Artificial Intelligence In Kidney Transplantation:

prediction of outcome/immunosuppression optimization

Farahnaz Dadras, MD.

Iran University of Medical Sciencess

Journal of
Clinical Medicine

MDPI

Review

Present and Future Applications of Artificial Intelligence in Kidney Transplantation

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J. Clin. Med. 2024, 13, 5939

- **Artificial intelligence** simulates **human intelligence** in computer systems, replicating the human brain's functions.

- **Machine learning** (ML) is a subfield of AI that focuses on **developing algorithms** and **models** that enable computers to learn from and **make predictions or decisions** based on **large amounts of data** without explicit programming.

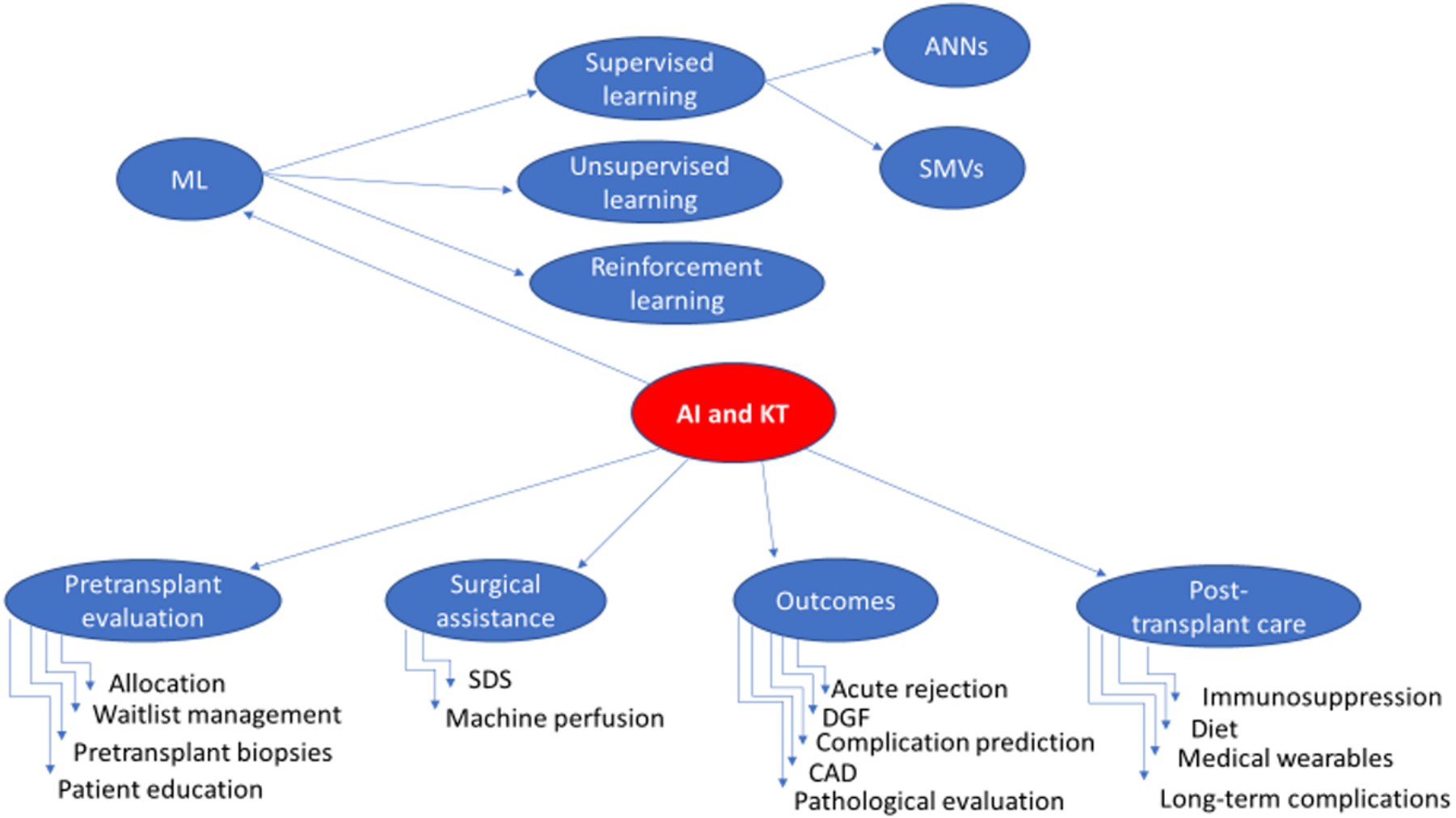


Figure 1. Applications of Artificial Intelligence in Kidney Transplantation. AI: artificial intelligence, KT: kidney transplantation, ML: machine learning, ANNs: artificial neural networks, SVMs: support vector machines, SDS: surgical data science, DGF: delayed graft function, CAD: computer-aided diagnosis.

Why AI in kidney transplantation now?

- **Wide adoption of the electronic health record system**
- **Growing availability of large**,
- : **demographics**, **labs**, **histology**, **imaging**, **molecular biomarkers**(dd cfDNA, gene expression)

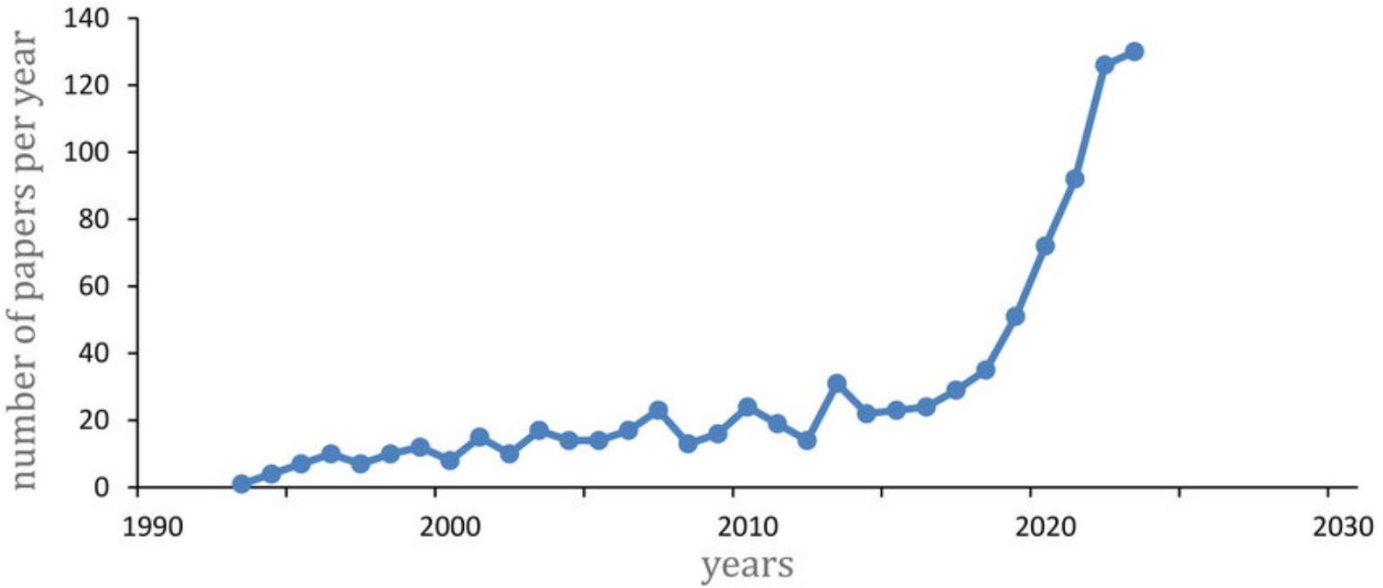
- **Complex** and **interactive clinical features**, which conventional statistics can not handle well.

Why AI in kidney transplantation now?

- **Advances in ML algorithms** (tree ensembles, gradient boosting, neural nets, and reinforcement learning) and interpretability tools.

- **Early evidence of improved predictive performance** vs traditional risk models in internal cohorts, **potential for personalized management**.

Artificial intelligence in kidney transplantation: a 30-year bibliometric analysis of research trends, innovations, and future directions



Global annual output trends.

Ying Jia He, et al. Renal Failure,February 202547(1):2458754

Overview of model types and data inputs

- **Data inputs**: donor factors (age, KDPI, cold ischemia time, perfusion data), recipient factors (age, comorbidities, PRA, HLA mismatch), intra-/post-operative data, early post-transplant labs, histology, molecular biomarkers.
- **Model types:**
  - **Outcome prediction models** (e.g., random forests, gradient boosting, Cox-ML hybrids)
  - Donor–recipient matching/simulation models
  - Immunosuppression optimization models (supervised learning, reinforcement learning, predictive risk scores)
  - **Multi-modal integrative models** (**clinical + pathology** + **molecular**)

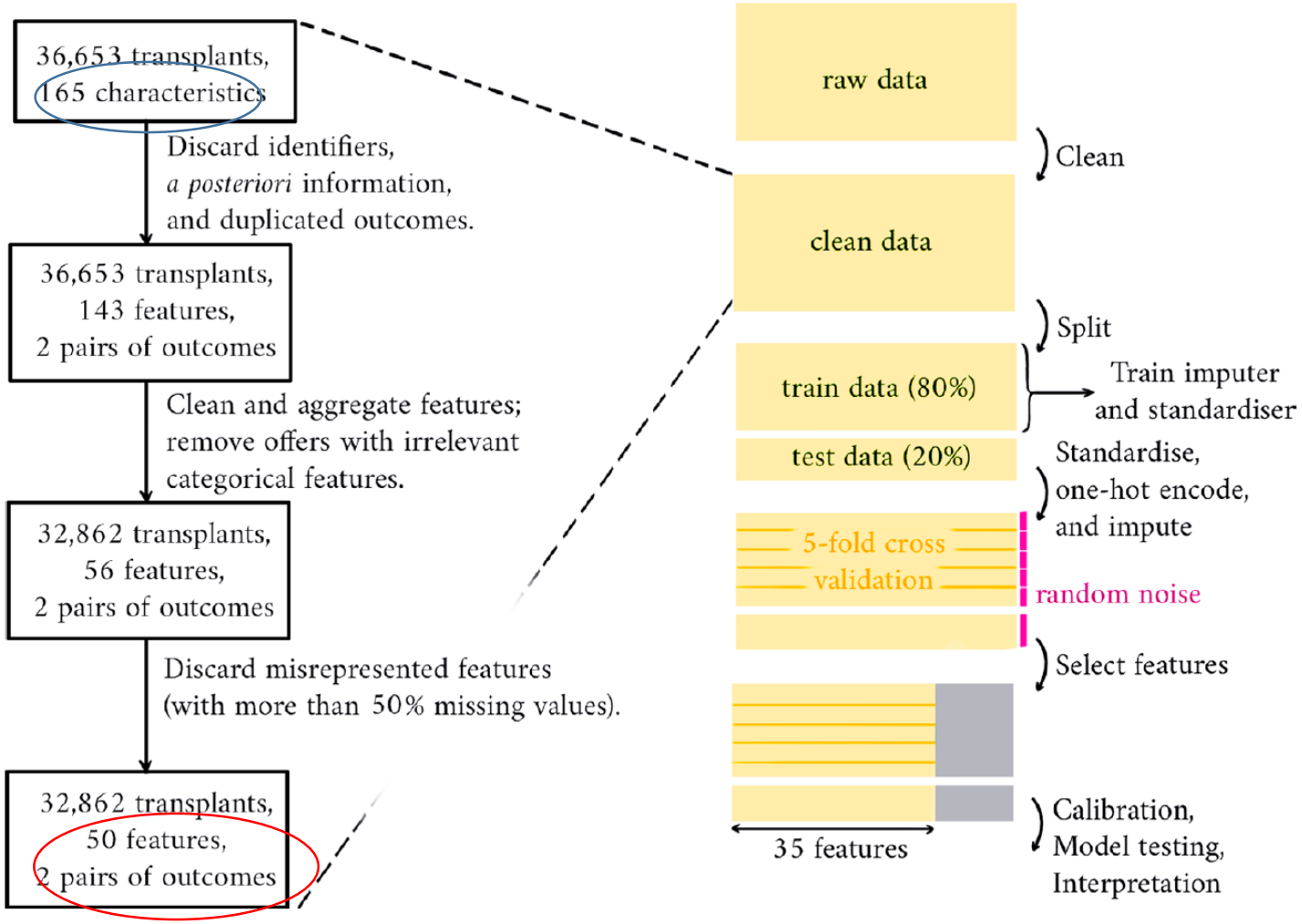
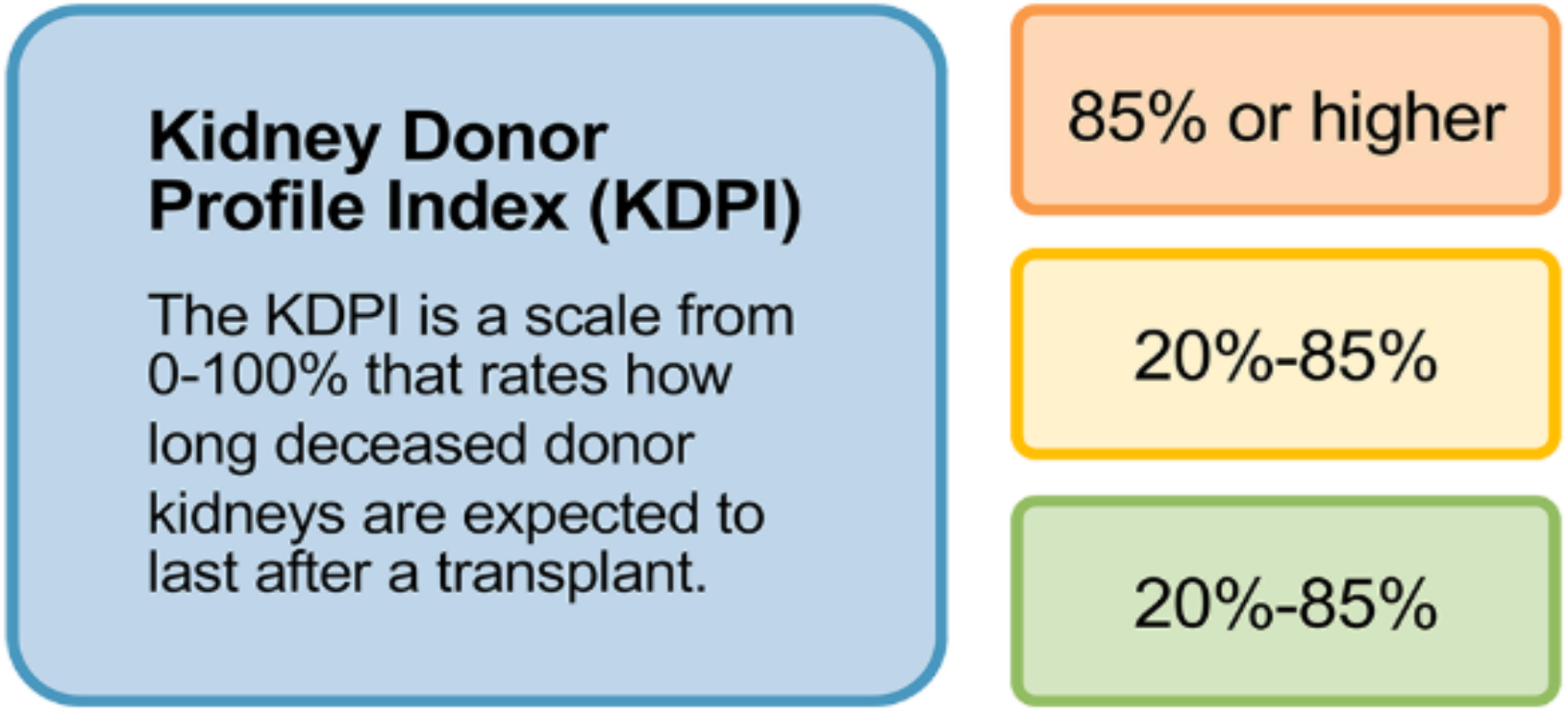


