. Future efforts must prioritize the development of ethically grounded, clinically validated systems that balance efficiency with equitable access across diverse patient populations.

The path forward requires sustained collaboration across disciplines—uniting clinicians, data scientists, ethicists, and policymakers—to ensure that technological advancements translate into tangible benefits for patients. By addressing these challenges, AI has the potential to revolutionize kidney transplantation, optimizing outcomes while upholding the principles of justice and patient-centered care. The promise of these tools is undeniable, but their ultimate impact will depend on our ability to bridge the gap between innovation and implementation in clinical practice.

Supplementary Information

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Supplementary Material 1

Supplementary Material 2

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Author contributions
F.F.: Conceptualized the study, designed the methodology, conducted the systematic literature review, extracted and analyzed data, and drafted the manuscript. A.A.P.: Supervised the research, validated the inclusion/exclusion criteria, contributed to the interpretation of clinical outcomes, and critically revised the manuscript for intellectual content. F.O.: Performed data extraction and quality assessment, synthesized evidence on AI/ML methodologies, and contributed to writing the technical sections of the manuscript. K.N.: Contributed to data extraction and synthesis, assisted in the

interpretation of clinical findings, and provided critical revisions to improve the clarity of the manuscript. M.K.: Assisted in literature review and data interpretation, contributed to drafting sections of the results, and provided critical feedback on the manuscript. G.R.: Supervised the clinical aspects of the study, provided expert input on kidney allocation practices, and critically revised the manuscript for intellectual and clinical accuracy. H.R.S.: Led the ethical framework analysis, evaluated fairness and transparency metrics across studies, and co-wrote the discussion and conclusion sections. All authors reviewed and approved the final manuscript.

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