Figure 1. End-to-end data processing pipeline, from raw data to model testing. Data cleaning is detailed on the left. Cross-validation is performed before and after feature selection.

- KDPI,KDRI, EPTS

Prediction of graft survival

- KDRI
- KDPI
- Donor Age
- Donor weight
- Donor hight
- Ethnicity
- Hx of HTN
- Hx of D.M
- Serum cr
- Cause of Death(CVA..)
- DCD
- HCV status



Estimated Post Transplant Survival (EPTS)

- **EPTS** estimates **post-transplant survival of the transplant recipient**.
- The primary purpose is for kidney allocation.
- **Recipient age**
- **Time on dialysis**(excluding time before age 18)
- **Prior organ transplantation**
- **Presence of diabetes**
- KDRI/KDPI, the EPTS score was developed through statistical analysis of data, specifically large data sets of transplant recipient outcomes.

EPTS Calculator

- EPTS is a numerical measure combining four recipient parameters (candidate's **age**
- and **time on dialysis**,
- current diagnosis of **diabetes**
- **prior solid organ transplants**)
- to predict **post-transplant survival** and aid the allocation of donor kidneys
- The current allocation system assigns priority to the top 20% of kidneys (as denoted by **KDPI < 20**) to patients with an **EPTS of ≤20.**

Artificial intelligence assisted risk prediction in organ transplantation: a UK Live-Donor Kidney Transplant Outcome Prediction tool

Hatem Ali, Arun Shroff, Tibor Fülöp, Miklos Z. Molnar, Adnan Sharif, Bernard Burke, Sunil Shroff, David Briggs & Nithya Krishnan

Renal Failure 2025, VOL. 47, NO. 1, 2431147

THIS STUDY ADDS:

- The development of the **UK-LTOP model** using artificial intelligence to **predict living-donor kidney transplant outcomes** in the UK, showcasing **superior discriminative performance** and calibration compared to existing models.
- • Insights into the **challenges of creating a universal risk calculator** for organ transplantation due to significant differences between healthcare systems in the USA and the UK.
- • Evidence that **machine learning techniques** can effectively use **regional transplant registry data** to predict transplantation outcomes, potentially applicable across Europe.

- The data source was the United Kingdom Transplant Registry (**UKTR**) database.
- From 1 January **2007** to 1 December **2022**, all **living-donor kidney** transplant recipients listed in the UKTR database were included.
- Patients were **monitored up until 31/05/2023**.
- The **maximum follow-up period was 16 years** post-transplant.
- Recipients *under 18 years* old, *ABO-incompatib*le recipients, recipients with *positive crossmatch* (by flow cytometry) transplants, or those who had *missing survival data* were excluded.

Results

- After applying the inclusion and exclusion criteria, the total number of **patients included** in the analysis was **12,661** (**8,863 patients in the training dataset** and **3,798 patients in the validation dataset**).
- The hierarchy of selection of the cohort study is demonstrated in Figure 1.
- The **total number of independent variables available** before transplant was **42.**
- **After applying feature engineering** and **RFE**, the **independent** variables used for our models were further **reduced to 22**.

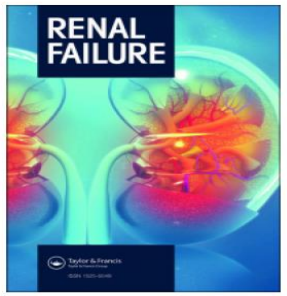
- ***Discriminative performance***
- The **XGBoost** had the **highest concordance index (0.72**), followed by the **random survival forest (0.71**).

- The **optimal decision tree** had the **lowest concordance (0.70**).

Re-evaluating the UK-LTOP performance on different subgroups

- **UK-LTOP gave a concordance index of 0.70** for the **more deprived** subgroup of patients and a concordance index of **0.74 for the less deprived** subgroup.

- ***Results for overall graft survival***
- We conducted **a reiteration of the XGBoost model**, altering the measured **outcome to overall graft failure** instead of **death-censored graft failure**.
- In the test group, the **concordance index yielded a value of 0.72**, while the IBS stood at 0.09.
- The **AUC** exhibited a range from **0.70 to 0.76.**



Renal Failure

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Improved survival prediction for kidney transplant outcomes using artificial intelligence-based models: development of the UK Deceased Donor Kidney Transplant Outcome Prediction (UK-DTOP) Tool

Hatem Ali, Arun Shroff, Karim Soliman, Miklos Z. Molnar, Adnan Sharif, Bernard Burke, Sunil Shroff, David Briggs & Nithya Krishnan

Renal Failure 2024, VOL. 46, NO. 2, 2373273

Table 1. Baseline characteristics and factors included in the final model: a comparison between the training and the validation groups.

	Training group ($n = 23,770$)	Test group ($n = 5943$)
Recipient factors		
Cause of renal failure: *n* (%)		
Diabetes/hypertension:	5463 (22.98%)	1340 (22.55%)
Glomerulonephritis/vasculitis:	4768 (20.06%)	1175 (19.77%)
Cancer:	127 (0.53%)	39 (0.66%)
Congenital:	4707 (19.80%)	1148 (19.32%)
Unspecified:	8566 (36.04%)	2211 (37.20%)
Vascular:	139 (0.58%)	30 (0.50%)
Recipient age: mean (standard deviation):	51.18 (13.50)	51.15 (13.40)
Pediatric at registration: *n* (%)		
-No:	18,958 (79.76%)	4768 (80.23%)
-Unknown:	4728 (19.89%)	1154 (19.42%)
-Yes:	84 (0.35%)	21 (0.35%)
Recipient weight in kg: mean (standard deviation):	77.24 (21.97)	77.43 (20.86)
-Missing data (*n*%):	93 (<1%)	257 (4.32%)
Recipient height in cm: mean (standard deviation):	169.59 (22.20)	170.63 (31.65)
-Missing data (*n*%):	5189 (21.80%)	1256 (21.13%)
Recipient body mass index in kg/m^2: mean (standard deviation):	26.73 (4.78)	26.70 (4.72)
-Missing data (*n*%):	5316 (22.36%)	1283 (21.58%)
Recipient ethnicity: *n* (%)		
White:	17,221 (72.45%)	4305 (72.44%)
Asian:	3539 (14.89%)	869 (14.84%)
Black:	2035 (8.56%)	515 (8.67%)
Other:	775 (3.26%)	200 (3.37%)
Not reported:	200 (0.84%)	54 (0.91%)
Waiting time in days: mean (standard deviation):	1005.717 (857.78)	979.74 (805.95)
-Missing data (*n*%):	118 (<1%)	24 (<1%)
Dialysis at registration: *n* (%):		
Hemodialysis:	11,468 (48.37%)	2861 (48.28%)
Peritoneal dialysis:	4069 (17.16%)	995 (16.79%)
Not on dialysis:	8018 (33.82%)	2033 (34.31%)
Unknown:	153 (0.65%)	37 (0.63%)

Graft number: *n* (%)		
One:	20,401 (85.82%)	5154 (86.72%)
Two:	2834 (11.92%)	678 (11.41%)
Three:	463 (1.95%)	103 (1.73%)
More than three:	70 (0.31%)	8 (0.13%)
Donor factors		
Donor age: mean (standard deviation):	49.41 (16.14%)	49.77 (15.99)
Donor height in cm: mean (standard deviation):	170.30 (11.78)	170.18 (12.03)
Donor weight in kg: mean (standard deviation):	78.04 (18.65)	77.86 (18.53)
-Missing data (*n*%):	22 (<1%)	8 (<1%)
Donor body mass index in kg/m^2: mean (standard deviation):	26.66 (5.44)	26.62 (5.47)
-Missing data (*n*%):	185 (<1%)	45 (<1%)
Donor urine output in the last 24 h in milliliters: mean (standard deviation):	2800.30 (1678.61)	2785.45 (1629.68)
-Missing data (*n*%):	8502 (35.76%)	2131 (35.85%)
Donor urine output in the last hour in milliliters: mean (standard deviation):	112.68 (111.10)	111.68 (119.35)
-Missing data (*n*%):	518 (2.1%)	140 (2.3%)
Donor creatinine in mmole/litre: mean (standard deviation):	81.38 (55.18)	81.83 (56.58)
-Missing data (*n*%):	1091 (4.5%)	260 (4.3%)
Donor history of hypertension: *n* (%)		
No:	16,987 (71.63%)	4205 (70.97%)
Yes:	6300 (26.57%)	1620 (27.34%)
Unknown:	483 (2%)	118 (1.69%)
Donor history of smoking: *n* (%)		
No:	10,552 (44.50%)	2633 (44.44%)
Yes:	12,984 (54.75%)	3254 (54.92%)
Unknown:	178 (0.75%)	38 (0.64%)
Donor amount of smoking: mean (standard deviation)	16.36 (12.64)	16.33 (12.46)
Transplant factors		
HLA A mismatch: *n* (%)		
0:	4679 (19.69%)	1105 (18.59%)
1:	11,496 (48.38%)	2912 (49%)
2:	7538 (31.72%)	1916 (32.24%)
Unknown:	57 (0.21%)	10 (0.17%)
HLA B mismatch: *n* (%)		
0:	3906 (16.44%)	910 (15.31%)
1:	15,433 (64.95%)	3920 (65.96%)
2:	4,374 (18.41%)	1103 (18.56%)
Unknown:	57 (0.21%)	10 (0.17%)
HLA DR mismatch: *n* (%)		
0:	10,097 (42.49%)	2528 (42.54%)
1:	11,605 (48.84%)	2883 (48.51%)
2:	2011 (8.46%)	522 (8.78%)
Unknown:	57 (0.21%)	10 (0.17%)
Match points: mean (standard deviation):	6.01 (2.37)	5.97 (2.38)
-Missing data (*n*%):	162 (<1%)	30 (<1%)
Matchability band: mean (standard deviation):	103.44 (105.21)	105.63 (105.84)
-Missing data (*n*%):	162 (<1%)	30 (<1%)
Calculated reaction frequency: mean (standard deviation):	21.88 (34.25%)	20.58 (19.74%)

Results

- Following the application of the inclusion and exclusion criteria, **29,713 patients in total** (**23,770 in the training dataset** and **5943 in the test dataset**) were included in the study.
- The **number of independent variables available before transplant** was **91**.
- After RFE and feature engineering, **the independent variables** used in our models were further **condensed to 26**.

- ***Results for the supervised learning methods***
- **Discrimination:** The **random survival forest** and the **XGBoost** obtained the **highest concordance indices (0.74**).
- The concordance was lowest (0.70) for the optimal decision tree.
- **The AUC was highest for the XGBoost model**.

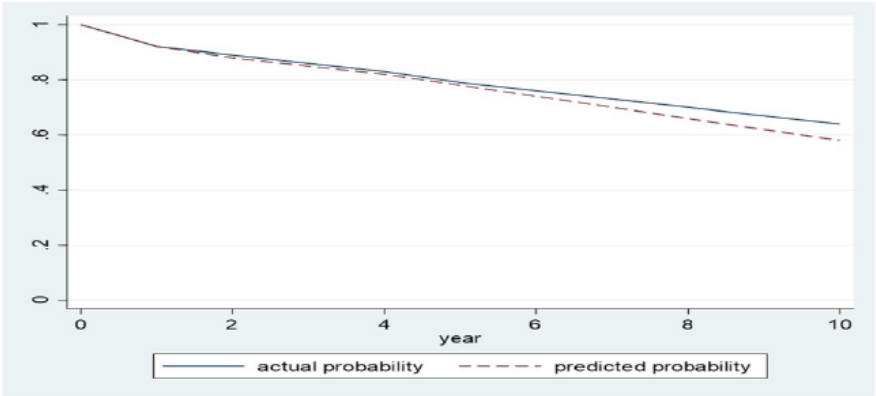


Figure 2. Actual survival probabilities were calculated using the Kaplan-Meier survival product estimator; then the average of these values was calculated at each time point. The average actual survival probabilities were plotted against the equivalent predicted probabilities at different time points.

Table 3. Comparison between the UK-DTOP and the UK-KDRI in terms of AUC score at different time points.

Year	UK-KDRI	UK-DTOP
Year 1	0.59	**0.72**
Year 2	0.61	**0.73**
Year 3	0.61	**0.74**
Year 4	0.60	**0.74**
Year 5	0.60	**0.75**
Year 6	0.60	**0.75**
Year 7	0.62	**0.76**
Year 8	0.63	**0.75**
Year 9	0.62	**0.75**
Year 10	0.64	**0.73**

The bold values are the highest values among in the comparison.

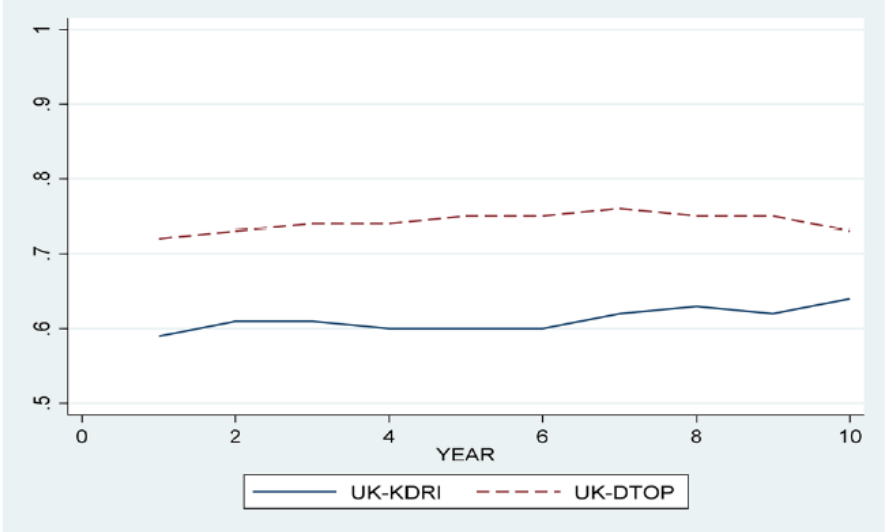


Figure 3. Comparison between the UK-DTOP and the UK-KDRI in terms of AUC over time.

Table 4. Evaluation of the AUC scores at different time points across the more deprived and the less deprived groups.

	Most deprived deprived group	Least deprived group
1 year	0.74	0.70
2 years	0.75	0.73
3 years	0.76	0.72
4 years	0.76	0.73
5 years	0.75	0.73
6 years	0.76	0.74
7 years	0.76	0.73
8 years	0.76	0.73
9 years	0.77	0.73
10 years	0.76	0.72

https://dtop.organpredict.ai/datainput

Deceased Donor Kidney Transplant

Graft Survival Prediction

Donor's age	
Donor's ethnicity	Asian
Donor's history of hypertension	No
Donor's history of diabetes	No
Donor's Cause of Death	Anoxia
Donor's Height (in cm)	
Donor's Weight (in kg)	
HLA-DR mismatch	0
Calculated PRA	
Donor's Creatinine	Units mg/dL
Cause of renal failure	Diabetes/hypertension
Recipient's ethnicity	Asian
Recipient's age	
Dialysis duration before transplant	Yes, duration less than 1 year
Recipient's HCV status	Negative
Recipient's height (in cm)	
Recipient's weight (in kg)	

Predict Survival

Prediction of Model

Survival Probabilities

Time (years)	Probability (%)
1	96.8
2	94.0
4	87.7
6	80.1
8	74.1
10	66.7
12	59.4
14	52.4

Back to Input Form

- The concern that the **calculator might inherently favor recipients** with **better prognostic** profiles, such as **younger, non-diabetic individuals**, touches on the critical issue of fairness and equity in **organ allocation**.
- The UK-DTOP model aims to **improve predictive accuracy of transplant outcomes**, informing but not dictating decisions.

.

- **To avoid biases and ensure equity**, the model should be integrated within a framework **respecting justice** and **broader allocation criteria**, including **urgency and waiting time**.
-

- **Regarding donor factors**, we **identified five distinct donor clusters**, each with unique characteristics impacting graft survival outcomes:
- **Cluster 1**: Comprised **younger donors** with the **best physiological** profiles, averaging **44.83 years** in age, **lower BMI**, and **lower creatinine levels.**
- The primary cause of death was **cerebrovascular incidents**, indicating **fewer complications due to the sudden nature** of these events.

- Cluster 2:
- **Slightly older** donors with an average age of **49.20 years** and **higher BMI values**, presenting a more varied health landscape.
- This cluster had more donors who **died from anoxia**, indicating specific **organ viability challenges** needing tailored management.

- Cluster 3:
- Consisted of the **oldest donors** with **significant health challenges**, the **highest BMI and creatinine levels**, and a substantial proportion of DCD donors.
- **Cerebrovascular deaths were** common, requiring specialized transplant strategies due to compounded medical complexities.

- Cluster 4:
- **Nearly half of the donors were DCD**, facing **challenges with rapid organ retrieval.**
- Similar to Cluster 3, this cluster had **elevated BMI and creatinine** levels, **necessitating careful handling** and innovative transplant approaches.

- Cluster 5:
- Featured the **most challenging donor profiles** with the **highest average age, BMI, and creatinine levels.**
- It had the **lowest matchability due to significant HLA mismatches** and the highest percentage of DCD donors.
- Donors often had histories of **diabetes, liver disease**, and **smoking**, requiring **rigorous pre-transplant assessments** and highly customized post-transplant care to optimize outcomes.

- The identification of a **fifth cluster indicates variations** in donor and transplant characteristics that the **KDRI's quartile system does not capture**.
- By identifying this extra group, our **model enhances donor assessment precision, potentially leading to more accurate matching between donors and recipients.**

Contents lists available at ScienceDirect

Transplantation Reviews

journal homepage: www.elsevier.com/locate/trre

Review article

The comparative performance of models predicting patient and graft survival after kidney transplantation: A systematic review

Joris van de Klundert [a,*], Francisco Perez-Galarce [b,f], Marcelo Olivares [c], Liset Pengel [d], Annelies de Weerd [e]

Transplantation Reviews 39 (2025) 100934

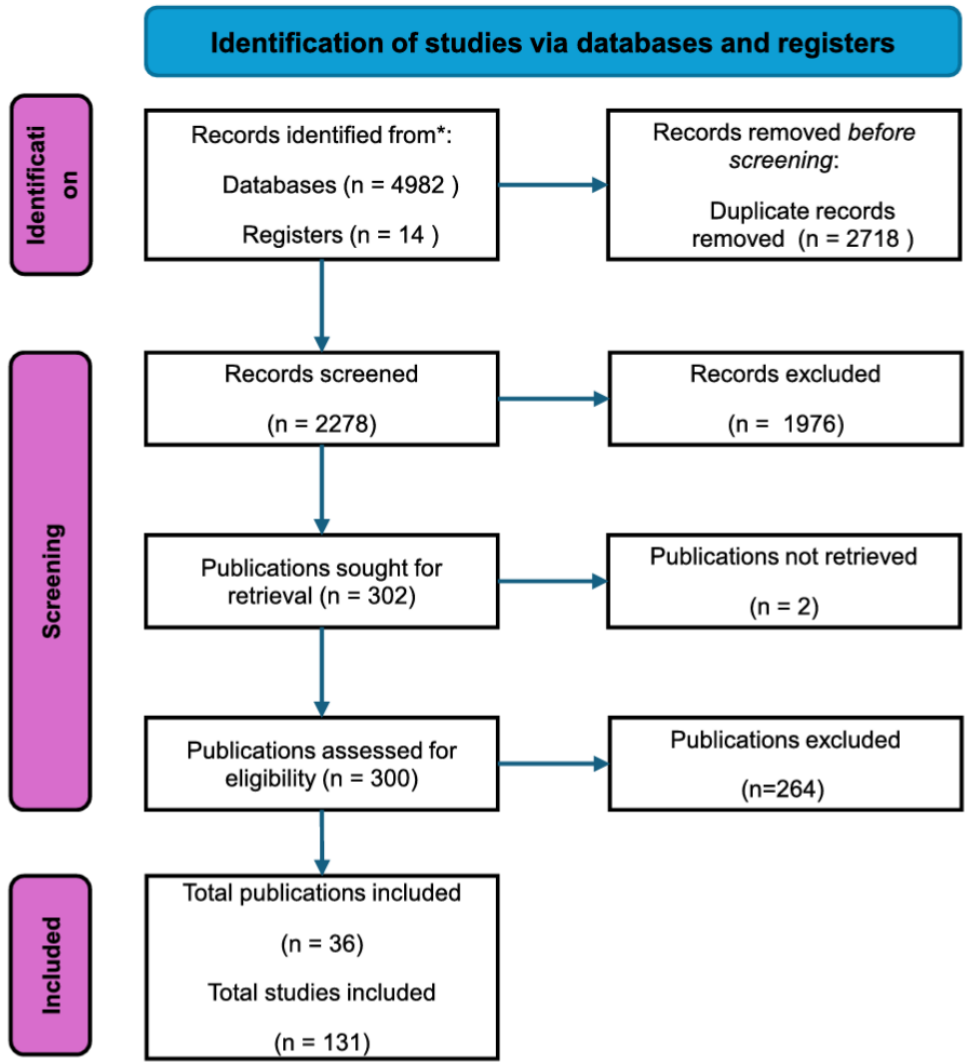


Fig. 1. Prisma flow chart.

Table 1
Included publications.

Authors	Publication year	Title	Recruitment Years		Study Site(s)
L. Fritsche, J. Hoerstrup, K. Budde, P. Reinke, H.-H. Neumayer, U. Frei and A. Schlaefer	2005	Accurate prediction of kidney allograft outcome based on creatinine course in the first 6 months posttransplant	1981	2004	Germany
R. S. Lin, S. D. Horn, J. F. Hurdle and A. S. Goldfarb-Rumyantzev	2008	Single and multiple time-point prediction models in kidney transplant outcomes	1995	2002	USA
A. Ald, A. M. Ismail and M. Ghoneim	2008	Prediction of graft survival of living-donor kidney transplantation: nomograms or artificial neural networks?	1976	2007	Egypt
F. Reinaldo, M. A. Rahman, C. F. Alves, A. Malucelli and R. Camacho	2010	Machine learning support for kidney transplantation decision making	No Informatoon	No Informatoon	Brazil
H. Tang, M. R. Poynton, J. F. Hurdle, B. C. Baird, J. K. Koford and A. S. Goldfarb-Rumyantzev	2011	Predicting three-year kidney graft survival in recipients with systemic lupus erythematosus	1985	2002	USA
A. H. Hashemian, B. Beiranvand and M. Rezaei	2013	Comparison of artificial neural networks and cox regression models in prediction of kidney transplant survival	2001	2012	Iran
D. M. Atallah and A. I. Eldesoky	2014	One-year renal graft survival prediction using a weighted decision tree classifier	2000	2009	Egypt
M. Fouad, M. Ellatif, M. Hagag and A. Ald	2015	Prediction of long term living donor kidney graft outcome: Comparison between rule based decision tree and linear regression	1976	2007	Egypt
L. Shahmoradi, M. Langarizadeh, G. Pourmand and A. Borhani	2016	Comparing Three Data Mining Methods to Predict Kidney Transplant Survival	2007	2013	Iran
K. D. Yoo, J. Noh, H. Lee, D. K. Kim, C. S. Lim, Y. H. Kim, et al.	2017	A Machine Learning Approach Using Survival Statistics to Predict Graft Survival in Kidney Transplant Recipients: A Multicenter Cohort Study	1997	2012	Korea
M. Z. Molnar, D. V. Nguyen, Y. Chen, V. Ravel, E. Streja, *M. Krishnan*, et al.	2017	Predictive Score for Posttransplantation Outcomes	2001	2006	USA
L. Tapak, O. Hamidi, P. Amini and J. Poorolajal	2017	Prediction of Kidney Graft Rejection Using Artificial Neural Network	1994	2011	Iran
M. Nematollahi, R. Akbari, S. Nikeghbalian and C. Salehnasab	2017	Classification Models to Predict Survival of Kidney Transplant Recipients Using Two Intelligent Techniques of Data Mining and Logistic Regression	2008	2012	Iran
Z. Hassani and N. Emami	2018	Prediction of the Survival of Kidney Transplantation with imbalanced Data Using Intelligent Algorithms	2006	2010	Iran
K. Topuz, F. D. Zengul, A. Dag, A. Almehmi and M. B. Yildirim	2018	Predicting graft survival among kidney transplant recipients: A Bayesian decision support model	2004	2015	USA
D. M. Atallah, M. Badawy, A. El-Sayed and M. A. Ghoneim	2019	Predicting kidney transplantation outcome based on hybrid feature selection and KNN classifier	1976	2017	Egypt
D. M. Atallah, M. Badawy and A. El-Sayed	2019	Intelligent feature selection with modified K-nearest neighbor for kidney transplantation prediction	1986	2019	Egypt
E. S. Pahl, W. N. Street, H. J. Johnson and A. I. Reed	2020	A predictive model for kidney transplant graft survival using machine learning	1995	2005	USA
S. Bae, A. B. Massie, B. S. Caffo, K. R. Jackson and D. L. Segev	2020	Machine learning to predict transplant outcomes: helpful or hype? A national cohort study	2005	2017	USA
S. A. A. Naqvi, K. Tennankore, A. Vinson, P. C. Roy and S. S. R. Abidi	2021	Predicting Kidney Graft Survival Using Machine Learning Methods: Prediction Model Development and Feature Significance Analysis Study	2000	2017	USA
S. Senanayake, S. Kularatna, H. Healy, N. Graves, K. Baboolal, M. P. Sypek and A. Barnett	2021	Development and validation of a risk index to predict kidney graft survival: the kidney transplant risk index	2007	2017	Australia and New Zealand
N. Taherkhani, M. M. Sepehri, R. Khasha and S. Shafaghi	2021	Determining the Level of Importance of Variables in Predicting Kidney Transplant Survival Based on a Novel Ranking Method	1987	2018	USA
C. L. Ramspek, M. El Moumni, E. Wali, M. B. A. Heemskerk, R. A. Pol, M. J. Crop, et al.	2021	Development and external validation study combining existing models and recent data into an up-to-date prediction model for evaluating kidneys from older deceased donors for transplantation	2006	2018	Netherlands and USA
S. Badrouchi, A. Ahmed, M. M. Bacha, E. Abderrahim and T. Ben Abdallah	2021	A machine learning framework for predicting long-term graft survival after kidney transplantation	1986	2019	Tunesia
Marc Raynaud et al	2021	Dynamic prediction of renal survival among deeply phenotyped kidney transplant recipients using artificial intelligence: an observational, international, multicohort study	2000	2016	Global
S. cerqueira, M. R. Campelos, A. Leite, E. J. Solteiro Pires, L. T. Pereira, H. Diniz, et al.	2022	How can we predict the kidney graft failure of Portuguese patients?	2013	2018	Portugal
F. X. Paquette, A. Ghassemi, O. Bukhtiyarova, M. Cisse, N. Gagnon, A. Della Vecchia, et al.	2022	Machine Learning Support for Decision-Making in Kidney Transplantation: Step-by-step Development of a Technological Solution	2000	2019	USA
L. Shahmoradi, A. Borhani, M. Langarizadeh, G. Pourmand, Z. A. Fard and S. Rezayi	2022	Predicting the survival of kidney transplantation: design and evaluation of a smartphone-based application	No Informatoon	No Informatoon	Iran
J. Rad, K. K. Tennankore, A. Vinson and S. S. R. Abidi	2022	Extracting Surrogate Decision Trees from Black-Box Models to Explain the Temporal Importance of Clinical Features in Predicting Kidney Graft Survival	2000	2014	USA

Table 1 (*continued*)

Authors	Publication year	Title	Recruitment Years		Study Site(s)
P. Moghadam and A. Ahmadi	2022	A machine learning framework to predict kidney graft failure with class imbalance using Red Deer algorithm	1994	2011	Iran
A. Atapour and M. Sattari	2022	Identifying the Factors Affecting the Survival Rate of Kidney Transplant Patients in Isfahan Using Classification Techniques	1992	2020	Iran
M. Nemati, H. Zhang, M. Sloma, D. Bekbolsynov, H. Wang, S. Stepkowski and K. S. Xu	2023	Predicting kidney transplant survival using multiple feature representations for HLAs	1987	2016	USA
W. Li, L. Li and B. C. Astor	2023	A comparison of two approaches to dynamic prediction: Joint modeling and landmark modeling	No Informatoon	No Informatoon	USA
G. Mulugeta, T. Zewotir, A. S. Tegegne, L. H. Juhar and M. B. Muleta	2023	Classification of imbalanced data using machine learning algorithms to predict the risk of renal graft failures in Ethiopia	2015	2022	Ethiopia
A. Truchot, M. Raynaud, N. Kamar, M. Naesens, C. Legendre, M. Delahousse, et al	2023	Machine learning does not outperform traditional statistical modeling for kidney allograft failure prediction	2005	2014	France
B. J. Chalissery and V. Asha	2023	An Optimized Survival Prediction Method for Kidney Transplant Recipients	1987	2023	USA

Table 3
Comparative Analysis for subgroup of studies reporting on GG and DCGF.

	Large Dataset - UNOS							Smaller Dataset Rest of the World							
	Num. of articles	6						*Num. of articles*	7						
	Num. of studies	23						*Num. of studies*	22						
		paired t-test			sign test				paired t-test			sign test			
		Dif	p-value	n	pos	neg	p-value		Dif	p-value	n	pos	neg	p-value	
Classication (AUC)	ANN - DT	0.005	0.384	8	5	2	0.453	ANN - DT	−0.001	0.886	5	1	4	NA	
	ANN - LR	0.007	0.444	6	4	1	0.375	**ANN** - LR	0.077	**0.021**	5	4	1	NA	
	Boost - RSF	−0.003	0.173	18	6	11	0.332	**Bayes** - LR	0.033	**0.012**	9	8	1	**0.039**	
	Cox - R(*S*)F	−0.009	0.197	8	1	7	0.070	**KNN** - SVM	0.097	**0.003**	6	6	0	**0.031**	
	RSF - SVM	0.022	0.072	11	10	1	**0.012**	LR - SVM	0.002	0.948	6	2	2	NA	
	Num. of articles	3						*Num. of articles*	4						
	Num. of studies	10						*Num. of studies*	27						
		paired t-test			sign test				paired t-test			sign test			
Discrimination (C-index)		Dif	p-value	n	pos	neg	p-value		Dif	p-value	n	pos	neg	p-value	
	Boost - Cox	0.008	**0.000**	9	9	0	**0.004**	**Cox** - DT	0.045	**0.036**	8	7	1	0.070	
	Boost - RSF	0.009	**0.001**	9	9	0	**0.004**	Cox - RSF	0.002	0.607	23	10	13	0.678	
	Cox - RSF	0.002	0.210	10	7	3	0.344	**Cox** - SVM	0.103	**0.000**	23	22	0	**0.000**	
								RSF - SVM	0.096	**0.000**	23	21	1	**0.000**	
	Num. of articles	3						*Num. of articles*	2						
	Num. of studies	3						*Num. of studies*	20						
Calibration (Brier score)									paired t-test			sign test			
									Dif	p-value	n	pos	neg	p-value	
								Boost - RSF	0.004	0.098	8	5	3	0.727	
	p-value < 0.05	p-value <0.10													

Models of this type are found **to outperform the classical Cox models** and RSF models for the C-index in the large UNOS/ SRTR data set, but the two other comparisons with RSF yield no significant differences in performance.

Moreover, the three comparisons between **RSF and Cox find no significant performance** differences.

scientific reports

OPEN

Predicting long-term outcomes of kidney transplantation in the era of artificial intelligence

Samarra Badrouchi[1,2,3]✉, Mohamed Mongi Bacha[1,2,3], Abdulaziz Ahmed[4], Taieb Ben Abdallah[1,2,3] & Ezzedine Abderrahim[1,2]

Scientific Reports | (2023) 13:21273 |

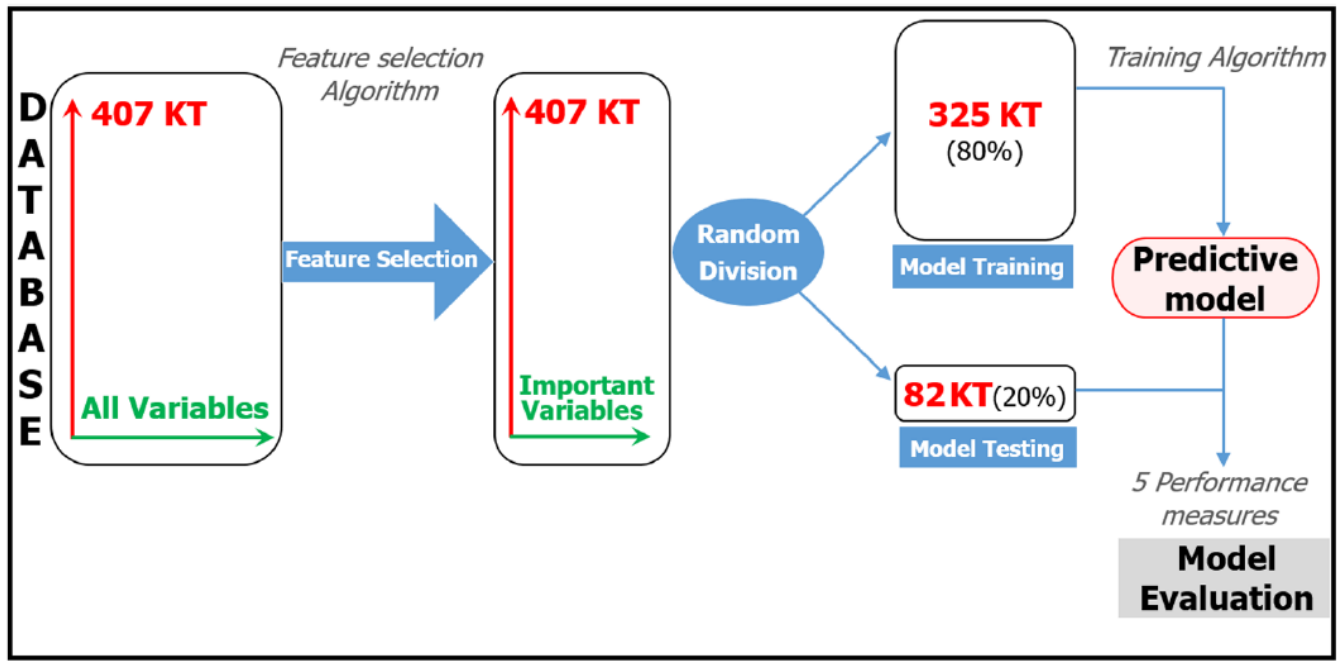


Figure 1. Process followed to develop a predictive model.

- Samarra Badrouchi et al. used five training algorithms: Artificial Neural Networks (**ANN**), Extreme Gradient Boosting (**XGB**), K Nearest Neighbors (**KNN**), **DT**, Logistic Regression (**LL**).
- The ability to **quickly and accurately predict 5-year graft survival** using **early**, **simple**, **noninvasive**, and **easy-to-collect variables** suggests that machine learning has the potential to **improve the prediction of renal transplantation prognosis** and to aid in healthcare decision-making.

- These variables included, in decreasing order of importance, the following: **hypertension, history of red-blood-cell transfusion, early acute kidney injury post-KT, early AR, CMV infection, length of first hospitalisation, MMF therapy, donor's age, three-month estimated GFR, and time on dialysis before KT**.
- They included **407 KTs** and divided them into two groups (group A, with a **graft lifespan greater than five years,** and **group B, with poor graft** survival).
- Among the **35 AI models developed**, the best model had an **AUC of 89.7%**(Sensitivity: 91.9%; Specificity: 87.5%).

	Variables		Group A	Group B	RR	95% CI	p
Recipient	Age/year (mean)		33.4	32	0.986	0.955–1.017	NS
	Gender (%)	Male	66.2	67.4	1	–	–
		Female	33.8	32.6	0.948	0.493–1.823	NS
	Hypertension (%)	No	39.9	32.6	1	–	–
		Yes	60.1	67.4	1.371	0.715–2.631	NS
	Diabetes (%)	No	94.7	97.8	1	–	–
		Yes	5.3	2.2	0.275	0.036–2.072	NS
	Viral hepatits B (%)	Negative	97	93.5	1	–	–
		Positive	3	6.5	2.220	0.596–8.271	NS
	Viral hepatits C (%)	Negative	85.2	86.5	1	–	–
		Positive	14.8	13.5	0.899	0.331–2.443	NS
	Nephropathy (%)	Vascular	8	6	1	–	–
		Glomerular	41.3	43.5	0.649	0.240–1.755	NS
		Tubulo-interstitial	21.6	15.2	0.434	0.135–1.399	NS
		Hereditary	5.8	2.2	0.230	0.026–2.057	NS
		Undetermined	23.3	26.1	0.690	0.238–2.007	NS
	Dialysis modality (%)	PD	19.4	10.9	1	–	–
		HD	74.5	87	2.082	0.792–5.471	NS
	Dialysis duration/year (Mean)		3.5	3.7	1.001	0.994–1.009	NS
	Transfusion (%)	No	38.2	26.1	1	–	–
		Yes	61.8	73.9	1.753	0.878–3.501	NS
	Cytotoxic antibodies (%)	Negative	85.9	82.6	1	–	–
		Positive	14.1	17.4	1.280	0.565–2.899	NS
	Total HLA MM (%)	0	17.5	19.6	1	–	–
		1–2	33.5	32.6	0.868	0.360–2.094	NS
		≥3	49	47.8	0.870	0.380–1.990	NS
	HLA- MM A (%)	0 MM	34.9	32.5	1	–	–
		1 MM	56.2	47.8	1.111	0.564–2.190	NS
		2 MM	14.4	15.2	1.096	0.401–2.994	NS
	HLA-MM B (%)	0 MM	29.4	36.9	1	–	–
		1 MM	56.2	47.8	0.676	0.344–1.327	NS
		2 MM	14.4	15.2	0.839	0.328–2.150	NS
	HLA-MM DR (%)	0 MM	40.4	43.5	1	–	–
		1 MM	50.7	47.8	0.878	0.461–1.670	NS
		2 MM	8.9	8.7	0.913	0.292–2.852	NS
Donor	Age/year (mean)		40.1	43.5	1.022	0.997–1.048	NS
	Age (%)	<45 years	63.2	43.5	1	–	–
		≥45 years	36.8	56.5	2.229	1.198–4.147	<0.02
	Gender (%)	Male	52.9	50	1	–	–
		Female	47.1	50	0.890	0.482–1.644	NS
	Gender match (%) Donor → recipient	M → M	30.5	28.3	1	–	–
		F → F	16.9	10.9	0.694	0.236–2.038	NS
		F → M	35.5	36.9	1.124	0.523–2.417	NS
		M → F	17.1	23.9	1.501	0.635–3.552	NS
	Donor type (%)	Living	84.8	82.6	1	–	–
		Deceased	15.2	17.4	1.171	0.519–2.645	NS
Procedure	Cold ischemia/hour (mean)		21.8	21.4	0.981	0.856–1.124	NS
	Cold ischemia (%)	<20 h	36.4	25	1	–	–
		≥20 h	63.6	75	0.880	0.189–4.085	NS
	Warm ischemia/min (mean)		38.2	40.2	1.018	0.990–1.046	NS
	Warm ischemia (%)	<30 min	18.6	17.4	1	–	–
		≥30 min	81.4	82.6	1.082	0.483–2.427	NS

Continued

	Variables		Group A	Group B	RR	95% CI	p
Immunosuppressive treatment	Induction (%)	Yes	88.9	91.3	1	–	–
		No	11.1	8.7	0.993	0.870–2.662	NS
	Polyclonal anti-lymphocyte (%)	No	20.5	19.6	1	–	–
		Yes	79.5	80.4	1.060	0.490–2.294	NS
	Anti-CD3 (%)	No	99.2	93.5	1	–	–
		Yes	0.8	6.5	8.326	1.629–42.547	< 0.02
	Anti-CD25 (%)	No	91.4	95.7	1	–	–
		Yes	8.6	4.3	0.467	0.108–2.018	NS
	Cyclosporine A (%)	No	43.8	54.3	1	–	–
		Yes	56.2	45.7	0.654	0.353–1.211	NS
	Tacrolimus (%)	No	65.7	60.9	1	–	–
		Yes	34.3	39.1	1.229	0.654–2.309	NS
	Azathioprine (%)	No	63.4	47.8	1	–	–
		Yes	36.6	52.2	1.893	1.021–3.507	< 0.05
	MMF (%)	No	20.8	47.8	1	–	–
		Yes	79.2	52.2	0.286	0.152–0.538	< 0.001
Post-KT	Length of 1st hospitalization/day (mean)		36.4	42.3	1.009	0.998–1.020	NS
	3-month eGFR ml/min (mean)		71	56.7	0.977	0.963–0.990	0.001
	Number of 1st year readmissions (%)	< 3	87.3	73.9	1	–	–
		≥ 3	12.7	26.1	2.417	1.168–5.001	< 0.02
	Delayed graft function (%)	No	88.7	73.9	1	–	–
		Yes	11.3	26.1	2.755	1.322–5.739	0.007
	Acute kidney injury (%)	No	64.8	34.8	1	–	–
		Yes	35.2	65.2	3.455	1.814–6.578	< 0.001
	Acute rejection (%)	No	78.4	58.7	1	–	–
		Yes	21.6	41.3	2.553	1.349–4.833	< 0.005
	Infections (%)	No	25.8	13	1	–	
		Yes	74.2	87	2.313	0.	
	Urinary tract infection (%)	No	60.7	58.7	1	–	
		Yes	39.3	41.3	1.085	0.	
	CMV infection (%)	No	80.3	69.6	1	–	
		Yes	19.7	30.4	1.787	0.	
	Surgical complication (%)	No	82	80.4	1	–	
		Yes	18	19.6	1.108	0.	

Table 1. Relative risk of 5-year graft failure in the univariate analysis. *MMF* mycophen
human leucocyte antigen, *MM* mismatch, *eGFR* estimated glomerular filtration rate, *CM*
NS not significant, *KT* kidney transplantation.

- donor age;
- MMF therapy;
- 3-month eGFR;
- DGF;
- number of hospital readmissions during the first year.

Donor AGE
MMF Therapy
3 Month eGFR
DGF
Number of hospital readmissions during the first year

Variable	Machine learning	Univariate LR*	Multivariate LR*
Donor age	✓	✓	✓
MMF therapy	✓	✓	✓
3-month eGFR	✓	✓	✓
Acute rejection	✓	✓	
Acute kidney injury	✓	✓	
CMV infection	✓		
Length of the 1st hospitalization	✓		
Hypertension	✓		
Transfusion	✓		
Dialysis duration	✓		
Readmissions 1st year		✓	✓
Delayed graft function		✓	✓
Azathioprine therapy		✓	
HLA MM A			
HLA MM DR			
Dialysis modality			
Proteinuria			

Table 2. Comparison between the results of machine learning and classical statistics. *MMF* mycophenolate mofetil, *eGFR* estimated glomerular filtration rate, *CMV* cytomegalovirus, *HLA* human leucocyte antigen, *MM* mismatch. *Bivariate and multivariate logistic regression (SPSS 25).

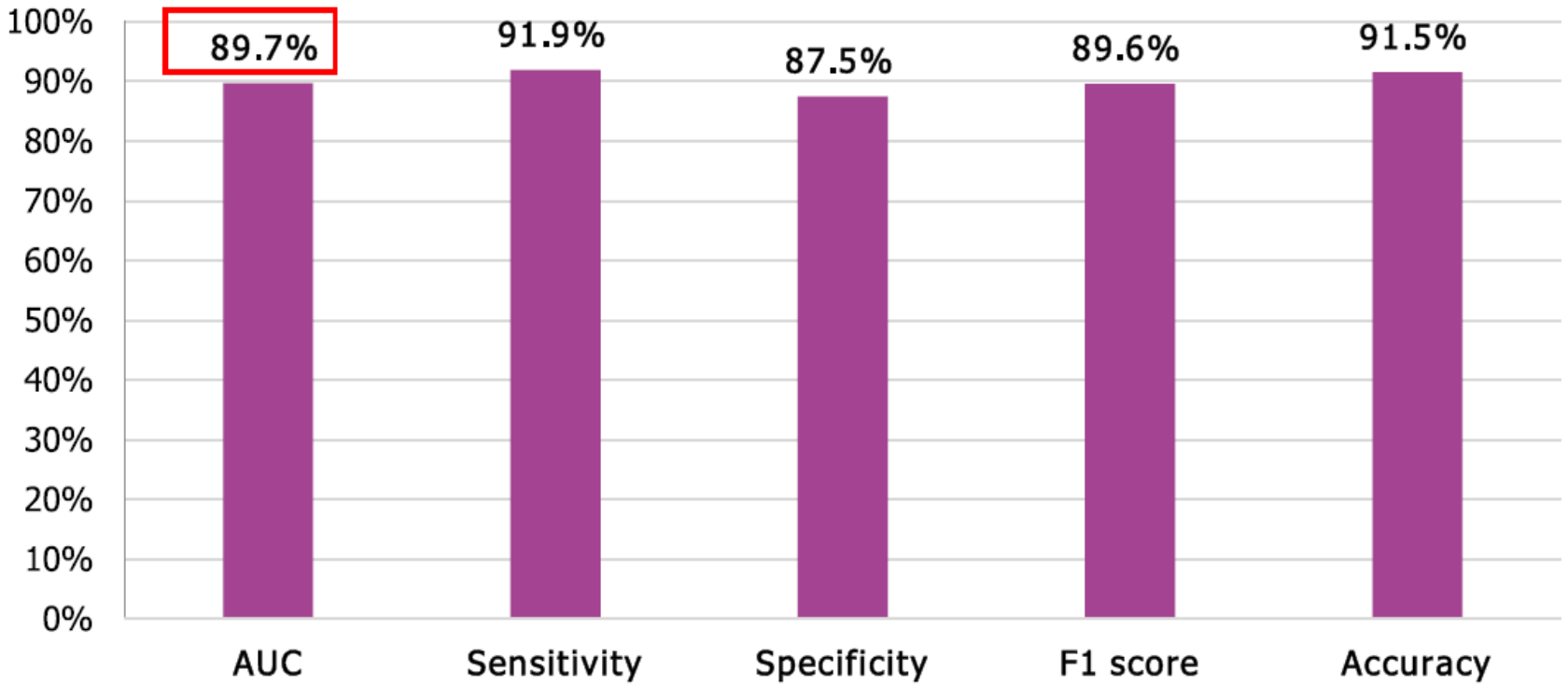


Figure 4. Performance measures of the best model.

Cardiac Risk Stratification in Renal Transplantation Using a Form of Artificial Intelligence

Thomas F Heston, MD [a,b,c] · Douglas J Norman, MD [a,b,c] · John M Barry, MD [a,b,c] · William M Bennett, MD [a,b,c] · Richard A Wilson, MD [a,b,c]

Am. J. Cardiol. 1997, 79, 415–417

- **Clinical risk factor screening** alone identified **95 of 189 patients as high risk**.
- These **95 patients underwent thallium-201 stress testing,** and **53 had either reversible or fixed defects**.
- The other **42 patients were classified as low risk**.

- This algorithm made up the "expert system," and during the 4-year follow-up period had a sensitivity of 82%, specificity of 77%, and accuracy of 78%.

- **An artificial neural network** was added to the expert system, creating an expert network. Input into the neural network **consisted of both clinical variables and thallium-201 stress test data**.
-
- **The expert network increased the specificity of the expert system alone from 77% to 90%** ($p < 0.001$), the accuracy from 78% to 89% ($p < 0.005$), and maintained the **overall sensitivity at 88%**

- An **expert network based** on clinical risk factor screening and thallium-201 stress testing had an **accuracy of 89% in predicting the 4-year cardiac mortality** among 189 renal transplant candidates.

Key study archetypes and what they show

- Example archetypes to mention
  - **DGF** and 1-year graft survival prediction using **donor/recipient variables** plus **perfusion data**
  - Models incorporating **Banff histology** features with **gene expression** for rejection risk
  - **Multi-omics augmentation** improves risk stratification

life

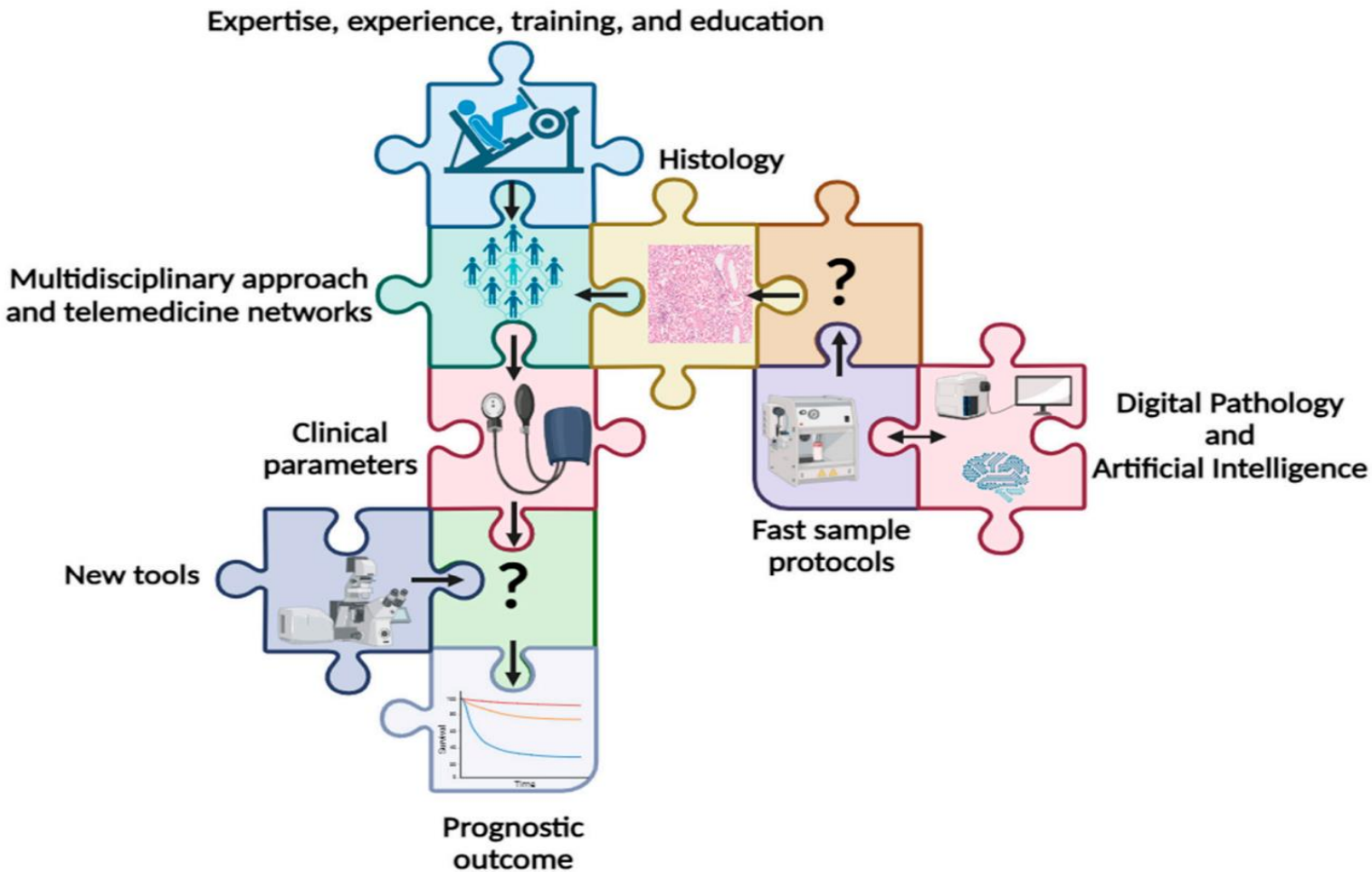
MDPI

Review

The Puzzle of Preimplantation Kidney Biopsy Decision-Making Process: The Pathologist Perspective

Albino Eccher [1,*], Jan Ulrich Becker [2], Fabio Pagni [3], Giorgio Cazzaniga [3], Mattia Rossi [4], Giovanni Gambaro [4], Vincenzo L'Imperio [3] and Stefano Marletta [5,6]

[1] Department of Medical and Sciences for Children and Adults, University of Modena and Reggio Emilia, University Hospital of Modena, 41100 Modena, Italy


Expertise, experience, training, and education
Histology
Multidisciplinary approach
and telemedicine networks
?
Clinical
parameters
Digital Pathology
and
Artificial Intelligence
Fast sample
protocols
New tools
?
Prognostic
outcome

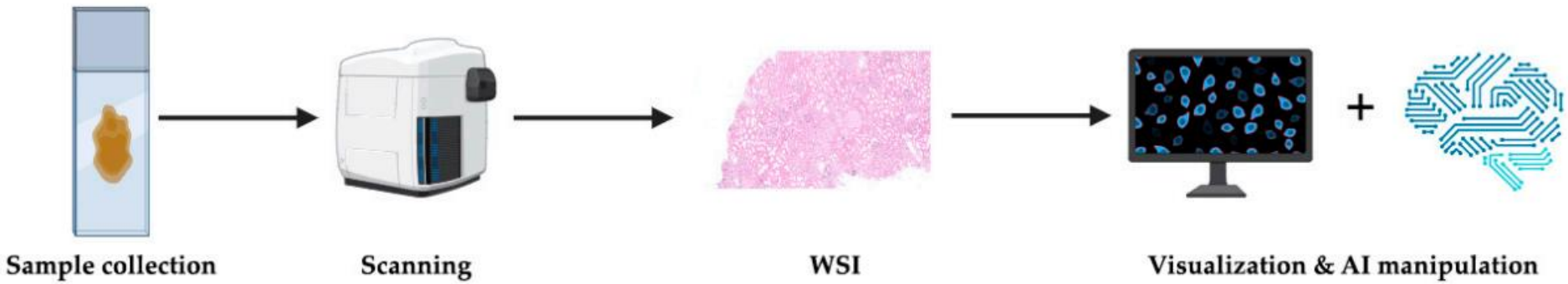


Figure 3. The digital pathology workflow: conventional histological slides are scanned to whole slide imaging (WSI) and then visualized on a computer monitor where they can be freely manipulated (rotated, zoomed in and out, etc. . .) by pathologists, eventually with the support of artificial intelligence (AI) tools.

- The **RENFAST** (Rapid EvaluatioN of Fibrosis And vesselS Thickness) is an AI-based algorithm developed to recognize **interstitial fibrosis** and changes in **vascular walls**.
- This tool was trained on a series of **300 renal biopsies** and achieved **better results** than previously tested software and conventional light microscopy.
- Furthermore, it performed much faster than the evaluation of glass slides, with a **2 min average time** of examination compared to 20 min with classic methods.

- In this view, **novel imaging techniques** coupled with machine-perfusion technologies offer the opportunity to **deeply investigate grafts' function** before transplantation in a non-invasive way.
- For instance, a **recent study applied magnetic resonance imaging** (**MRI**) to kidneys during ex vivo normothermic machine perfusion (35–37 ◦C).
- The investigators showed how this technique may work as a reliable method for **assessing both renal metabolism and physiology**, providing clinicians with a realistic picture of critical biological parameters, including microenvironmental oxygen availability, local perfusion flow, and drug distribution, among others.

- Similarly, another work aimed to estimate the **oxidative metabolism** of renal grafts during ex vivo organ perfusion by a **3-Tesla MRI scanner** was able to **detect the oxygen-17 isomer** .
- The authors elegantly **recorded the levels of oxidative metabolism** in the organ, with higher rates in the **renal cortex** and lower in the **medulla**, likely reflecting its functional quality.
- To note, MRI techniques have been employed for years to indirectly study the functionality of renal tissue. On this tissue, brilliant articles showed the ability of **31P MRI spectroscopy during the cold ischemia** period to **forecast the likelihood of developing acute tubular necrosis** immediately after transplantation.

ORIGINAL CLINICAL SCIENCE—GENERAL

A Machine Learning Prediction Model for Immediate Graft Function After Deceased Donor Kidney Transplantation

Quinino, Raquel M. MD[1]; Agena, Fabiana PhD[1]; Modelli de Andrade, Luis Gustavo MD, PhD[2]; Furtado, Mariane MA[3]; Chiavegatto Filho, Alexandre D.P. PhD[3]; David-Neto, Elias MD, PhD[1]

Transplantation 107(6):p 1380-1389, June 2023.

January 1**, 2010,** and December 31, **2019**

Variables related to the **donor**, **recipient**, **kidney preservation**, and **immunology** were used.

Popular machine learning algorithms were used: eXtreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine, Gradient Boosting classifier, Logistic Regression, CatBoost classifier, AdaBoost classifier, and Random Forest classifier.

Of the **859 patients**, **21.7% (n = 186) had IGF**.
The best predictive performance resulted from **the eXtreme Gradient Boosting model** (**AUC, 0.78**; 95% CI, 0.71–0.84; **sensitivity, 0.64; specificity, 0.78**).

urine output, **mean arterial pressure**, **blood glucose** and the **administration of high-dose vasopressors** were associated with DGF.

A machine learning prediction model for immediate graft function after deceased-donor kidney transplantation

Single center

859 kidney transplant

Retrospective

2010-2019

Exclusion Criteria

<18 y

Re-KTx

PRA >10%

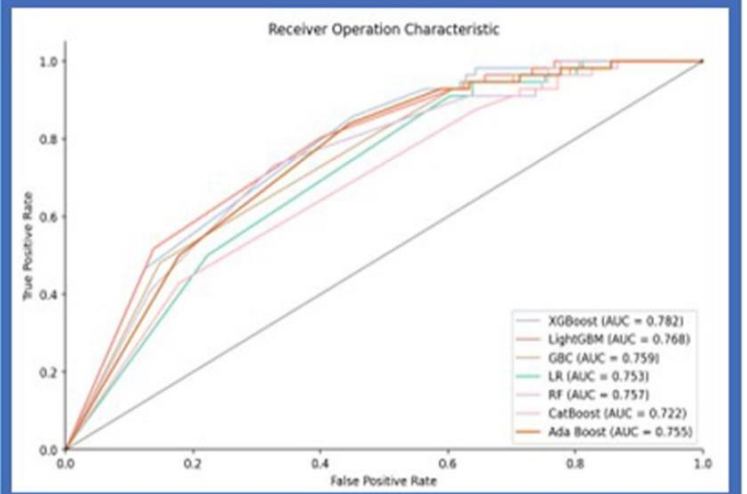
Multiple Organ Tx

Results

Immediate graft function 21.6%

Slow graft function 28.9 %

Delayed graft function 49.5 %



Best performance algorithm: XGBoost

AUC: 0.78

Recall: 0.64

Specificity: 0.77

PPV: 0.44

NPV: 0.92

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journal homepage: www.elsevier.com/locate/retram

General review

The impact of artificial intelligence and machine learning in organ retrieval and transplantation: A comprehensive review

David B. Olawade [a,b,c,d,*], Sheila Marinze [e], Nabeel Qureshi [e], Kusal Weerasinghe [b], Jennifer Teke [b,f]

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[b] Department of Research and Innovation, Medway NHS Foundation Trust, Gillingham ME7 5NY, United Kingdom
[c] Department of Public Health, York St John University, London, United Kingdom

Current Research in Translational Medicine 73 (2025) 103493

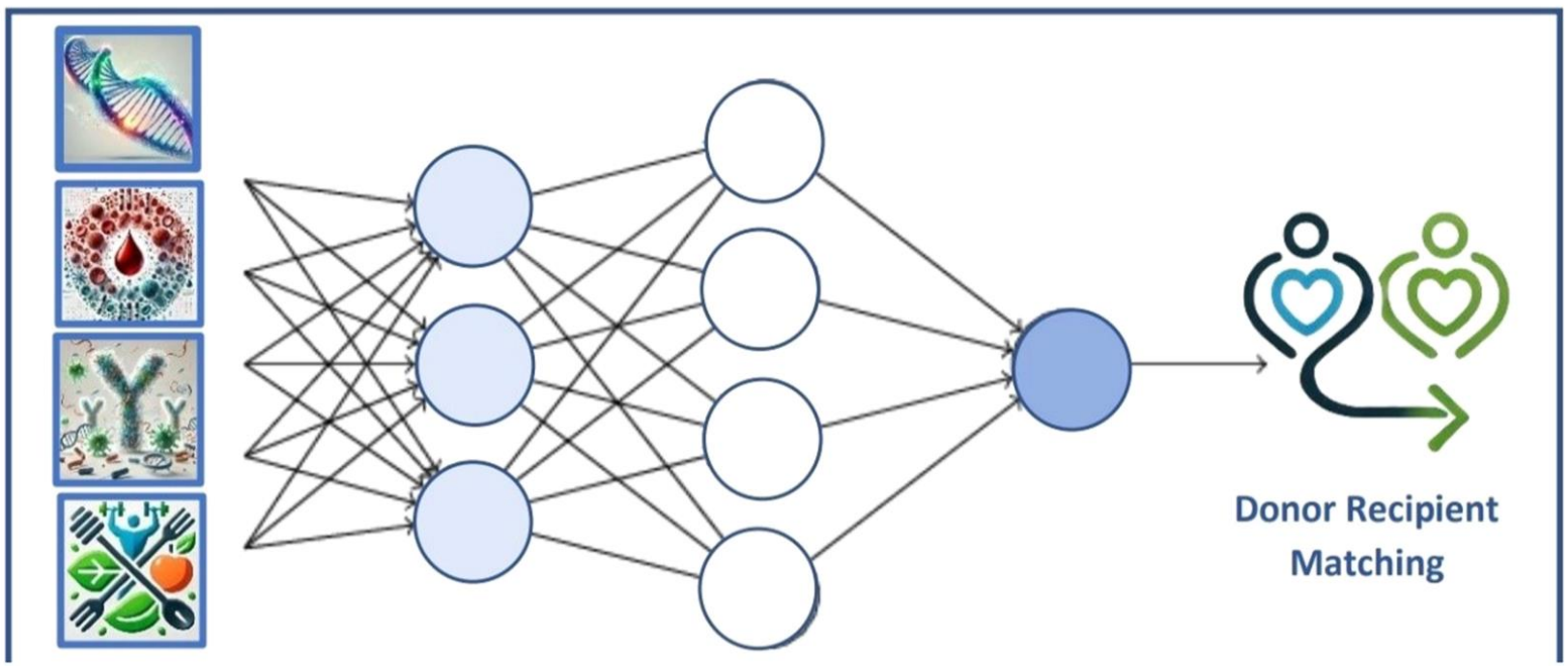

Fig. 1. AI Systems Leveraging Comprehensive Data Analysis to Uncover Patterns and Enhance Donor-Recipient Matching.

Table 1
Applications of AI and ML in donor-recipient matching for organ transplantation.

Aspect	Description	Benefits	Examples	Type of AI Tools and Models
Data Integration [27]	Combines clinical, genetic, and demographic data from donors and recipients.	Enables comprehensive analysis and more precise matching.	AI systems integrating EHRs, genetic profiles, and medical histories for compatibility assessment.	Natural Language Processing (NLP) for data extraction, Integration platforms using ML algorithms
Predictive Modeling [28]	Uses historical data to predict outcomes such as graft survival and rejection risk.	Enhances decision-making and personalized treatment plans.	ML models predicting the likelihood of organ rejection based on pre- and post-transplant biomarkers.	Regression models, Decision trees, Random forests, Neural networks
Real-Time Matching [29]	Continuously updates and analyzes data for real-time donor-recipient matching and organ allocation.	Reduces waiting times and increases the efficiency of organ allocation.	AI algorithms in platforms like UNOS dynamically prioritizing recipients based on current data.	Real-time data processing algorithms, Dynamic prioritization algorithms, rank search algorithms
Genomic Integration [30]	Incorporates genomic data to assess immunological compatibility and personalize immunosuppression.	Improves graft survival and reduces adverse reactions.	AI analyzing genetic markers to tailor immunosuppressive therapies for individual patients.	Genomic data analysis tools, Machine learning models for genetic compatibility assessment
Operational Efficiency [31,32]	Optimizes logistical aspects, including scheduling surgeries and managing inventory.	Streamlines workflows and improves resource utilization.	AI systems forecasting organ demand and optimizing surgery schedules to minimize cold ischemia time.	Predictive analytics platforms, Inventory management systems using ML, Scheduling optimization algorithms

Table 2
Applications of AI and ML in image analysis and surgical planning for organ transplantation.

Aspect	Description	Benefits	Examples	Type of AI Tools and Models
Automated Organ Segmentation [51]	AI algorithms segment organs from imaging data such as CT and 18F FDG PET images.	Improves accuracy and speed of organ identification and assessment.	AI systems segmenting liver from surrounding tissues to assess suitability for transplantation.	Convolutional Neural Networks (CNNs), Image segmentation algorithms
Anatomical Feature Identification [52]	AI models identify and annotate critical anatomical structures within medical images.	Enhances surgical planning and precision.	Identification of blood vessels, nerves, and tumors in pre-operative imaging for detailed surgical mapping.	Image recognition models, Deep learning algorithms
Predictive Surgical Outcomes [53]	ML models analyze pre-operative data to predict surgical outcomes and complications.	Informs surgical decision-making and risk management.	Predictive analytics for assessing risks of organ rejection or complications based on patient-specific factors.	Predictive modeling tools, Statistical analysis software
Personalized Surgical Planning [43]	AI creates detailed and personalized surgical plans based on patient data.	Increases the precision and effectiveness of surgical interventions.	Customizing surgical approaches in kidney transplants based on anatomical variations and pre-existing conditions.	Personalized medicine platforms, AI-driven surgical planning software
Real-Time Surgical Navigation [47]	AI-driven systems provide real-time guidance during surgeries using augmented reality.	Enhances intraoperative accuracy and reduces the risk of errors.	Augmented reality overlays of critical structures during liver transplantation to guide surgeons.	Augmented reality (AR) systems, Real-time image processing algorithms
Minimally Invasive Surgery [49]	AI supports the development of minimally invasive surgical techniques through detailed imaging.	Reduces patient recovery time and minimizes post-operative complications.	AI-guided laparoscopic procedures in organ transplantation, improving precision and outcomes.	Robotic surgery platforms, AI-assisted laparoscopic systems
Post-Operative Monitoring [54]	AI analyzes post-operative imaging to monitor organ function and detect complications early.	Ensures timely intervention and better management of post-surgical recovery.	Monitoring graft health and early detection of issues such as thrombosis or rejection using AI analysis of follow-up scans.	AI-based monitoring systems, Post-operative imaging analysis tools
Training and Simulation [55]	AI-driven simulations and training programs for surgeons using real patient data.	Improves surgical skills and prepares surgeons for complex procedures.	Virtual reality simulations for transplant surgeons to practice intricate surgical techniques.	Virtual reality (VR) training platforms, AI simulation tools
Interoperability and Data Integration [56]	Integration of AI tools with existing hospital IT systems and imaging devices.	Streamlines workflow and ensures seamless data sharing and usage.	AI platforms integrated with hospital EHRs and imaging systems for comprehensive patient data analysis.	Interoperability software, Data integration tools using AI

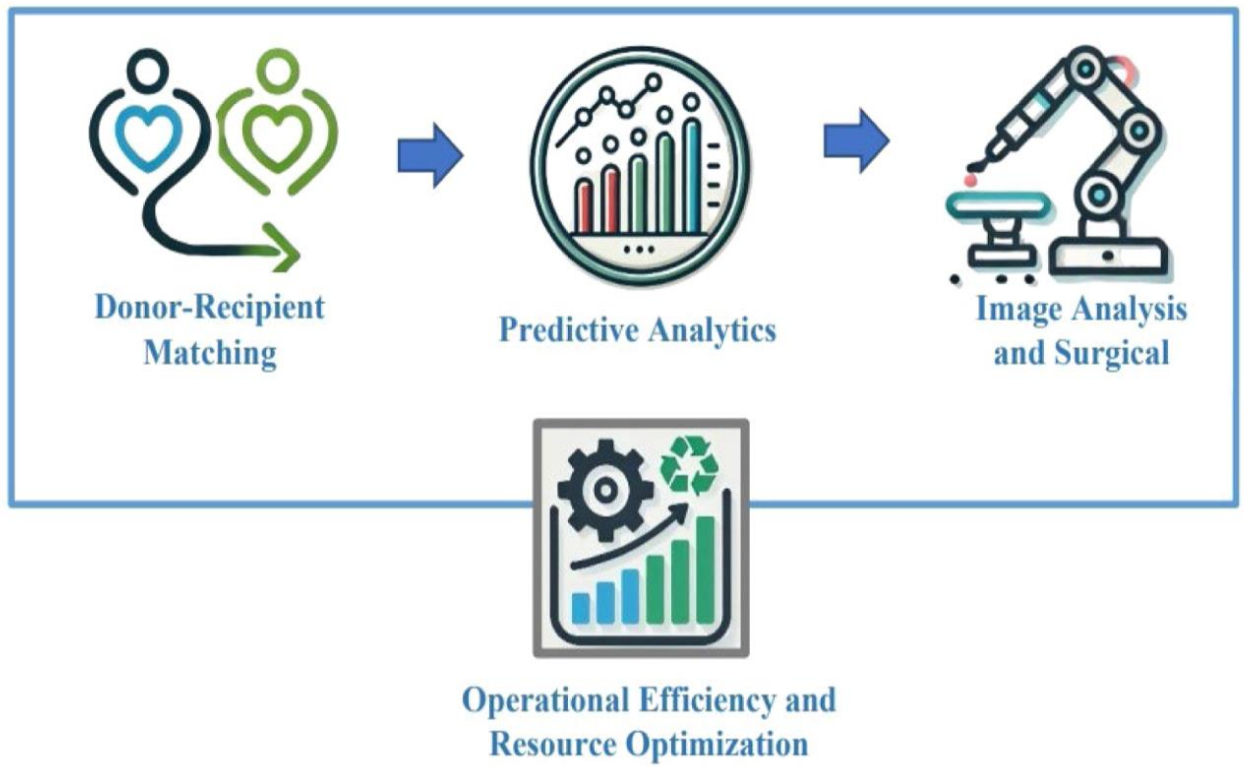

Fig. 2. Applications of AI and ML in organ transplantation.

AI in allocation: simulation and policy implications

- Use cases: prioritizing pairs with **lower predicted risk**, balancing **equity** and utility.
- Important caution: ensure models **do not introduce biases against certain groups**

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https://doi.org/10.1007/s40472-021-00336-z

EXPANDING ROLE OF TECHNOLOGY IN ORGAN TRANSPLANT (D AXELROD AND J SCALEA, SECTION EDITORS)

Technology-Enabled Care and Artificial Intelligence in Kidney Transplantation

Issac R. Schwantes[1] · David A. Axelrod[2]

Accepted: 30 June 2021 / Published online: 28 July 2021

AI-guided immunosuppression optimization

- **Personalize induction**, **maintenance** regimens, and **trough level** targets
- Approaches:
  - **Predictive risk modeling** to calibrate intensity
  - **Reinforcement learning** to propose **dosing trajectories**
  - **Biomarker-driven signals** (e.g., dd-cfDNA, gene expression) guiding de-escalation/escalation
- Outcome signals: **balancing rejection risk** against **infection/toxicity**

Journal of
Clinical Pharmacy and Therapeutics

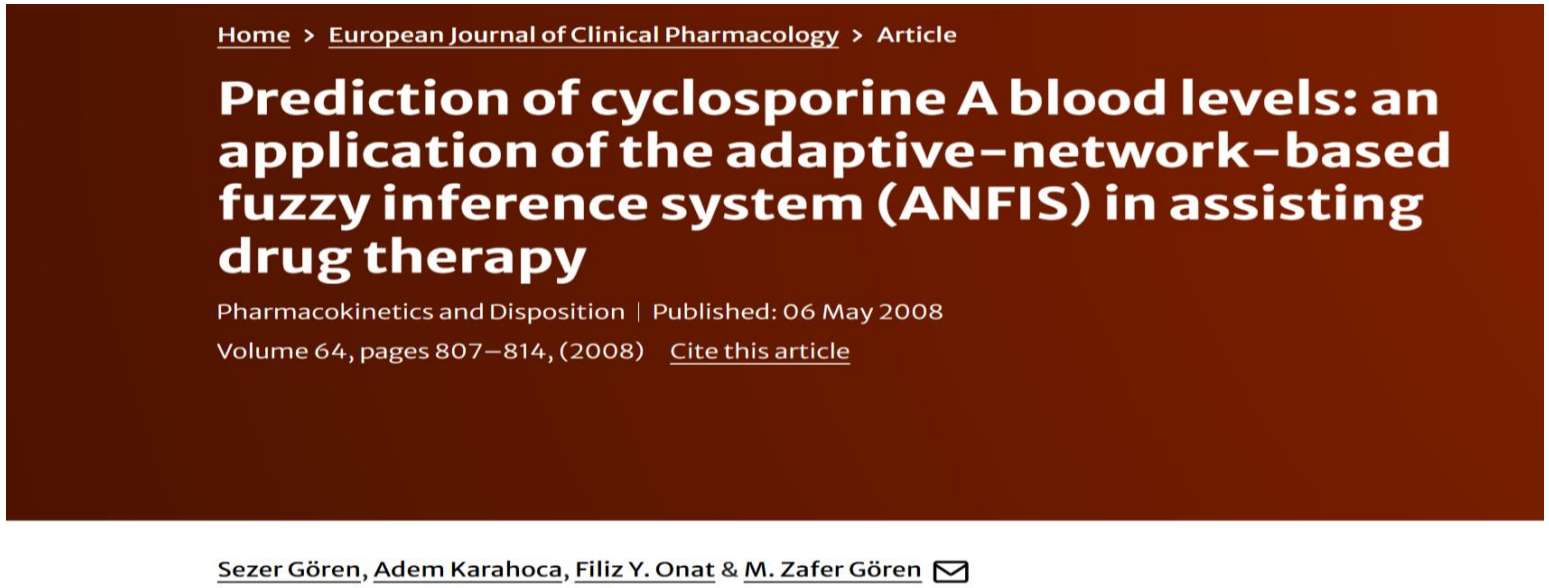
ORIGINAL ARTICLE

A novel random forest integrative approach based on endogenous CYP3A4 phenotype for predicting tacrolimus concentrations and dosages in Chinese renal transplant patients

Ningfang Cai MD, Xiujin Zhang BSc, Chao Zheng MD, Lijun Zhu BSc, Minfeng Zhu MD, Zeneng Cheng PhD, Xi Luo PhD

J Clin Pharm Ter.2020 Apr;45(2):318-323.

- Cai et al. evaluated the association between **Tacrolimus concentrations** and endogenous **CYP3A4 phenotype**, **CYP3A5 genotype** and clinical variables in **182 KT recipients** using **RF algorithms**.
- The results suggested that the endogenous CYP3A4 phenotype was the **most important biomarker for predicting Tacrolimus concentrations and dose requirements**, with the RF models exhibiting high goodness of fit and high predictability.



- They developed their model using data from **138 KT patients** and **20 input parameters**, concluding that it can serve as a **decision support system** to **assist physicians** in determining the optimal therapeutic drug dose in clinical settings.

Clinical Pharmacology & Therapeutics

Article

Mycophenolic Acid Exposure Prediction Using Machine Learning

Jean-Baptiste Woillard ✉, Marc Labriffe, Jean Debord, Pierre Marquet

First published: 24 February 2021 | https://doi.org/10.1002/cpt.2216 | Citations: 40

- Their model was trained on 12,877 **MPA AUC values from 0 to 12 h** requests, collected from **6884** transplant patients.
- They developed **two ML models** based on **two or three concentrations of MPA** measured at least at three sampling times (**20 min, 1 and 3 h after** dosing).

- Their **ML models** performed **better** than maximum a posteriori (MAP) **Bayesian** estimation in four independent full pharmacokinetic datasets, leading the authors to conclude that they can be used for routine **exposure estimation** and **dose adjustment.**

- : https://cistem.wustl.edu

An interactive tool, the **CISTEM Immunosuppression Complication Risk Rejection Tool**, has been made available online for **predicting complications based on immunosuppression**, utilising **data from both donors and recipients.**

Multi-modal integration: combining imaging, histology, and molecular data

- Rationale: single data streams may miss signals; integration yields robust risk stratification
- Typical gains: improved early rejection detection and graft function prediction
- Biomarkers: **dd-cfDNA**, **RNA-based signatures**, **integrated Banff features**

Dynamic prediction of renal survival among deeply phenotyped kidney transplant recipients using artificial intelligence: an observational, international, multicohort study

Marc Raynaud, Olivier Aubert*, Gillian Divard, Peter P Reese, Nassim Kamar, Daniel Yoo, Chen-Shan Chin, Élodie Bailly, Matthias Buchler, Marc Ladrière, Moglie Le Quintrec, Michel Delahousse, Ivana Juric, Nikolina Basic-Jukic, Marta Crespo, Helio Tedesco Silva Jr, Kamilla Linhares, Maria Cristina Ribeiro de Castro, Gervasio Soler Pujol, Jean-Philippe Empana, Camilo Ulloa, Enver Akalin, Georg Böhmig, Edmund Huang, Mark D Stegall, Andrew J Bentall, Robert A Montgomery, Stanley C Jordan, Rainer Oberbauer, Dorry L Segev, John J Friedewald, Xavier Jouven, Christophe Legendre, Carmen Lefaucheur, Alexandre Loupy*

www.thelancet.com/digital-health Vol 3 December 2021

- In a large international, multicohort study including **13.608** KT recipients, researchers developed **DIPSO**, a **dynamic, integrative system for predicting outcomes.**
- They created deeply **phenotyped cohorts of transplant recipients**, incorporating various data: clinical, histological, **immunologica**l variables and repeated measurements of **eGFR and proteinuri**a to assess long-term allograft survival.
- Their **Bayesian mode**l demonstrated high prediction performance (overall dynamic **AUC 0.857** [95% CI 0.847–0.866]) and was validated on a large scale, making it **a potential tool for decision-making and guiding clinicians in managing KT recipients**.

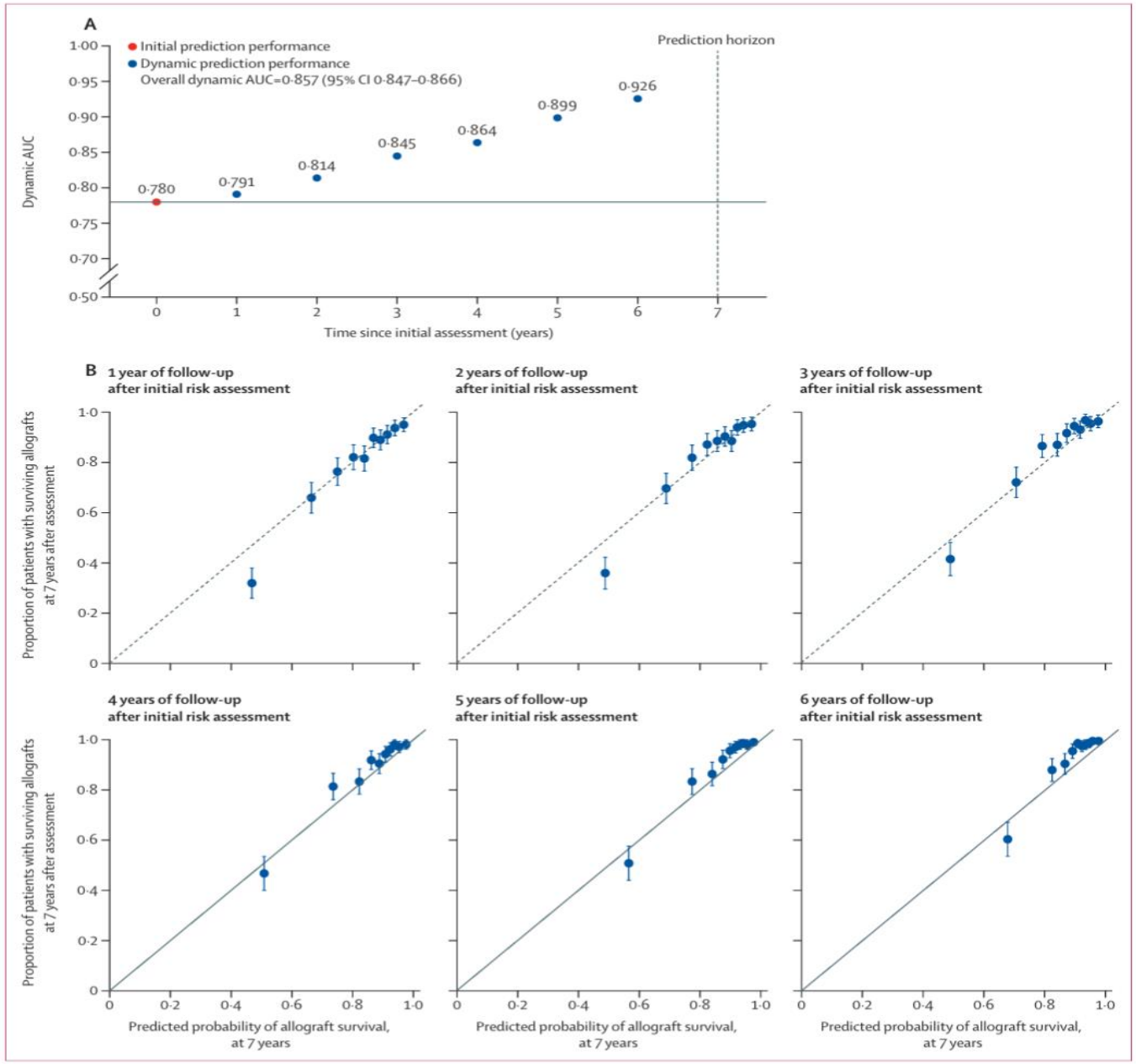


Figure 2: **Performance of DISPO in the development cohort**

(A) Discrimination—ie, ability to separate patients who lose their allografts from those who do not, according to patient follow-up ranging from 1 to 6 years after initial risk assessment, with a prediction horizon at 7 years after initial risk assessment. We calculated the overall dynamic AUC by averaging dynamic AUCs from 1 year

Take-home messages

AI can **augment decision-making** in kidney transplantation across prediction, matching, and immunosuppression

- Success hinges on **data quality**, **robust validation**, and thoughtful integration into care pathways
- **Ethics**, **equity**, and **governance** are essential for responsible deployment

AI for intraoperative applications

- AI can be used not only in various predictive analyses, but also for **high-precision surgical operations**.
- **Robot-assisted kidney transplantation** is a minimally invasive approach to kidney transplantation, and has already achieved good therapeutic results.

- Currently, AI shows great potential in preoperative care, diagnosis, risk prediction, and **surgical optimization**.
- To date, more than **680 robotic-assisted kidney transplants** have been performed in Europe, and **21/27 transplants after living kidney** donation in **Germany** have been performed in the form of **RAKT.**

- From 2011 to 2023, 2,716 donor nephrectomies were performed, of which 1,872 (69%) were performed retroperitoneally using a laparoscopic system, **209 were performed using the da Vinci Xi system robot (8%)**, and the remaining 635 (23%) were *via* a standard open approach.
- The **robotic donor nephrectomy technique** gave **better donor outcomes** compared to endoscopic surgery.

AI and postoperative management (integrated management)

- Currently, the **DRSA-U-Net denoising algorithm developed by Hang Liu et al.** has a high clinical application value by **processing MRI images** of kidneys, ureters and their surrounding tissues, which can significantly improve the clarity of the images in order to help doctors more accurately **assess the occurrence of complications after kidney transplantation.**

Hindawi
Contrast Media & Molecular Imaging
Volume 2022, Article ID 8930584, 7 pages
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WILEY | Hindawi

Research Article

Artificial Intelligence Algorithm-Based MRI in the Diagnosis of Complications after Renal Transplantation

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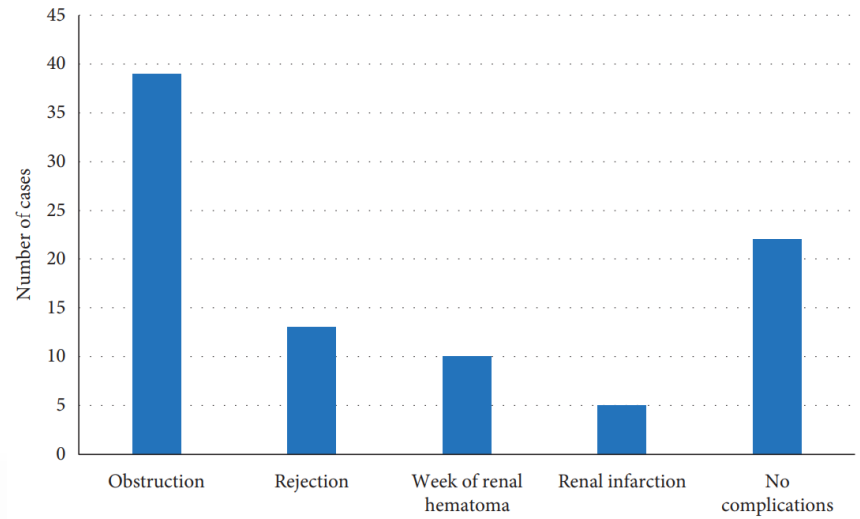

Figure 5: Examination results of 89 patients.

- Many researchers began to use **portable devices** to collect **physiological data** from patients at home and transmit these data **electronically to clinician**s, thus enabling **remote patient monitoring** (RPM).

- In addition, with the popularity of **mobile drug monitoring apps,** studies have shown that these apps can significantly reduce the **volatility of immunosuppressive drugs such as tacrolimus** in patients, **especially in the first year** of postoperative drug concentration variability, with remarkable clinical results.

- The **application** of this technology not only helps clinicians to better **monitor patients' drug responses**, but also **improves the precision** of treatment, thereby effectively **reducing the incidence of post-transplant rejection** and **improving patients' long-term prognosis**.

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- An **international prospective trial** initiated by **Philip F Halloran** et al. the **Trifecta study**, explored the application of machine learning at the **genetic level**, particularly in the **molecular diagnosis of renal transplant rejection** [34].
- By analyzing the **relationship between dd-cfDNA levels** and **gene expression** in renal transplant recipients **prior to biopsy**, the study demonstrated through **multivariate randomized forests** and logistic regression that **molecular rejection variables are better predictors of dd-cfDNA (%) than histological variables**, and that there is a potential to **reduce unnecessary biopsies**.

- **Big data approaches** are considered important tools for **profiling immune responses** during kidney transplantation.
- **Konrad Buscher** et al. developed a new method based on **gene expression profiling, KID9plus3,** which is a kidney-specific analysis tool based on gene deconvolution that successfully identifies **molecular signatures of renal health states** and **immune responses**, and in further analyses, the investigators applied the **PRESTO tool** to analyze gene co-regulatory networks in transplanted samples, **identifying seven different immune phenotypes** that **cover different functional states from kidney graft stabilization** to **rejection** and **fibrosis,** and can provide **more sensitive prognostic information than traditional histological diagnosis**.

- In particular, in the **graft survival analysis**, using the **KID9plus3** and **PRESTO** methods, **phenotype D** (stable) was found to be associated with better graft survival, whereas **phenotypes A and E** (representing different types of immune responses) showed **poorer graft survival**.
- In addition, **LOXL2+ macrophages** were identified as a marker of **early graft dysfunction** and **LOXL2 expression was** associated with **post-transplant fibrosis**.
- **Immune surveillance** after renal transplantation provides important **molecular tools and reveals cellular and genetic signatures** associated with **graft survival**, potentially helping the clinic to achieve a more accurate **assessment of immune tolerance** and personalized treatment.

Virtual Biopsy

- The study by Yoo et al. introduced a novel machine learning-based virtual biopsy system aimed at **predicting histological lesions** in kidney transplant recipients by utilizing routinely available donor characteristics.

- A comprehensive analysis was performed on **14,032 protocol biopsies** collected from **17 international centers**, with a focus on the following four key types of renal injury:
- **arteriosclerosis**, **arteriolar hyalinosis**, **interstitial fibrosis**, and **tubular atrophy.**

- In one study, deep learning algorithms were applied to analyse whole-slide images from **2431 kidneys**, allowing for the automated recognition of key renal compartments, such as glomeruli, arteries, and tubules, with a high degree of **accuracy(90–96%).**

- The model extracted abnormality features like **glomerulosclerosis**, **arterial intimal fibrosis**, and **interstitial abnormalities**, correlating them with pathologists' scores and **post-transplant outcomes**, including graft loss and renal function.
- This led to the development of a **Kidney Donor Quality Score (KDQS)**, which improved graft survival prediction and could **potentially reduce unnecessary organ discard.**

- Their **accessibility** and **practicality** for use in predictive modeling.

- **Overfitting** is especially prevalent in complex models with a high number of parameters, where the **risk of encoding irrelevant information** is substantially increased.

- Another major limitation stems from the **reliance on retrospective data,** which is often sourced from **single institutions or homogenous patient** populations.

- This can introduce **selection bias**, as the data may not adequately represent the heterogeneity of the broader population, thereby limiting the model's generalizability.

- This **lack of transparency** can impede **clinical acceptance**, as healthcare professionals **require clear**, **interpretable rationales** for predictions in order to make informed decisions.

- Furthermore, the **inability to interpret** model decisions **complicates the identification of biases or errors** in the predictions, which can undermine the model's clinical credibility and reliability.

- **Ethical concerns**, particularly related to bias in training data, further exacerbate these limitations.

- If the datasets used **to train ML models** are not **representative of diverse populations,** the resulting models may perpetuate or even exacerbate existing healthcare disparities.

Conclusions

- In conclusion, the integration of AI technologies in kidney transplantation presents a promising avenue **for enhancing patient outcomes** through **improved predictive modelling** and **personalized treatment strategies**.

- As we demonstrated, AI may be an effective tool in **predicting the graft** survival, **immunosuppressive agent dosage estimation**, **virtual biopsy**, or **donor–recipient pairing**.

- .

- Yet, we hypothesize that **numerous unknown variables** and **their hidden interactions**, which may be exceptionally challenging to detect using traditional methods, can significantly **influence the predictions and treatment** outcomes in patients following kidney transplantation. .

- In the future, AI has the potential to **empower researchers** to identify and **comprehensively investigate these factors** and their **interactions.**

- However, addressing challenges such as **data quality**, **algorithmic bias**, and the **need for model interpretability** is crucial for the successful implementation of these advanced tools in clinical practice.

- . Continued research and **collaboration among clinicians** and **associate professionals** will be essential to fully realize the benefits of AI in this field.